

To the Graduate Council:

I am submitting herewith a dissertation written by Sewoong Kim entitled “Intelligent Fault Tolerant Control for Telerobotic System in Operational Space.” I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Engineering Science.

William R. Hamel
Major Professor

We have read this dissertation
and recommend its acceptance:

G.V. Smith

Reid L. Kress

J. Wesley Hines

Lynne E. Parker

Accepted for the Council:

A n n e M a y h e w
Vice Provost and Dean of
Graduate Studies

(Original signatures are on file with official student records.)

Intelligent Fault Tolerant Control for Telerobotic System in Operational Space

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Sewoong Kim

December 2002

Copyright ©, 2002 by Sewoong Kim

All rights reserved.

To my family

Acknowledgments

I would like to thank my supervisor Dr. Hamel for his encouragement and support. He gave me a chance to study telerobotics and has guided me in this work. The fact that this dissertation is interested in the operational space is due to Dr. Hamel, and this dissertation could not be finished without his experience, knowledge and patience. I would like to thank my advisors Dr. Smith, Dr. Parker, Dr. Hines, and Dr. Kress for their advices, guidance, and discussions. Their advice and discussions enlightened me to the points and areas I missed. I would also like to thank Dr. Douglass, Dr. Lumsdaine, and Mr. Mark Noakes for their experience and enthusiasm in the research of Remote Task Space Analysis (RTSA), Human Machine Cooperative Telerobot (HMCT), and Transmission Based Actuator (TBA) projects.

I would like to thanks Ge Zhang for his friendship and cooperation in the RTSA and HMCT projects, and Larry Carvagno for proof reading of this dissertation. I also wish to thank all the students that have worked together in the RTSA, HMCT, and TBA projects: Sriram Sridharan, Kalyana Ganti, Renbin Zhou, Karthi Perumal, and Kelley P. Brown.

This research is impossible without the researches: RTSA and HMCT supported by the Department of Energy Grant.

Abstract

Telerobotic systems combine conventional teleoperation with industrial automation techniques, such as control, vision, planning, etc, to improve work efficiency, and have been expanding their applications from hazardous and remote areas to unstructured industrial uses. Unstructured environments and uncertainties in task space require human-in-the loop control to ensure and supervise safe operation since present autonomous capabilities cannot handle the vast range of tasks and uncertainties. The inherent characteristics of telerobotic systems make operational faults more likely, and require autonomous fault detection, isolation (FDI) and recovery abilities since the nature of task space makes it difficult for human operators to detect and recover from faults in a timely manner.

This dissertation addresses the issues of developing operational fault detection, isolation, and recovery strategies, and combines the developed methodologies with overall telerobotic system design. First, the framework for FDI and the associated supervisory control scheme are proposed to effectively integrate the FDI approaches into telerobotic systems. Secondly, for the generalization of the proposed FDI methodologies, the characteristics of operational faults and the relevant sensor signals are classified, and then typical operational faults, which can represent the other operational faults and telerobotic systems, are selected using classification and appropriate criteria. Next, the fault detection

methodologies for the selected operational faults are proposed considering the characteristics of the sensory data. In this way, the proposed methodologies are generalized for operational FDI of telerobotic systems. The proposed methodologies are tested with an experimental telerobotic system or a computer simulation, and test results demonstrate the methodologies are feasible.

Contents

Chapter 1	Introduction	1
1.1	Telerobotic systems.....	1
1.2	Operational faults in telerobotic systems	5
1.3	Generalization of FDI strategies	7
1.4	Contributions	11
1.5	Dissertation structure	12
Chapter 2	Background	13
2.1	FDI algorithms.....	13
2.1.1	Model-based approach.....	15
2.1.2	Knowledge-based approach.....	16
2.2	Artificial intelligence	17
2.3	Neural networks.....	18
2.4	Fuzzy logic.....	24
2.5	Wavelet Analysis.....	28
2.6	Operational fault detection in industrial applications	32
Chapter 3	Experimental Telerobotic System.....	39
3.1	System description.....	39
3.2	Experimental test procedures	41

3.3	Hardware specifications.....	43
3.3.1	Manipulator.....	43
3.3.2	RTSA sensor head.....	43
3.3.3	Band saw.....	48
3.3.4	Acoustic noise acquisition	48
Chapter 4	Framework and Supervisory Control.....	51
4.1	Introduction.....	51
4.2	Framework for generalized FDI	52
4.3	Supervisory control system.....	58
4.4	Summary.....	61
Chapter 5	Operational Fault Detection Strategies.....	63
5.1	Power spectrum analysis of acoustic data.....	64
5.1.1	Extraction of the signatures in the spectrum of the cutting noise	71
5.1.2	Analysis	86
5.2	Time based monitoring of end-effector position data	86
5.2.1	Time based monitoring of the ac components	95
5.2.2	Time based monitoring using wavelets.....	103
5.2.3	Analysis	107
5.3	Tool grasping fault detection using neural networks	112
5.3.1	Control system of the two link manipulator	115
5.3.2	Development of NN with present data	116
5.3.3	Development of NN with time delay data	126

5.4	Summary.....	130
Chapter 6	Fault Recovery Strategies	131
6.1	Introduction.....	131
6.2	Contact force control using fuzzy logic	133
6.2.1	Computer assistance functions.....	133
6.2.2	Control strategy	137
6.2.3	Contact force and task environment modeling	138
6.2.4	Fuzzy logic controller design.....	140
6.2.5	Results.....	143
6.3	Summary.....	148
Chapter 7	Implementation Issues.....	149
7.1	Related control system issues	149
7.2	FDI implementation issues	152
Chapter 8	Summary	154
8.1	Overall conclusions.....	154
8.2	Future research.....	155
Bibliography		159
Appendix		179
	Appendix A: Simulink Model of Two Link Manipulator	180
	Appendix B: Simulink Program for Signal Analysis.....	187
	Appendix C: Simulink Program for Load Estimator using Neural Network	190
	Appendix D: Simulink Program for Fault Recovery using Fuzzy Logic	192

Vita.....	194
------------------	------------

List of Tables

Table 1.1	Classification of operational faults in telerobotic systems.	7
Table 1.2	Frequency characteristics of sensory data.	9
Table 5.1	Selected system noise of the manipulator and tool (band saw).	71
Table 6.1	Some of the fuzzy rules for the moving pattern.	143

List of Figures

Figure 1.1	Elements of a telerobot.	3
Figure 1.2	Mapping between joint space and Cartesian space.	4
Figure 2.1	Structure of a neuron.	20
Figure 2.2	Structure of artificial neural network.	21
Figure 2.3	Activation functions.	22
Figure 2.4	Fuzzy inference process.	26
Figure 2.5	Examples of wavelet functions and scaling functions.	29
Figure 2.6	Example of three level wavelet decomposition tree.	31
Figure 2.7	Examples of sensor location.	35
Figure 2.8	Location of sensors for the Titan 3 manipulator.	37
Figure 3.1	Configuration of experimental telerobotic system.	40
Figure 3.2	Task sequence of sawing operation in autonomous mode.	42
Figure 3.3	Schilling Titan II manipulator.	44
Figure 3.4	Mockup for experimental test.	45
Figure 3.5	Hydraulic power unit.	46
Figure 3.6	Stereo camera sensor head.	47
Figure 3.7	Milwaukee band saw.	49
Figure 3.8	Camcorder for recording of acoustic noise.	50

Figure 4.1	Data flow diagram of telerobot system.	55
Figure 4.2	Framework of the FDI system for operational fault.	57
Figure 5.1	Power spectrum of acoustic data for the manipulator.	65
Figure 5.2	Power spectrum of acoustic data for the manipulator and band saw.	66
Figure 5.3	Series of power spectra of acoustic data during the pipe cutting.	68
Figure 5.4	Selected noise components of the manipulator and band saw.	72
Figure 5.5	PSD of pipe cutting noise after the system noise is cancelled.	74
Figure 5.6	PSD of pipe cutting noise (with soft blade) after the system noise is cancelled.	81
Figure 5.7	Position data of end-effector during the pipe cutting task.	89
Figure 5.8	Power spectrum density of position data (z-axis) during oscillation.	90
Figure 5.9	Pipe cutting task and definition of the x - y - z coordinate frame.	91
Figure 5.10	Position data of end-effector during the pipe cutting (Test1).	92
Figure 5.11	Position data of end-effector during the pipe cutting (Test 2).	93
Figure 5.12	Position data of end-effector during the pipe cutting (Test 3).	94
Figure 5.13	Mean and slope of the position data.	96
Figure 5.14	Comparison of the dc component removal methods.	97
Figure 5.15	Subtraction of the linear slope when the signal changes abruptly.	99
Figure 5.16	AC component of the position by the subtraction of the slope (Test 1).	100
Figure 5.17	AC component of the position by the subtraction of the slope (Test 2).	101

Figure 5.18 AC component of the position by the subtraction of the slope (Test 3).	102
Figure 5.19 DWT of the position data of the end-effector during the cutting (Test 1).	104
Figure 5.20 DWT of the position data of the end-effector during the cutting (Test 2).	105
Figure 5.21 DWT of the position data of the end-effector during the cutting (Test 3).	106
Figure 5.22 Comparison of the results.	108
Figure 5.23 Joint space PD control scheme in Simulink.	116
Figure 5.24 Neural network used in the development with present data.	118
Figure 5.25 Training result of the NN.	120
Figure 5.26 Position data of the joint 1 and 2.	121
Figure 5.27 Test results of the NN with 5 kg load.	122
Figure 5.28 Test results of the with 10 kg load.	123
Figure 5.29 Response time of the neural network.	124
Figure 5.30 Generalization test of the NN.	125
Figure 5.31 Time delay neural network.	127
Figure 5.32 Training result of the time delayed neural network.	128
Figure 5.33 Test results of time delay NN including generalization test.	129
Figure 6.1 Human machine cooperative telerobot control scheme.	135
Figure 6.2 Force assistance scheme for the HMCT.	137

Figure 6.3	Simulation block diagram.	138
Figure 6.4	Mass-spring model for contact force.	139
Figure 6.5	Definition of the displacement of x and y displacement,.....	139
Figure 6.6	Planned trajectories and actual environment.	141
Figure 6.7	Membership functions.	144
Figure 6.8	Simulation results without the force assistance function.	146
Figure 6.9	Simulation results with the force assistance function.	147
Figure 7.1	Finite state machine and mode selection blocks.	150
Figure 7.2	High level controller.	151
Figure A.1	Two-link planar manipulator.	181
Figure A.2	Top level of the Simulink program.....	181
Figure A.3	Two link manipulator Simulink block.....	182
Figure A.4	Simulink block for F_v	182
Figure A.5	Simulink block for Inverse $B(q)$	183
Figure A.6	Simulink block for $C(d, dq)$	183
Figure A.7	Simulink block for $g(q)$	184
Figure A.8	Simulink block for Transpose of Jacobian.	184
Figure A.9	Simulink block for parameters of two link manipulator.....	185
Figure A.10	Simunlink block for the parameters (subsystem).	186
Figure A.11	Simunlink block for the parameters (subsystem1).	186
Figure B.1	Simulink block for PSD analysis of acoustic noise data.	187
Figure B.2	Simulink block for detrend analysis of position data.	188

Figure B.3 Simulink block for detrend analysis (subsystem1: Detrend for position).	
.....	188
Figure B.4 Simulink block for DWT analysis of position data.	189
Figure B.5 Simulink block for DWT analysis (subsystem1: DWT for position). ...	189
Figure C.1 Simulink block for neural network load estimator.	190
Figure C.2 Simulink block for load change.....	191
Figure C.3 Simulink block for time delay data.	191
Figure D.1 Simulink block for the fuzzy force limiter.	192
Figure D.2 Simulink block for the pre-process.	193

Chapter 1

Introduction

1.1 Telerobotic systems

Since the first modern teleoperation (which is remote manipulation through direct and continuous control by a human operator using a master-slave system and sensory feedback) was developed around 1940, its application areas have been extended from atomic physics to other hazardous or remote areas such as underwater, space, surgery, and nuclear power plants. More recently, there is an effort to develop a system for industrial environments in which the industrial robots are impractical, such as industrial repair environments [1, 2, 3]. However, the poor work efficiency of teleoperation, which is ten to hundreds of times slower compared to direct contact operation by humans, restricts its application domain to hazardous, remote, or highly unstructured areas such as the aforementioned areas. The unstructured and uncertain properties in teleoperation make the full automation of the teleoperation process impossible or impractical with the present state of technology. Hence, instead of full automation, much research has focused on efficiency improvement in the subtasks and subcomponents by integrating industrial automation technologies, such as control, planning, vision, sensing, and 3D modeling. This is a relative new emerging

research area known as telerobotics, and recently the need for this research has rapidly increased [3~11].

Figure 1.1 shows a typical configuration of telerobotic systems. In the teleoperation mode, a human operator controls the remote manipulator directly and continuously. In the autonomous mode, tasks are implemented automatically by the controller after the human operator makes decisions and builds a task plan. The dedicated human-machine interfaces are embedded, and human-in-the-loop control ensures and supervises safe operation in the autonomous mode. However, the unstructured and uncertain properties make human operator cannot recognize and respond to some faults effectively not only in the autonomous mode, but also in the teleoperation mode. Thus, the fault tolerant control system becomes essential in telerobotics to improve system reliability. In this dissertation, a fault means undesired system state which can be recoverable with degraded performance at least, and a failure means a manifestation of the fault and it is not usually recoverable. The fault tolerant control not only means fault detection, isolation and identification, but also includes fault recovery, which makes it possible for the system to continue with degraded task execution [12, 13].

A manipulator's position and orientation are represented in joint space or Cartesian space, and the representation in a space can be mapped to the other space using the kinematics and inverse kinematics as shown in Figure 1.2. Joint space is referred to as the space that is described by joint variables and entire set of joint variables. Cartesian space is the space where each position and orientation of the end-effector is given with three numbers and entire set of the six variables. Sometimes the terms task space and

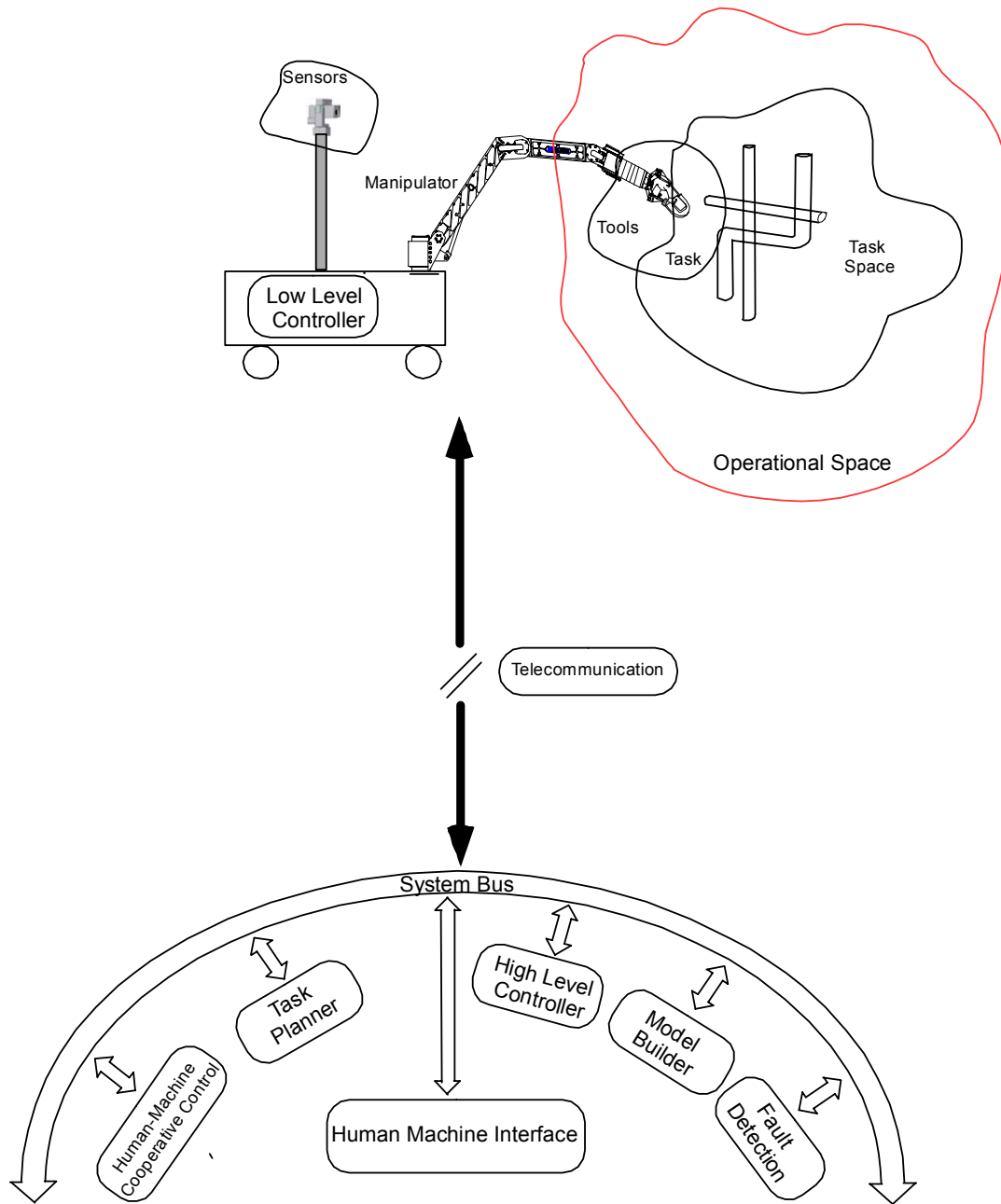


Figure 1.1 Elements of a telerobot.

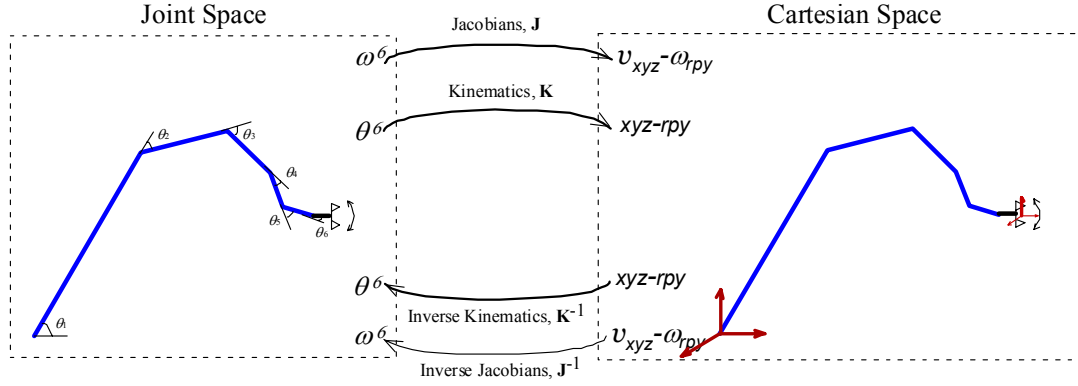


Figure 1.2 Mapping between joint space and Cartesian space.

operational space is used for Cartesian space. Also, workspace is usually defined as the space where the manipulator can reach in the task space [135, 136]. In telerobotics, since in general the system has mobility, workspace is the reachable space of manipulator(s) for a given mobile platform position, and task space is task environment within the current workspace [4]. Operational space as used in this dissertation is the operational space of a telerobotic system, which includes manipulators, tools, sensors, task space of manipulators, and task/subtask execution.

The operational state space is particularly driven by the uncertainties in the task space and the anomalies during the task execution. This dissertation uses the term internal system space to refer to the manipulator, system computer, software, other hardware, and communications. The faults and failures in the internal system space are any malfunctions in the subset, such as joint failure of the manipulator, severe line noise, computation error, etc. The faults in the operational space are those associated with task execution and the performance of tools, sensors, manipulators, etc. Unlike the internal system faults,

operational faults can occur without hardware and software failures in the internal space. Typical operational faults are tooling malfunctions such as jamming of saw blades, misalignment of wrench, and dropping of tools. An unexpected manipulator collision with the environment and mistakes by the human operator in the teleoperation mode are also operational faults, and the faults in the internal system space can cause the faults in the operational space. For example, faults in the actuator of the gripper lead to tool grasp errors [4, 16, 17].

1.2 Operational faults in telerobotic systems

Industrial automation and robotics have made high demands on the improvement of system reliability and safety, and fault tolerant control opens new dimensions for such improvements. Fault tolerant control plays a key role in intelligent robotics since it is required for effective fault detection and isolation (FDI), and fault recovery for continuous task execution with minimal human intervention [14, 15]. In the case of industrial robots, the workspace is limited and pre-designed for a specific manufacturing process, and consequently anomalous task executions do not occur often. So, operational faults in industrial robotics occur rarely, and even when they happen, they can be readily addressed by human technicians since the operational space is accessible in general. Thus, most FDI studies for industrial robotics have been interested in the faults in the internal system space, such as joint drive malfunctions, to reliability. In the case of telerobots, operational faults are more practical problems than the faults in the internal system space since the uncertainties and diversities in the operational space make such faults more probable.

Further, the remote and hazardous task space of telerobots makes it more difficult to detect and recover from operational faults effectively.

One of the general behaviors of the operational faults is that the small oscillations of tool and manipulator can be amplified by task environmental conditions and manifest themselves as operational faults. The severe tool/manipulator oscillations not only deteriorates work quality, but also may lead to operational faults, such as tool breakage, jamming, and dropping of the tool. Also, the various workpiece materials in the task space increase the possibility of the operational faults since it is often difficult to correctly recognize material properties/characteristics that effect tooling processes. For example, in sawing operations, the errors in the recognition of workpiece material can result in attempting to cut with a blade that is inherently too soft. The limited number and types of sensors are general limitations in the development of fast and reliable FDI systems. Also, communication time delay is a major potential obstacle for real-time FDI when the mobile telerobot is located far from the human operator and high level controller.

In this dissertation, operational faults are classified based on the features of the tasks and subspace, where the faults occur, as shown in Table 1.1. The operational space is divided into: (1) manipulator & sensor space (external sensors like cameras), (2) tool space, and (3) environment space or task space. The operational faults in the manipulator & sensor space include incorrect position and orientation of the external sensors and the grasped tools, and the relevant FDI sensory data are force, position, etc. The tool space is separated into two spaces associated with tool and environment interactions. Examples of faults, relevant data, and typical recoveries in each space are listed in Table 1.1.

Table 1.1 Classification of operational faults in telerobotic systems.

Space			Examples of Faults	Related Data	Recovery
Internal space			joint failure, line noise	joint torque, angular speed, and position	Redundant control
Op. space	Manipulator & Sensor		improper gripping of tool (dropping, misorientation)	gripper torque/force, gripper position	Regrasp
	Tool	non-env. contact	water jet, plasma torch / clogged supply line, leak	input power, tool speed, pressure, acoustic noise	Replacement
		env. contact	band saw, drill / tool breakage, jamming, worn away, oscillation	input power, tool speed, acoustic noise, contact force	replacement, force control
	Environment		collision, deformation	contact force, acoustic noise, temperature,	force control

1.3 Generalization of FDI strategies

For the generalization of the proposed FDI methodologies, this dissertation selects typical operational faults considering the subspaces of operational space, characteristics of relevant sensory data, general behaviors of operational faults, limitations of telerobotic systems, and common features of operational fault. These criteria for the selection of operational faults make the selected operational faults represent general telerobotic systems, and help the proposed methodologies to broaden the range of operational faults which can be dealt with.

For the selection of representative operational faults, firstly, the typical operational

faults in each subspaces of the operational space are considered and selected. In this dissertation, the operational space is divided into four subspaces as shown in Table 1.1, and the selected typical faults in each space are: (1) the dropping and misorientation of a wear tool in the manipulator & sensor space, (2) hardware (tool) failure, oscillation, and worn away in the tool space, (3) collision, deformation of environment in the environment space. Secondly, the characteristics of the sensory data, which relate to the selected operational faults in the first stage, are considered. Some of the selected operational faults in the first stage relate to same sensory data as shown in Table 1.1, and one of them can represent the others. For example, the hardware failure, jamming, and wear effects relate to same sensory data: tool input power. If a FDI system uses tool input power to deal with the hardware failure, the approach can be used to detect the jamming or wear of a tool. Also, the consideration of the signal characteristics narrows down the selection of operational faults. For the characterization of the sensor signals, this dissertation categorizes the sensor signals into two domains based on the periodicity of signals: (1) non-periodic signal, (2) periodic signal, and each domain is divided into low sampling frequency and high sampling frequency as shown in Table 1.2. The classification of signals shows that the tool input power and acoustic noise of tooling has the same characteristics. This means that the tool input power can represent the acoustic noise or vice versa, and the analysis algorithm applied to the tool input power can be applied to the acoustic noise. Thus, the selection of the signals, which can represent the broad range of operational faults and relevant signals, must consider other factors, such as performance of FDI system, availability of the sensor, general behavior of operational fault, etc.

Table 1.2 Frequency characteristics of sensory data.

Frequency of Signal	Sampling Frequency	Examples
Non-periodic	Low ^{(1),(2)}	contact force, joint position
	High ⁽³⁾	temperature, acoustic noise(impact)
Periodic	Low	oscillation of tool
	High	Tool input power, tooling acoustic noise

(1) Low sampling frequency is under a few hundred Hz.

(2) The sampling frequency of the sensors inside manipulator is usually less than 500 Hz.

(3) The sampling frequency of the external sensors is usually higher than 1 kHz.

Thirdly, general behaviors of operational faults and limitations of a telerobotic system are considered. As mentioned earlier, a typical behavior of operational fault is that the uncertainty and diversity in the task space manifests itself in the oscillation of the tool and manipulator. This occurs in the transient state, and typical limitations of telerobotic systems have limited number of sensors and restricted sensor locations. The use of tool input power not only needs an additional sensory system for each tool, but also may have problems in the interface with telerobotic systems since the tool can be changed during a mission. The usage of acoustic noise for operational FDI is more preferable than the use of tool input power since most telerobotic systems have camera and microphone to monitor the task space and task execution.

Through the consideration of the criteria, three operational faults are selected as general

operational faults in telerobotic systems: (1) tool drop in the manipulator & sensor space (non-periodic signal), (2) oscillation in the tool space (periodic signal with low sampling frequency, position data), and (3) tool worn away in the tool space (periodic signal with high sampling frequency, acoustic noise). For the development of fault recovery strategy, this research selects force control to limit the contact force since the other recovery strategies in the Table 1.1, such as regrasping of the dropped tool and replacement of damaged part of tool in autonomous mode, is still a long-term challenge. For the recovery strategy of the collision, force control using the fuzzy logic is proposed.

For the analysis of the selected faults and signals, this research considers some general rules to select proper analysis algorithm. Generally, when the signal is periodic and the sampling frequency is higher than twice the Nyquist frequency, the sampled signal can be recovered to the original signal and the analysis of the sampled data in the frequency domain using Discrete Fourier Transform (DFT) provides good information. For example, the analysis of tool input current in the frequency domain can detect not only the faults inside the motor, such as a broken rotor bar, but also the breakage and wornness of teeth of a tool. Also, the signatures in the frequency domain allow the FDI system to isolate the faults. In some applications, the Power Spectral Density (PSD) is used instead of the DFT analysis since the PSD can provide more clear signatures in the frequency domain. This research uses PSD to analyze the acoustic noise to detect tool wear.

When the sampling frequency is lower than twice the Nyquist frequency, DFT analysis of the sampled signal does not provide useful information. Another important feature of DFT is that time information is lost after Fourier transformation and it cannot tell when a

particular event occurred. Thus, when the signal is non-periodic or the sampling frequency is low, the signal is usually analyzed in the time domain, and the traditional method in the time domain is limit value or threshold of the signal checking. The position signal of tool oscillation has not only low sampling frequency, but also non-periodic properties. For the analysis of the oscillation, this dissertation propose Discrete Wavelet Transform (DWT), which can localize information in both time and frequency domain.

In this study, a pipe cutting task using a band saw tool is used as an experimental context for the validation of the proposed approaches. Band saw cutting is a difficult process to control and provides a rich signal environment for FDI.

1.4 Contributions

The most significant contribution of this dissertation to telerobotics is the development of a generalized fault tolerant control framework. This dissertation has developed specific concepts for selected operational faults, which can represent broad range of operational faults, and used a new scheme for operational FDI and fault recovery. First, the concepts of the operational space and operational faults for telerobotics are introduced, and criteria for fault classification and selection as general faults are presented. Secondly, the modular FDI framework and flexible supervisory control system architecture are proposed. Thirdly, use of a neural network for the problem of manipulator load estimation and application of a fuzzy logic to the problem of position command modification are first attempts at telerobotic FDI. Fourthly, the particular use of discrete wavelet transforms for fault detection has a degree of originality.

1.5 Dissertation structure

This dissertation describes the development of a fault tolerant control methodology for telerobotic systems in operational space, that is able to realize and alert the human operator when it cannot achieve task objectives, and to assist the operator in achieving proper recovery strategies. The background of fault detection and isolation (FDI), artificial intelligence (AI), and DWT relevant to this work will be discussed in Chapter 2. Chapter 3 describes the experimental telerobotic system used in this research. The framework of the FDI system and supervisory control scheme for telerobotic system are proposed in Chapter 4, and then the development of the fault detection methodologies for the selected faults are described in Chapter 5. The fault recovery strategy using force control is described in Chapter 6. Chapter 7 concludes with discussion of the contribution of this work and future work.

Chapter 2

Background

The concept, configuration and current research areas of telerobotics are briefly reviewed in the Chapter 1. In this Chapter, the concept and technical approaches of fault tolerant control, fault recovery, and fault tolerant control in the operational space are described, and also the basic theory of artificial neural networks and fuzzy logic, which are used in this dissertation, are reviewed in this Chapter.

2.1 FDI algorithms

Humans have pursued more reliable, safer, and maintenance free systems since the development of automatic devices in early industrialization. The demand for more reliable and safer systems has grown with increasing automation. Ironically, the modern control system, which is designed to make the system insensitive to the variation of parameters and external disturbances, also means that changes in the process cannot be reflected in the outputs. As a result, the control system masks fault symptoms and makes early fault detection very difficult. Also, the development and use of more complicated autonomous systems in the area where human access are limited making the issues become

even more important and critical. Therefore, most modern control system needs a dedicated system, which operates independently and supervises the overall system, for effective fault detection, isolation, and recovery. Such a dedicated system is fault tolerant control and it opens a new dimension for the improvement of system reliability and safety, and also for the extension of maintenance period [18, 13]. The fault tolerant control can play a key role also in the autonomous and intelligent robotics since the intelligent robots are required to have the ability of effective fault detection and recovery to continue the execution of the task or degrade the performance without the need of immediate human intervention. The fault tolerant system includes fault detection, fault isolation, fault identification and fault recovery. According to Gertler [19], the terminology is defined: (1) fault detection is the indication that something is going wrong in the system, (2) fault isolation is the determination of the exact location of the failure, (3) fault identification is the determination of the size of the failure.

The traditional approach for the fault detection is limit value checking of system parameters and outputs. The FDI system monitors the measured system parameters and outputs, and declares a fault state when the signal exceeds a threshold. The main advantages of this method are simplicity and reliability. However, this method works well when the plant operates in the steady-state, and it can react after a relatively large change of the values. Above all, the weakness of the limit value checking is that it cannot provide fault isolation, and the fault signature of the signal must be in the time space. One of the advanced approaches to overcome the weakness of the limit checking is using the spectral signatures of the signals, generated using the Fast Fourier Transform (FFT), emanating

from the machines or tools. In spectrum analysis, the low-level signals are not masked out by the high-level signals, and the analysis of signatures can provide not only detection of the fault, but also isolation of the fault. However, the approach using the FFT is useful when the signals do not change much over time (stationary) since the time information of the signal is lost through the FFT. If the signals have non-stationary characteristics such as drift, abrupt changes, and trends, the FFT is not appropriate to analyze the signals. Recently, wavelet analysis, which can adjust the size of time interval for the analysis, is introduced for the FDI to overcome this deficiency [18, 20~23].

2.1.1 Model-based approach

Most of the recent studies for the FDI are model-based approaches and knowledge-based approaches. The model-based approach known as second generation FDI uses the system qualitative model (analytical model) to generate a residual. The residual is the difference between the estimated system parameters or outputs and the measured values. In ideal situation, the residual is zero during normal operating conditions. When the system operates in abnormal conditions, the residual deviates from zero, and the system is deemed to be in a fault state as the residual transgresses the threshold. Some of the advantages of the model-based approach are: (1) the approach does not need additional sensors since the sensory data used in the FDI approach is already available in the control system, (2) the approach can use the un-measurable system information and parameters if they are observable, (3) the approach not only provides on-line fault detection, but also makes it possible to detect a fault early (predictive) [24~27]. The first requirement of the

analytical model based approach for reliable FDI is an accurate model of the system. However, the uncertainty in the modeling in non-linear plants by the non-linearity of the plant, time varying parameters, and modeling errors make it virtually impossible to build an accurate mathematical model. Also, the noise and disturbances of the system degrade the FDI performance and cause false alarms. This necessitates the development of robust FDI algorithms, which can detect the fault even in the presence of the modeling uncertainties, noise, and disturbances. The robust FDI is important issue in the model-based approach, and most studies for robust FDI combine the analytical model-based techniques with knowledge-based techniques, such as neural networks, fuzzy logic [14, 24, 28~35].

2.1.2 Knowledge-based approach

The knowledge-based techniques utilize human heuristic knowledge and experience including problem solving strategies. For the representation of the human knowledge and implementation of the problem solving ability, many researchers use decision table-based methods, knowledge-based expert system, and fuzzy logic-based systems. Generally, the fault diagnosis using the knowledge-based approaches consists of: (1) a knowledge base which includes knowledge of facts and rules, (2) a data base which includes information about the present state of the process, (3) an inference engine which performs forward or backward reasoning. The advantages of the knowledge-based approach are fast and robust implementation, and the approach does not need analytical modeling of the system. However, the knowledge-based system can lead to false alarms when it is confronted with

novel fault situations for which no specific rules exist [21, 31, 36~38].

The imperfections and disadvantages of the analytical model-based approach and the knowledge-based approach naturally lead to studies to integrate the two approaches or complement each other. The combination of the mathematical model-based approach with the knowledge-based approach in a meaningful way makes a robust FDI system, which can detect a fault accurately even in the presence of the uncertainty in the modeling [34, 39]. For example, in [33], the fuzzy logic is used to improve a residual evaluation by building an adaptive threshold, and compensating the deviation of residual due to the modeling error. The neural network is used in [32, 34] to build a nonlinear estimation model and generates residual to cope with the bounded uncertainties in the robotics. The expert system is combined with analytical model-based method in an effective way by coupling numerical and symbolic information for hydraulic systems [24].

2.2 Artificial intelligence

Intelligence, which is an inherent human ability, enables us to understand concepts and facts such as what and why, and allows us to draw conclusions from implicit facts or relationships with aid of knowledge. Artificial intelligence is a research area seeking to implant the human intelligence into a machine. The application area of artificial intelligence is not only the area where the intelligent ability is required, such as speech recognition and decision making, but also the area where the traditional methodologies based on mathematical modeling and analysis are not appropriate. For example, advanced modern control theories based on mathematical analysis have contributed to the

achievement of high performance and high quality control. However, the plants and processes of the control are limited to linear systems or linearized non-linear systems since an effective and generally applicable control algorithm for non-linear systems has not been developed. Inherently, diversity of the nonlinearity makes it difficult to get a unique general solution, and hence, the conventional approaches cannot be applied to highly non-linear system, which cannot be linearized effectively. Usually, the traditional approaches are not appropriate in the applications, which have following characteristics: 1) non-linearity, 2) uncertainty, 3) complexity, 4) difficulty in measurement [59]. The term “artificial intelligence” has been commonly used since the conference at Dartmouth College in 1956, and it is defined as [60]:

“Computer processes that attempt to emulate the human thought processes that are associated with activities that require the use of intelligence.”

This definition of artificial intelligence restricts to the area such as speech recognition, decision-making, image recognition, game playing, robotics, expert systems and so on. But, usually, artificial intelligence encompasses a number of technologies that includes artificial neural networks (often called neural network), genetic algorithms, fuzzy logic systems, cellular automata, chaotic system, anticipatory systems, and wavelets [61~64].

2.3 Neural networks

Professor Lofti Zadeh proposed the concept “hard computing” for precise computation and “soft computing” for approximate computation. According to this, conventional

algorithms using the mathematical model are classified as hard computing and expert systems are also classified as hard computing since it uses crispy number in the rules. Soft computing includes the fuzzy logic, neural networks, and genetic algorithm. The intelligent ability in soft computing like the inference ability of fuzzy logic and learning ability of neural networks offer methods of implementing real-time control, monitoring, and diagnostics in many applications. Neural networks use the structural characteristics of human brain, and have the most similar structure to human brain among the artificial intelligence technologies. The neurons of human brain, shown in Figure 2.1, are interconnected, and receive and combine signals through the thousand of input paths dendrite. When the combined input signal is strong enough, the neuron is fired and transmits the output signal along the axon. The axon connects to the dendrites of other neurons. Each input signal passes through the synaptic junction in the dendrite, and acceleration or delay of the input signals by the neurotransmitter fluid lead to memory and learning. Like the human brain, a neural network is a collection of interconnected basic processing units called neuron or node as shown in Figure 2.2 (a). In the neurons, all inputs are summed and then passed to the output through the filter called activation function as shown in Figure 2.2 (b). The selection of the activation function depends on the task and learning algorithm of the neural network, and some of the possible activation functions are shown in the Figure 2.3. The linear activation function can be used only when the linear mapping capability of neural network is required since the neural network loses the nonlinearity and cannot model nonlinear phenomena with the linear activation function. The output of a neuron is connected to the inputs of the other neurons with

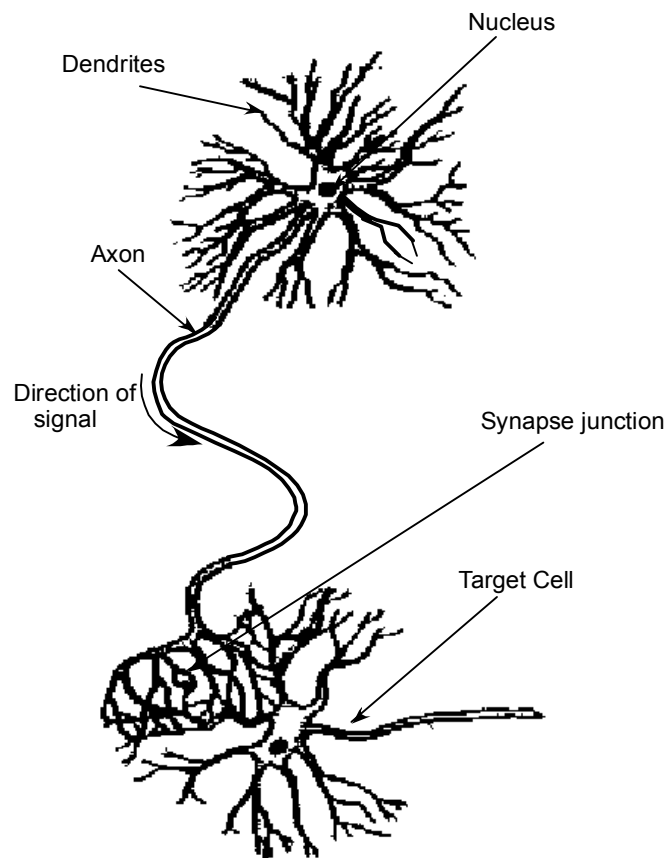
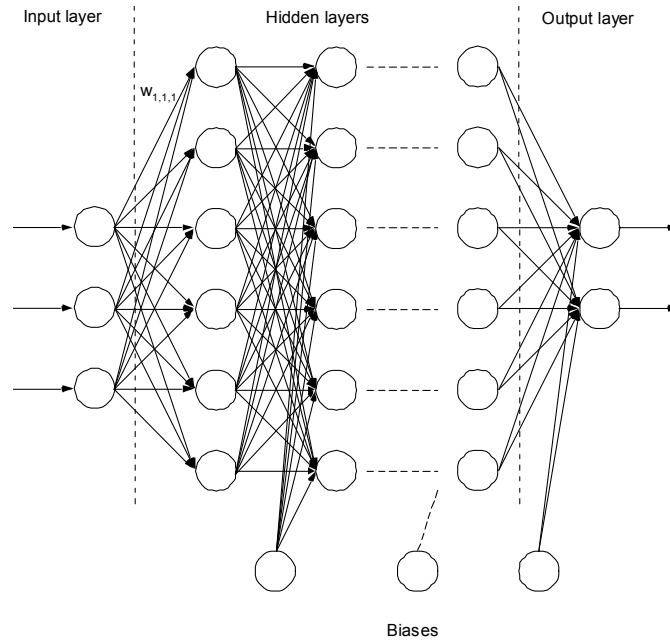
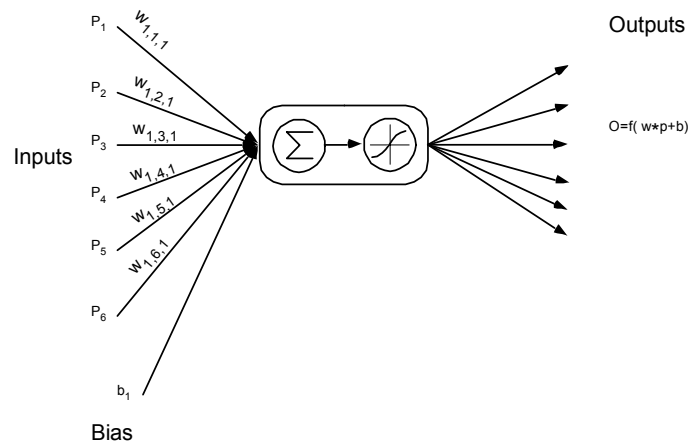


Figure 2.1 Structure of a neuron.



(a) Layers



(b) Neuron

Figure 2.2 Structure of artificial neural network.

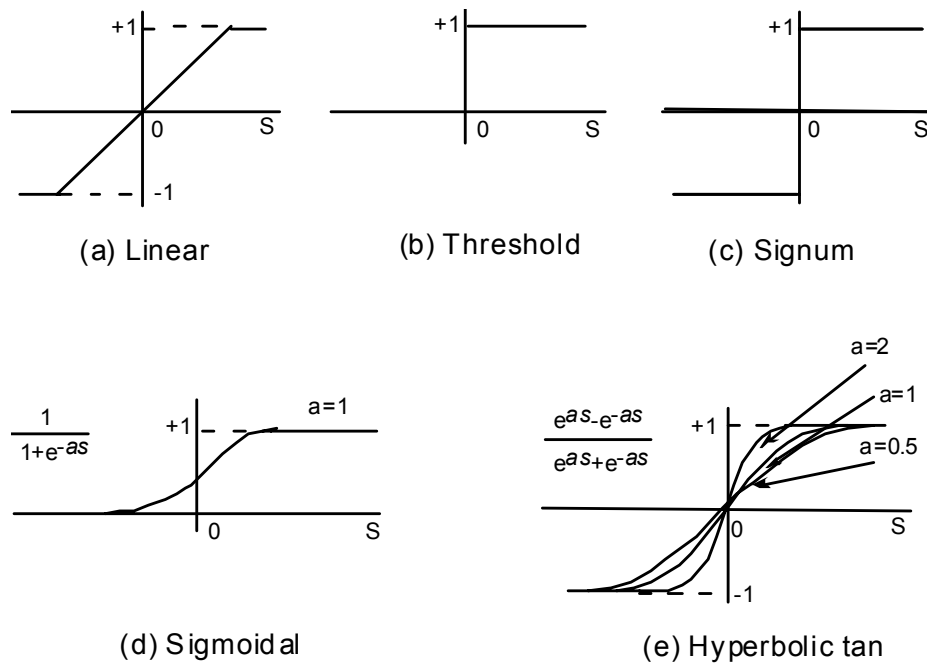


Figure 2.3 Activation functions.

weights, and the weights are adjusted by the training or learning process to minimize the error between the desired mapping and actual mapping in a least squares sense. The learning of neural network means the updating of weights, and the knowledge learned by a neural network is distributed in the weights, not stored in any single memory [19, 60, 62~66].

The most commonly used neural network is a multilayer feedforward network, which has three layers: (1) input layer, (2) hidden layers, (3) output layer as shown in Figure 2.2 (a). The nodes in the input layer accept and buffer the data presented to the network, and distribute the data to the nodes in a hidden layer, and, usually, the nodes in the input layer do not have the weights and activation function for neural computing. The output layer nodes generate outputs respond to a given inputs. The number of hidden layers can be more than one, and the role of hidden layers is to form the internal representation of the pattern presented at the input layer. The number of nodes in the input layer and output layer are equal to the respective number of signals. There is no straightforward rule to determine the number of hidden layers and the nodes in the hidden layer. A suitable trained neural network performs predictions and generalization accurately at high speed.

Important characteristics of neural network are: (1) it can perform nonlinear mapping, (2) it is a parallel input-parallel output multidimensional system, (3) it is a distributed associated memory system, and it can draw a close match from partial inputs, (4) it is fault tolerant since the failure of some neurons or weights will slightly degrade the performance, (5) it is less sensitive to noise and easily implemented in hardware. However, the neural network has the following drawbacks: (1) it needs massive training data, and the training

process is very time consuming according to the task, (2) Its black-box characteristics make the heuristic knowledge from operators or experts not be utilized, and the operator cannot know and explain the reasons why the neural network reaches the conclusion, (3) it will generalize incorrectly on new input data, and it needs retraining.

Basically, neural network is universal function approximator, which is capable of approximating any continuous function, and there are many applications and studies to use two important functions of neural network; pattern classification and function approximation. The typical applications of pattern classification include a diagnosis, monitoring, and financial analysis, and the function approximation includes system identification, control, and noise cancellation [22, 24, 36, 61~64, 67~71].

2.4 Fuzzy logic

Fuzzy logic maps input space into output space like a neural network, but fuzzy logic emulates the reasoning process using ambiguous linguistic meanings as humans do. Human can reason and understand uncertain facts and relationships, and use a natural language to express such ideas like “the error is big” or “the performance is good”. Fuzzy logic uses a natural language and If-Then rules to capture and utilize the human knowledge and experience. Thus, fuzzy logic is a very useful tool when the process has nonlinear and uncertain property, which is difficult to be expressed and modeled by mathematical forms [26, 49, 72~74, 78~80].

Fuzzy sets theory was proposed by Zadeh first in 1965, but its first application to a real problem (control of steam engine) was performed by Mamdani in 1974. In the first

application, Mamdani proposed a fuzzy inference, which is an actual process of formulating the mapping from a given input to an output. The fuzzy inference consists of five components: (1) fuzzification of input variables using membership function, (2) application of fuzzy operator, (3) application of implication method, (4) aggregation of all outputs, (5) defuzzification [75~77,60,81,82]. Figure 2.4 shows the procedure of the fuzzy inference system applied to heater control as an example, and the role and process of the five components of the fuzzy inference are described using the example of Figure 2.4.

1) Fuzzification: In this process, the crispy input (10°C) is expressed in terms of the fuzzy variables (hot, moderate, and cool) and the degrees to the each fuzzy variables or sets are determined via the membership function. In the example, the 10 has 0.3 degree to “hot” and 0.6 degree to “moderate”, and 0.1 degree “cool”.

2) Application of fuzzy operator: If the rule has more than one part, the fuzzy operator is applied to obtain one number, which is defined as the degree of fulfillment (DOF) of the rule and represents the result of the antecedent of the rule. For example, if the humidity of the room is considered to control the heater and the fuzzy sets of “high” and “low”, the antecedent of the rule is expressed as

If temperature is cool and (or) humidity is high, *then*

The antecedent has two parts, each of which has a degree of membership. The fuzzy

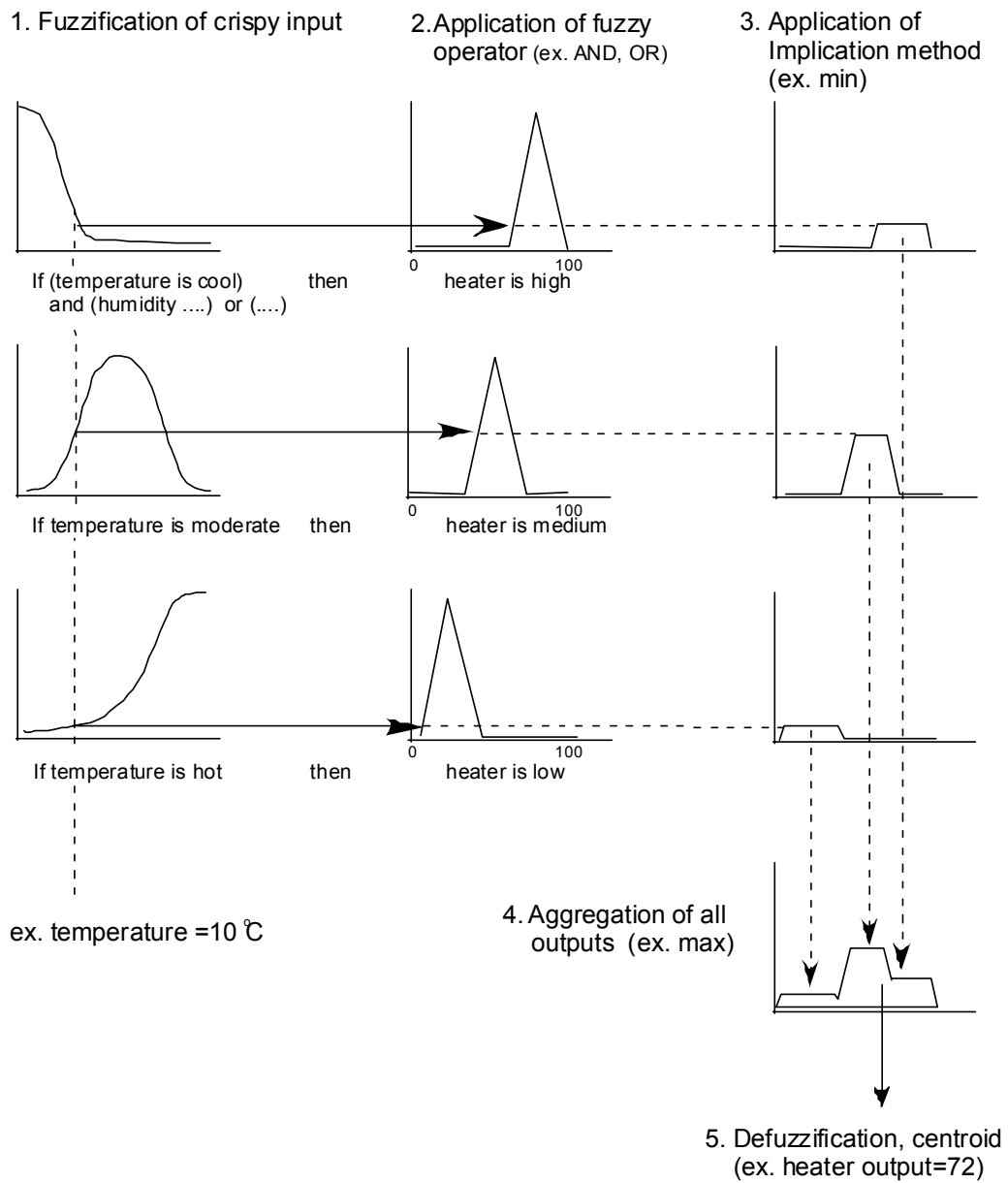


Figure 2.4 Fuzzy inference process.

operator “AND”, “OR” selects the one membership value, and the “AND” operator selects the minimum values in the membership values and the “OR” operator selects the maximum values in the membership values. The output of the application of fuzzy operator is applied to the output function.

3) Application of implication methods: The implication reshapes and evaluates the consequent of rule using the result of antecedent of rule. The input of implication is one single value and the output of implication is fuzzy sets. There are two methods commonly used “AND” and “Product”. The “AND (min)” truncates the output fuzzy sets as shown in the Figure 2.4, and the “Product” scales the output fuzzy sets

4) Aggregation of all outputs: Aggregation combines the fuzzy outputs which represent the outputs of each rule to result in a final fuzzy output set. The inputs of the aggregation process are the list of truncated (or scaled) output membership functions, and the output is one fuzzy set for each output variable. Commonly used methods are “Max” and “Sum”, and the example shows the result of “Max” aggregation.

5) Defuzzification: In this process, the fuzzy output set is converted to crisp output. There are some methods for Defuzzification like Centroid, bisector, and middle of maximum. The Centroid, which finds the geometric center of area (or gravity) of the fuzzy set, is commonly used.

2.5 Wavelet Analysis

A wavelet is a waveform of effectively limited duration with zero average value, and the wavelet transform (WT) is a linear transformation using wavelets as basis. Similar to the Fourier transform (FT), the WT is the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet ψ called mother wavelet. The continuous wavelet transform (CWT) is defined as

$$C(\text{scale}, \text{position}) = C(\alpha, \beta) = \frac{1}{\sqrt{|\alpha|}} \int_{-\infty}^{\infty} f(t) \psi\left(\frac{t - \beta}{\alpha}\right) dt \quad (2.1)$$

where α is a scale factor and β is the translation factor of the wavelet. Some of the wavelets and scaling functions are shown in Figure 2.5. The results of the CWT are wavelet coefficients C , and they are function of scale and time. Although the WT decomposes a signal into a time-scale domain, many researches use “frequency” instead of “scale” since there is a correspondence between the scale and frequency. The high scale makes the wavelet more stretched and the WT measures the slowly changing feature of the signal. The low scale makes the wavelet compressed and the WT measures the rapidly changing feature of the signal. Thus, the high scale corresponds to low frequency and the low scale corresponds to high frequency. This makes the WT localize information in both time and frequency domain, and the wavelet analysis is more appropriate than the Fourier analysis for the analysis of non-stationary signals, such as drift, trend, and abrupt change.

When the scale and position are selected based on the powers of two, the Discrete

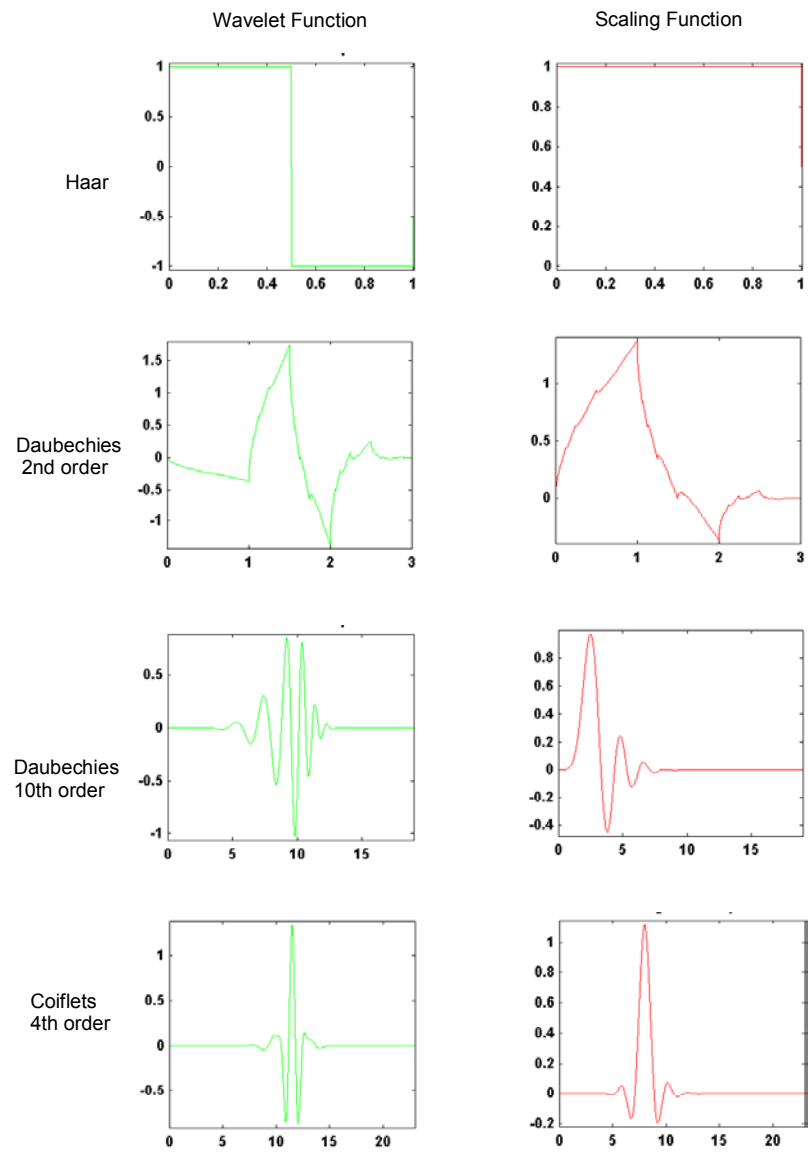


Figure 2.5 Examples of wavelet functions and scaling functions.

Wavelet Transform (DWT) provides a fast algorithm for computation of the wavelet coefficients using a multi-rate digital filter. When the $\alpha = 2^k$ and the $\beta = 2^k n$, the DWT of $f(t)$ and the inverse transform of the DWT are given by

$$C(k, n) = \int_{-\infty}^{\infty} f(t) 2^{-k/2} \bar{\psi}(2^{-k} t - n) dt = \int_{-\infty}^{\infty} f(t) \bar{\psi}_{k,n}(t) dt \quad (2.2)$$

$$f(t) = \sum_{k=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} C(k, n) \psi_{k,n}(t) \quad (2.3)$$

where $\bar{\psi}_{k,n}(t) = 2^{-k/2} \bar{\psi}(2^{-k} t - n)$, Complex Conjugate of $\psi_{k,n}(t)$. It has been proved that the signal can be reconstructed by wavelet functions and the scaling functions, which is orthogonal to the wavelet functions.

$$f(t) = \sum_n a(n) \varphi_{k,n}(t) + \sum_n \sum_{k=0}^{K-1} d_k(n) \psi_{k,n}(t) \quad (2.4)$$

$$a(n) = \langle f, \varphi_{k,n}(t) \rangle$$

$$d_k(n) = \langle f, \psi_{k,n}(t) \rangle$$

where a , called approximation, and d_k , called detail, are the coefficients of the discrete wavelet transform. An efficient way to compute a and d_k coefficients was developed by using filter bank as shown Figure 2.6. This practical algorithm yields a fast wavelet transform. In the algorithm, the high pass filter relates to the wavelet function and the low pass filter relates to the scaling function. The output sequence of each filter is down

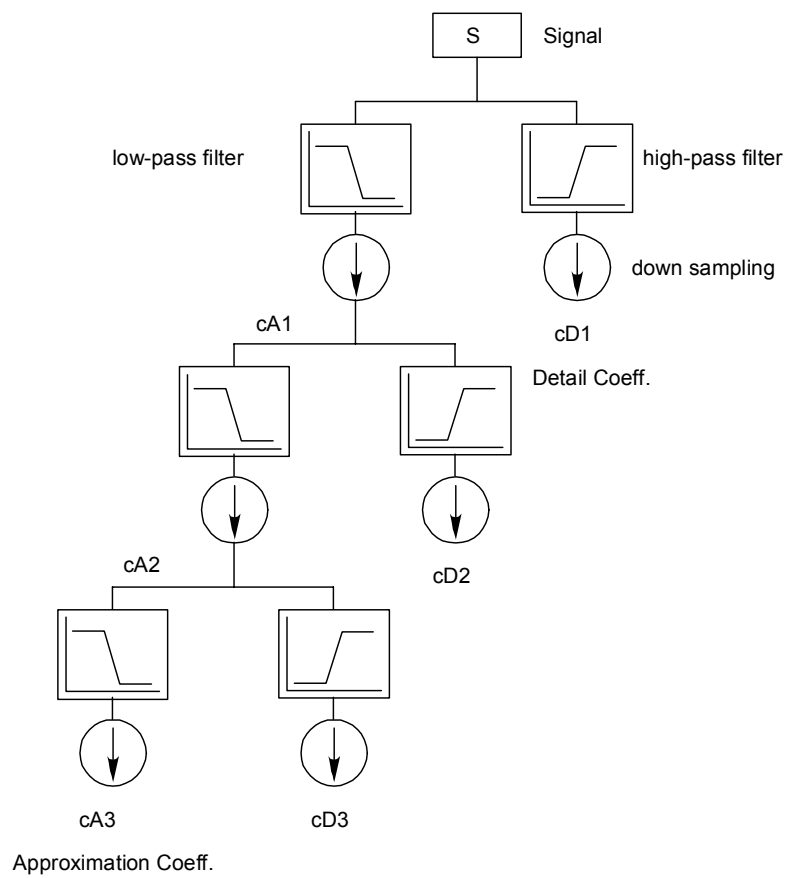


Figure 2.6 Example of three level wavelet decomposition tree.

sampled to avoid redundant information. For each analysis, the approximation coefficients are obtained from the output of the low pass filter and the detail coefficients are obtained from the output of the high pass filter. The fast DWT algorithm and its inherent time-frequency localization property make the analysis an effective tool in analyzing fault transient for fault detection and diagnosis [129~133].

2.6 Operational fault detection in industrial applications

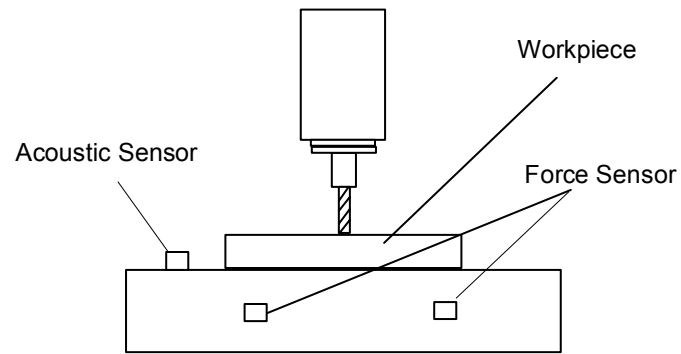
The purposes of FDI in industry are extending maintenance periods, preventing sudden process stoppages, and predicting the need of maintenance. Although any faults in the internal space and operational space have an affect on the performance of a system, the faults in the internal space, especially in the hardware, have a greater impact on the system. The hardware faults can immediately degrade the system's performance, deteriorate the quality of outputs, and stop the process, but the operational faults in industrial applications usually do not stop the process immediately and can be detected and recovered relatively easily. Thus, most research on the FDI for industrial applications has concentrated on the faults in the internal space, and some active research for industrial applications includes the detection of motor failures (such as broken rotor bars, damaged bearings, and faults in inverters) [23,66,71,83~88] and tool breakage in the milling process [67,89~103]. Although, in robotics, most research on the FDI is interested in the detection and recovery of faults in the internal space, such as joint failure [12, 33, 43~46, 52, 104~113], some research suggests the need for operational faults detection and recovery as a part of an overall fault tolerant system for critical applications. Tso et al. [38] proposed a concept of

fault tolerant intelligent robotic control which integrates system/hardware level fault tolerance with the task level handling of uncertainties and unexpected events. The errors in the task level include anomalies and uncertainties, such as a weak grip force or a slipped object, associated with the physical environment during task execution. Gini and Smith [51] classified faults at four different levels in the development of knowledge-based programming techniques: (1) mechanical level, (2) hardware level, (3) controller level, and (4) environment level. The errors in the environment level include collisions, jammed parts, gripper slippage, misorientation, alignment errors, and missing parts. Schneider and Frank [50] developed observer-based supervision for the faults in the internal space and discussed the use of the approach for external faults detection. Even though some research is interested in the operational faults and has developed the concepts of the operational faults using different terminologies, there is no research which is interested in the development of practical and effective FDI methodologies for the operational faults. The difference between the task space and tasks of telerobots and those of industrial applications makes the methodologies used in the industrial applications for the internal faults not applicable. However, the basic approaches and algorithms are still useful for the operational fault detection and recovery. Thus, in this section, the typical methodologies used in industrial applications are reviewed and the limitations of those approaches for use in the telerobots are discussed.

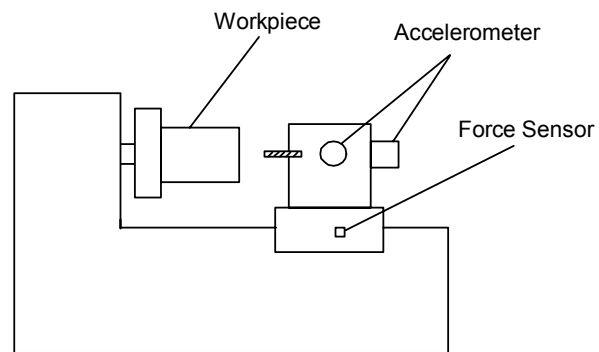
A typical methodology for the FDI of internal faults uses the signature of sensor outputs in the frequency domain or time domain. In the case of motor fault detection, many researchers use an FFT analysis of motor current or vibration to distinguish the spectrum

signature of faults, which can not only detect the faults, but also isolate the faults. For example, Benbouzid et al [83] utilizes high-resolution spectral analysis of stator current to detect and localize electrical-based faults such as unbalanced voltage and single-phasing effects. Consoli et al [85] shows that the analysis of harmonic contents of stator current is able to detect the damaged bearing and broken rotor bar with the aid of fuzzy logic. Li et al [86] use the power spectrum of the vibration signal for motor bearing fault diagnosis. However, the methodology using the signature in the frequency domain has an inherent drawback since time information is lost by the FFT. Thus, it cannot tell when the fault happens. In the case of tool breakage detection, most researches use the time series of dedicated sensor outputs, such as force, vibration, acoustic noise, and displacement sensors. In addition to the use of the dedicated sensors, these approaches usually install the sensors on the workpiece to minimize the effects of the inherent uncertainties in the cutting process. Figure 2.7 shows the typical locations of the sensors. Also, the algorithms use some specific features, which are related to the workpiece material, tool, and work conditions, such as tool diameter, cutting depth. For example, Yan et al [98] uses both cutting forces and acoustic emission to monitor the tool condition. The force sensor is installed on the workpiece, and the sampling frequency of measurement is synchronized with tool frequency which is function of the number of teeth and diameter of the tool.

Although these results show the reliability of tool monitoring in industrial applications, the limitations of the approaches and the characteristics of telerobot task space make these approaches inappropriate for operational fault detection and isolation in telerobots. First, generally, the sensors, such as force sensors and accelerometers, are not available in



(a) Sensor setup of Milling Process [95].



(b) Sensor setup of N/C [101].

Figure 2.7 Examples of sensor location.

telerobotic systems, and, especially, it is not realistic to install the sensors on the workpiece in many applications, such as D&D operations. Therefore, the algorithms that depend on these types of sensor signals are inappropriate in the task space. Secondly, some available data in telerobotics are less accurate than those in industrial applications. Thus, although the approaches using the data provide very reliable results in industrial application, same approaches are less reliable in telerobotics. For example, the position and displacement of a tool in Cartesian cannot be measured directly in telerobotics, and then they have to be calculated using the joint angular position data and the direct kinematics. Figure 2.8 shows the locations of the joint sensors. Thus, the errors in each joint angular position data and the errors in the parameters of the kinematics propagate through the transformation and may worsen the accuracy of the position and displacement data. The less accuracy of the data will deteriorate the reliability of the algorithm output using the data. The uncertainty in the task space is another factor which threatens the reliability of the sensor outputs. Some sensors, like force sensors, are easily damaged by the large inputs outside the normal input range. In the case of industrial applications, the pre-designed and pre-selected task space, tool, and workpieces keep the sensor operating in the normal range, and thus the sensors do not usually need calibration or maintenance as often. However, in the case of telerobots, the uncertainty in the task space can lead to collisions between the manipulator and environment or severe oscillation during the execution of a task, and then the sensors may be damaged by resulting impulse effects requiring recalibration or repair. Thirdly, many algorithms depend on the features of the workpiece and tool. Thus, the simple feature changes, such as workpiece material and diameter of

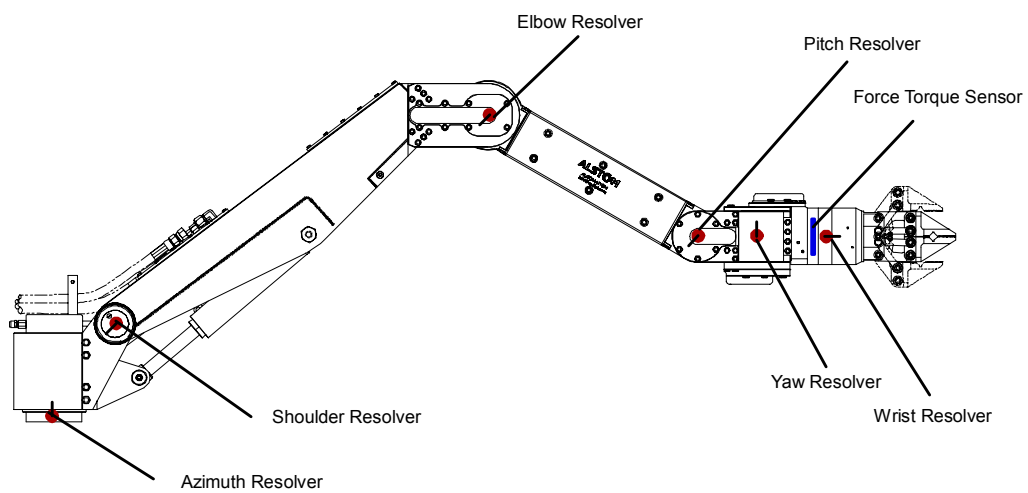


Figure 2.8 Location of sensors for the Titan 3 manipulator.

tool, require different tuning parameters used in the algorithm. In the case of industrial applications, such features are not usually changed in a task, or the parameters of the algorithm can be adjusted according to the change since the changes are usually pre-known and scheduled. However, usually, telerobots must deal with various workpieces which have different materials in a task and the change of the features cannot be predicted in general. Thus, the parameters of the algorithm cannot be practically tuned online.

These features and limitations of telerobotics make it impossible to build a highly reliable FDI system for the faults in the operational space of telerobotics. Therefore, this research aims to build a system which can provide meaningful information to the human operator about the operational faults even though the reliability and accuracy of the FDI system cannot be comparable to that of typical industrial applications.

Chapter 3

Experimental Telerobotic System

3.1 System description

The experimental telerobotic system, which has been developed in support of the D&D robotic work at the Oak Ridge National Laboratory and United States Department of Energy, is shown in Figure 3.1. The telerobotic system consists of two main telerobotic components: the Robot Task Space Analyzer (RTSA) and the Human Machine Cooperative Telerobotics (HMCT). In RTSA, the human operator builds a 3D model of the task space, and decides a task type and related parameters, such as cutting point. After the human operator decides the task type and parameters, the RTSA generates task plan file, which describes detail work procedures to execute the task. These autonomous functions (3-D Modeling and task plan file) of RTSA increase the work efficiency in autonomous mode and improve the system reliability by allowing the operator to preview operations by examining the 3-D [1, 4]. The HMCT interprets the task plan file, and controls the manipulator according to the work procedures of the task plan file in autonomous mode. Also, in teleoperation mode, the assistance functions of HMCT modify the human commands to remain the manipulator motion or end-effector within pre-defined constraints during the task execution. The assistance function allows the human operator to control

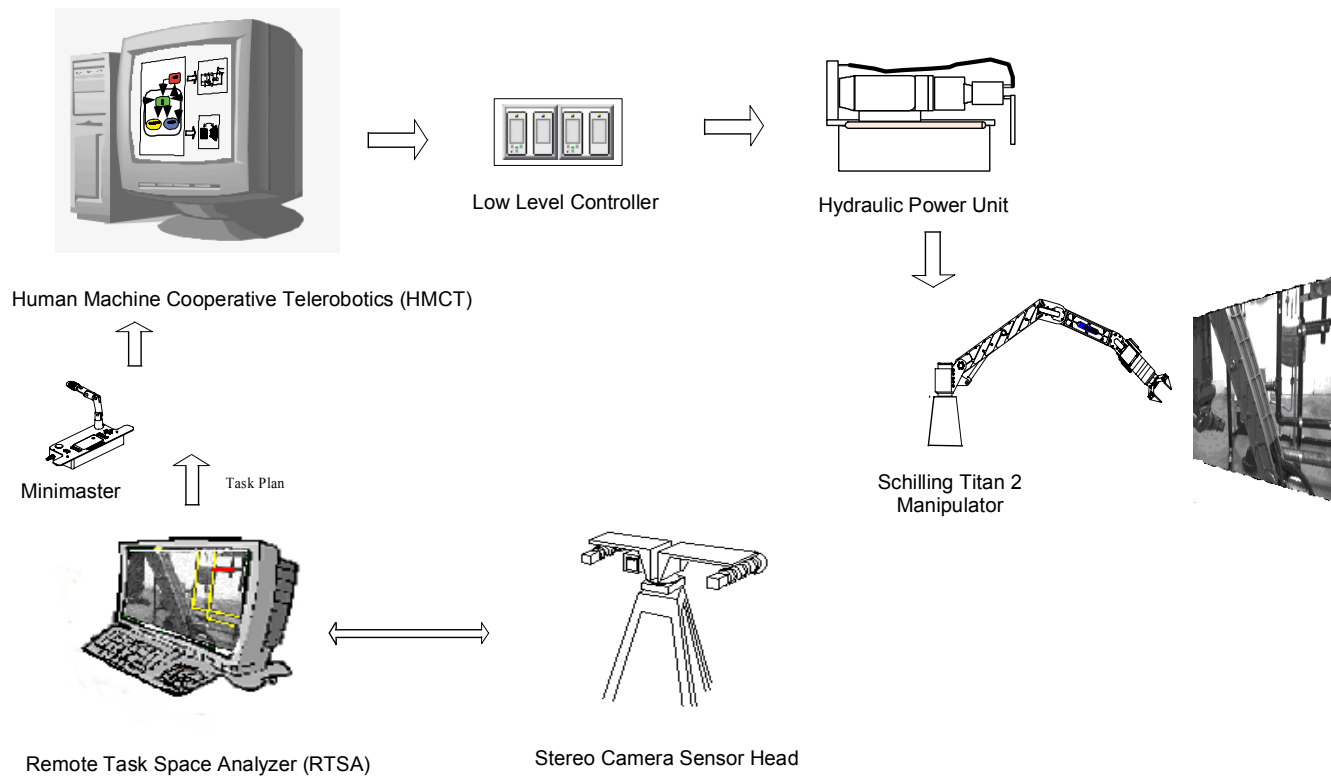


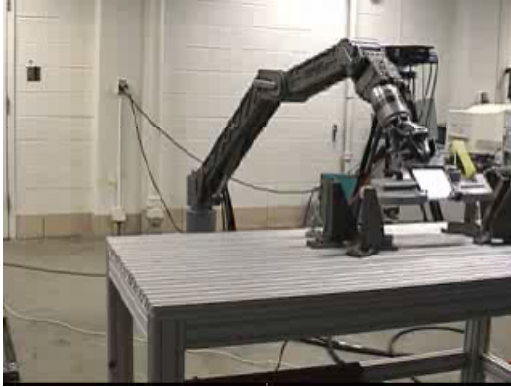
Figure 3.1 Configuration of experimental telerobotic system.

the manipulator without worries of collision with environment or deviation from the proper path for the task execution, and improves the low work efficiency in the teleoperation mode [41, 119, 124].

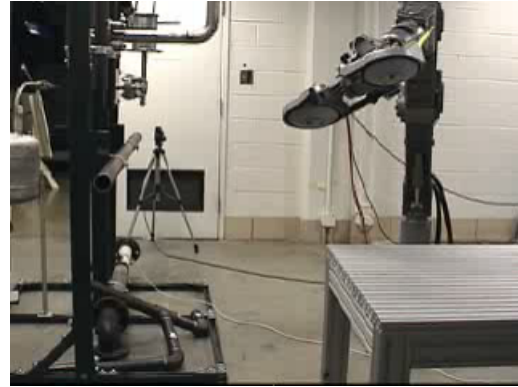
3.2 Experimental test procedures

The experimental tests for this research were a sawing operations using a band saw, and they were executed autonomously with the aid of the RTSA and HMCT. The RTSA built the task plan file, which describes the manipulator motion from the tool pickup to the tool return including the pipe cutting motion. The HMCT executed the task plan file without any assistance functions. Before the experimental tests, several primary tests were executed to select a proper pipe in the mockup and cutting parameters, which make the manipulator motion stable. The selected task plan file in the primary tests was used in every experimental test, and only the pipe and blade were changed for experiments. Thus, every experimental test was executed in the same conditions, and the success or failure of the sawing operation was determined by the uncertainties in the environment (mockup) and cutting process. Figure 3.2 shows the sequence of the sawing operation.

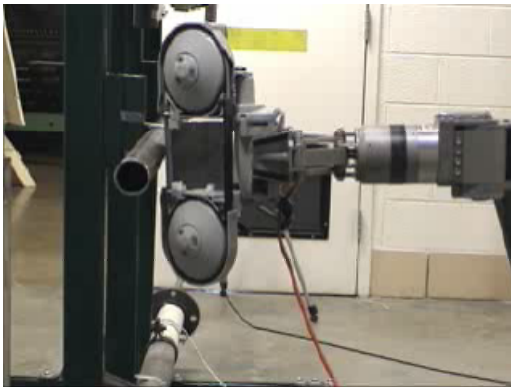
The position data for the analysis are acquired using the manipulator joint angular position data. The joint angular position data are sampled at 10 msec intervals (100 Hz), and the data in joint space are mapped to Cartesian space by the kinematics of the manipulator. The position data of the end-effector in Cartesian space were used for FDI. For the analysis of pipe cutting acoustic noise, the acoustic noises were recorded using the microphone of camcorder. The camcorder is located between the mockup and hydraulic



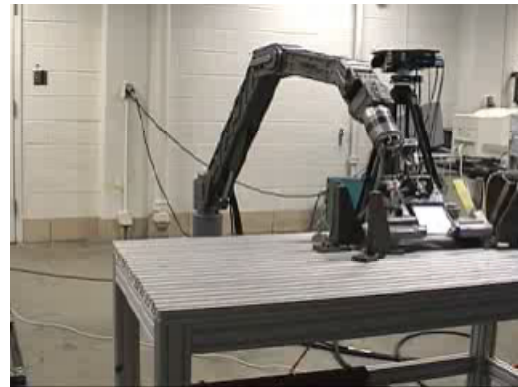
(a) tool pickup



(b) motion in free space



(c) pipe cutting



(d) tool return

Figure 3.2 Task sequence of sawing operation in autonomous mode.

power unit, which is one of the highest noise areas. The sampling conditions of the acoustic noise are 8 kHz sampling frequency, 8 bit A/D conversion, and one channel (mono). The sampled position and acoustic data were saved in the files, and the signal analysis program implemented in Simulink and Matlab used the saved data at each sampling frequency for the analysis.

3.3 Hardware specifications

3.3.1 Manipulator

The Schilling Titan II (Figure 3.3) is a six-degree-of-freedom hydraulic manipulator constructed primarily of titanium and weighing 200 pounds, with a reach of approximately 78 inches, a payload at full extension of 240 pounds, and maximum slew rate at shoulder of 7 rpm. It has a two-finger gripper with a maximum opening of 4.2 inches. The manipulator is securely mounted on the lab floor and is used to test the RTSA/HMCT telerobotic system on a mockup (Figure 3.4). The Hydraulic Power Unit (Figure 3.5) provides pressurized hydraulic fluid to the Schilling manipulator at 5 gpm at 3000 psig. It consists of a hydraulic pump, electric motor, 15 gallon fluid reservoir, motor controller, filtration system, and heat exchanger unit.

3.3.2 RTSA sensor head

The RTSA sensor head (Figure 3.6) is comprised of two digital charge-coupled device (CCD) cameras, a one-dimensional laser range finder, and a frame which can be rotated around two axes. It is mounted on a tripod behind the workspace of the Schilling

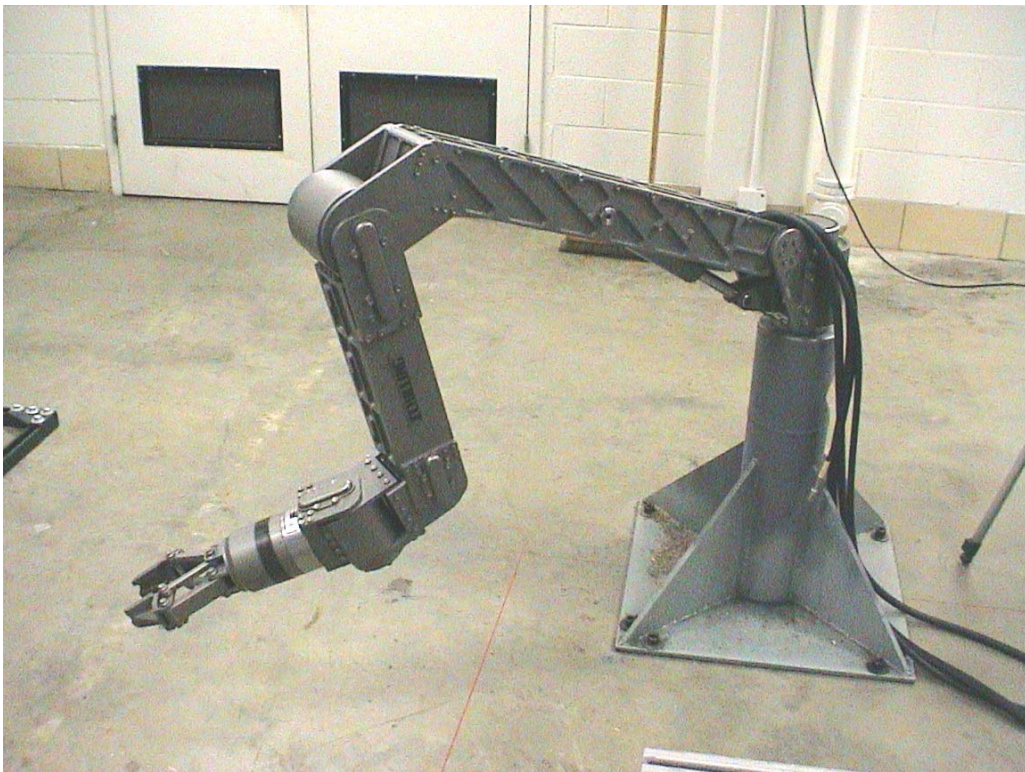


Figure 3.3 Schilling Titan II manipulator.



Figure 3.4 Mockup for experimental test.

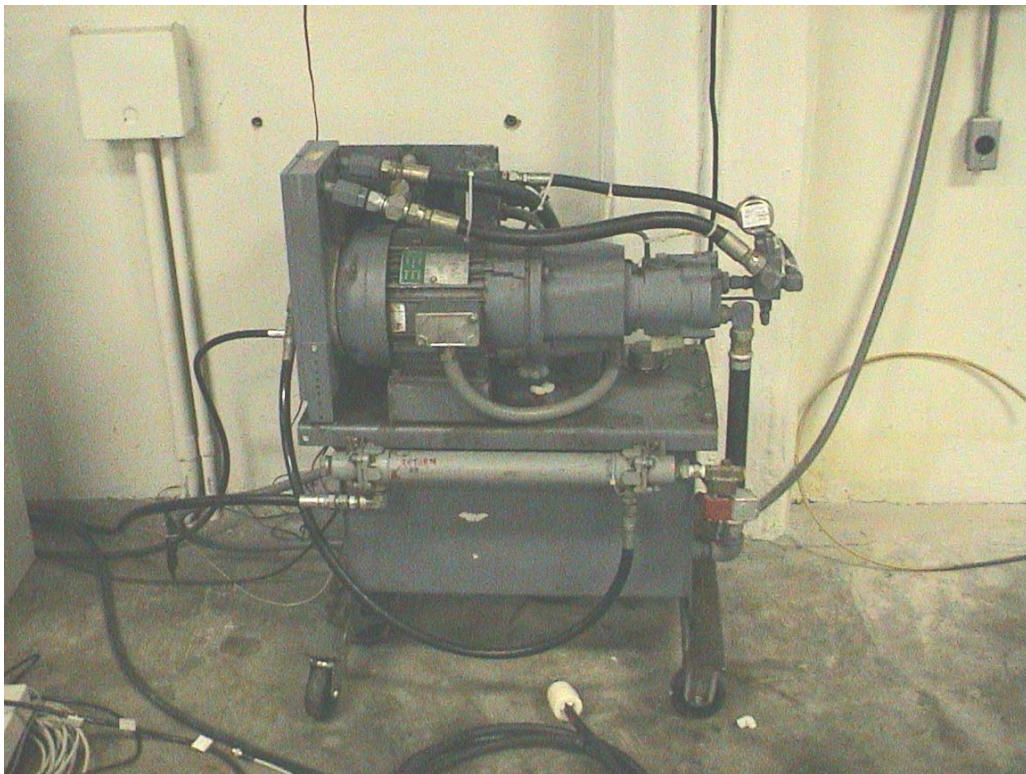


Figure 3.5 Hydraulic power unit.



Figure 3.6 Stereo camera sensor head.

manipulator. The camera is the Servolens of Electronique-Informatique Applications (EIA), and each includes three motors which drive the focus, zoom, and diaphragm. The laser range finder is DME3000 of Sick-Optic Electronic. It is capable of measuring distances up to 16 meters at a resolution of 1 mm at a rate of about 30 Hz. The two cameras and the laser range finder are rigidly connected to the pan-tilt frame and they point in the same direction. The pan-tilt frame can rotate around a horizontal axis to tilt the camera gaze vector, and this assembly is mounted so that it can pan around a vertical axis. The entire pan-tilt assembly is mounted on a tripod of about 6 feet in height at a calibrated position behind the manipulator.

3.3.3 Band saw

The Milwaukee Portable Band Saw, model 6230 (Figure 3.7) is used in the tests. It can operate at variable speeds from 0-350 SFPM. The saw has a maximum capacity of 4 3/4" x 4 3/4" for square stock and 4 3/4" diameter round stock. The saw was modified by installing a handle designed to fit the channel in the Titan gripper. The handle was placed directly over the motor housing of the saw to reduce the moment at the wrist of the Titan II.

3.3.4 Acoustic noise acquisition

The acoustic noise of pipe cutting is recorded using the Sony camcorder, model TRV830 and CCD-TR700 (Figure 3.8), and it is located between the hydraulic pump and mockup where the highest noise area is located. The recorded acoustic noises are sampled at 8 kHz using the ATI board (model DV Wonder) which is also used for video capture.

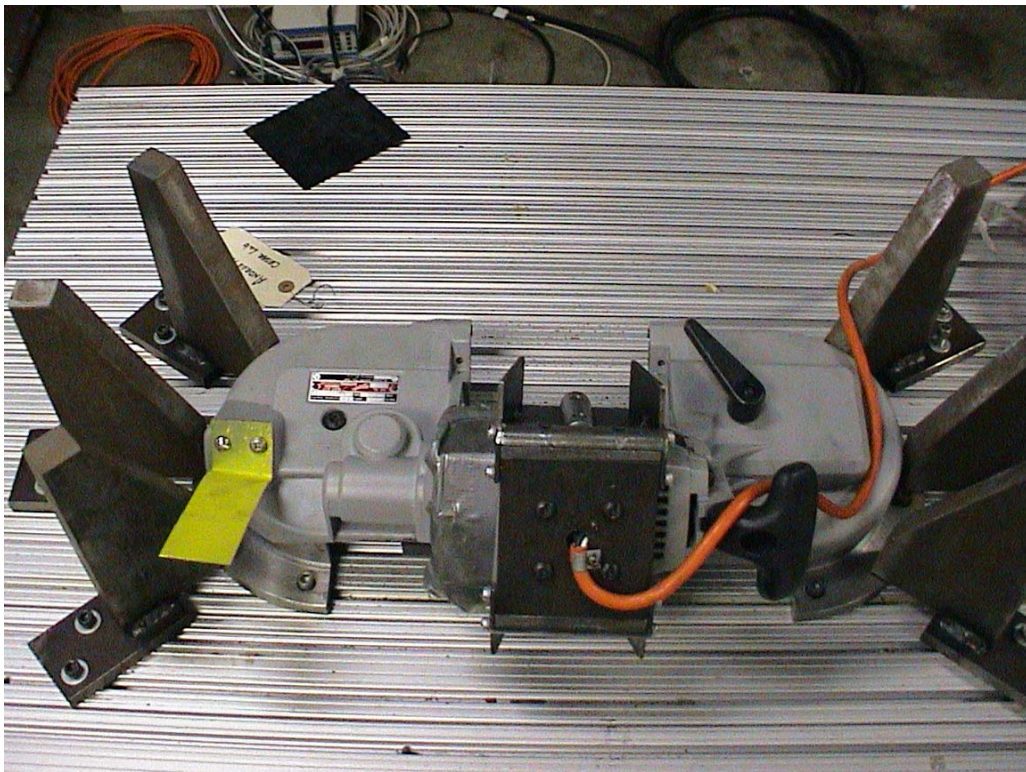


Figure 3.7 Milwaukee band saw.



Figure 3.8 Camcorder for recording of acoustic noise.

Chapter 4

Framework and Supervisory Control

4.1 Introduction

The supervisory control system is functionally essential in fault tolerant control systems. The supervisory control system monitors the state of system and manages the information for the detection and isolation of faults. After the fault state is declared, the supervisory system takes appropriate actions according to the fault recovery strategy. The traditional way to declare a fault occurrence is a single limit value check. This method provides the advantages of simplicity and reliability, and works well when the system usually operates in a steady state and the faults cause relatively large change of system parameters. Uncertainty and nonlinearity in systems results in false alarms and makes the methods based on the single limit value checking obsolete. In general, many fault tolerant systems for internal faults have suffered from uncertainty, and many researchers have studied the adaptive supervisory system or intelligent supervisory system to correctly detect and isolate the occurrence of fault under the circumstances caused by uncertainty [2, 13, 39].

In the case of FDI for telerobot operational faults, the inherent nature of the operational space has higher uncertainty than other spaces, and thus the supervisory system must adopt

adaptive and intelligent technologies. Furthermore, the poor quality of the sensory data caused by the low sampling rate of system control and the various operational faults in a task require the supervisory system to monitor and evaluate more and various different signals to improve the system reliability than the supervisory system for internal faults does. Features, such as uncertainty, poor quality of sensory data, and various operational faults in a task, increase the number of functional blocks, and make the fault tolerant control system structurally complicated. If the fault tolerant control system adds new telerobotic tasks, not only does the number of new functional blocks increase, but also some of them are interlinked and duplicate other functional blocks used for the FDI of other telerobotic tasks. Thus, the FDI system for operational faults is more complicated than the FDI system for internal faults, and the structural complexity of the FDI system leads to inefficiency. There is a need to develop the framework for an operational fault control system, which can integrate disparate detection techniques and minimize the number of functionally duplicated blocks in such a way that the fault tolerant control system can operate without the loss of system efficiency and reliability when a telerobotic task is added or removed from the FDI.

4.2 Framework for generalized FDI

Although the optimization of a framework, which can integrate disparate functions in such a way as to improve the system efficiency, is an important issue in the FDI system for internal faults, there is a little research on the framework for the FDI system. J. Shin, et al [110] proposed the framework for the free-swing joint failures. R. Rengaswamy [126]

proposed the conceptual framework integrating the monitoring and diagnosis system for effective process management. The framework of [110] is devised for the implementation of the specific fault detection and recovery strategy for free-swing joint failure, and the framework of [126] is more interested in the implementation of the proposed process trend monitoring technology using a neural network. There is no clear definition of all functions in the framework, and integration with other functions, such as the control system, and the planning system, were left as future work. The generalized framework of a fault tolerant control system for industrial robots was studied by Visinsky et al [127]. They proposed a three layer framework, which consists of a servo layer, an interface monitor layer, and a discrete supervisor layer. The three layer framework is designed to speed up the response time of the FDI system and modularize the fault detection technologies to more easily adapt to a variety of robot structures. The framework provides a structure to link the FDI algorithms within the robotic control system.

However, the integration of the fault tolerant control system with an existing control system may unnecessarily increase the system complexity. In this study, the FDI system is separate from other sub-systems, such as the high level controller of telerobot. The functions of the FDI system are restricted to only the detection and isolation of operational faults. The fault recovery strategy is also separated from the FDI system although it is a part of the fault tolerant control system. The functional separation of the FDI system from other sub-systems improves the efficiency in the development of the FDI system and makes it easy to use the FDI system in other telerobotic system. The framework of the FDI system is designed based on the assumption of the functional separation of the FDI

system. The proposed framework of the FDI system is designed to have a modular architecture to easily add and remove functional blocks for other operational faults. The developed framework easily adapts not only to other various telerobotic systems, but also to various telerobot tasks.

Figure 4.1 shows the data flow diagram of the telerobot based on the elements of the telerobot (Figure 1.1). The data flow of the FDI systems are represented by the dotted line. In the proposed scheme, there are two separated FDI systems for operational faults and internal faults, and there is one fault recovery strategy depository. The recovery strategies in the depository are used in both FDI systems. In the proposed scheme, the FDI systems have to exchange data to check whether a fault is operational or internal before the occurrence of the faults is declared. This functional separation of the two FDI systems allows the developer to concentrate on the effects and the features of the operational faults without worrying about the internal faults or vice versa. This reduces the load in the design process of the FDI system, and makes it possible to build the FDI systems in a more compact form. If each system has individual fault recovery strategy depository, the depositories will have the same functional blocks, which be applied for both the operational fault and internal fault. The sharing of the fault recovery strategy depository eliminates the need for duplication of the functional blocks used for operational faults and internal faults. These features of the proposed scheme will improve the efficiency in the process of development of the FDI system and the system efficiency in the operation of the system.

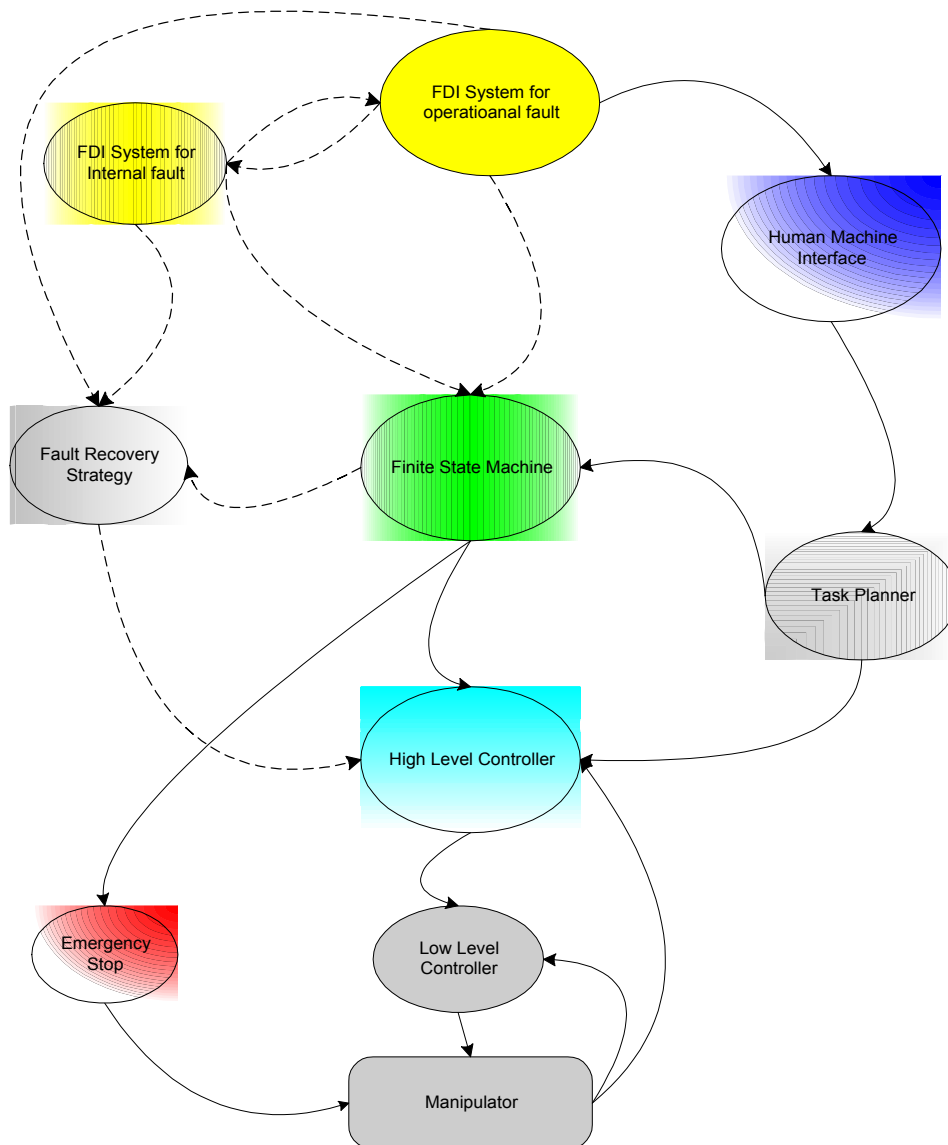
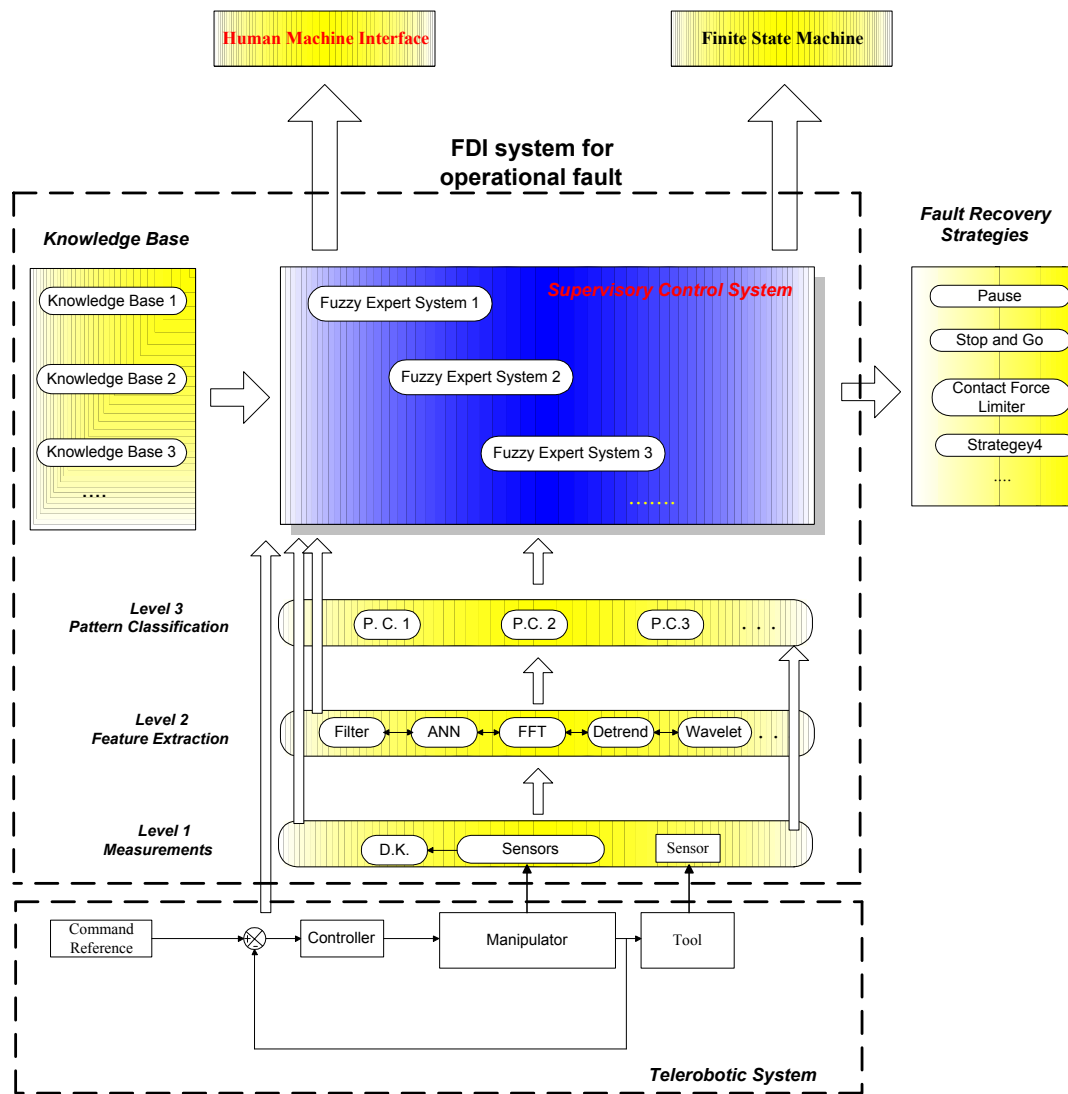


Figure 4.1 Data flow diagram of telerobot system.

After the supervisory system decides the occurrence of the operational faults, the FDI system selects the proper fault recovery strategy corresponding to the fault, and sends the information to the human operator and the Finite State Machine (FSM). After receiving the information of the fault and recovery strategy, the FSM changes the control structure of the high level controller and enables the functional block to implement the recovery strategy. Every process from the detection of the fault occurrence to the implementation of the fault recovery strategy is reported to the human operator before and after the events, and all of the process is supervised by the human operator.

The proposed operational FDI system based on the proposed data flow is shown in Figure 4.2. The proposed architecture for the detection and isolation of operational fault has two important features: (1) cascade structure of signal process consisting of three levels, (2) modular structure of the supervisory control system and knowledge base. In the level one of signal processing, the sensory data are measured with different sampling rates. The sampling rate of the sensory data used in the control system is determined by the sampling time of the control system, which is usually in the range of 100~200 Hz. In case of the sensory data for other subsystems, such as the FDI system and the HMI, the data are sampled at more high frequency. The sampling frequencies of the sensory data are decided considering the characteristic of the sensor data and the algorithm for the analysis of the data. In the level two of signal processing, the fault features of the sensory data are extracted using the signal processing techniques, such as FFT, Wavelet, ANN, etc. A signal process needs pre-processing of the sensory data by the other signal process, such as the de-trend of the position data before the FFT analysis of the position data. Thus, the



P.C.: pattern classification, D.K.: direct kinematics.

Figure 4.2 Framework of the FDI system for operational fault.

outputs of the signal process blocks in the level two are transmitted not only to the level three in series, but also to other processors in the level two. The outputs of the signal processors in the level two have various formats depending on the algorithm used the analysis. Some of them can be used directly in the supervisory system, but some of them, like the PSD results, cannot be used without further analysis of the data. In the level three of signal processing, the pattern classification evaluates the results of the signal processing in the level two or the raw sensor data in the level one and represents the information embedded in the data for the supervisory control system. The pattern classification can evaluate some raw sensory data at the same time to decide the degree of system condition. The sensory data may reach the supervisory control system pass through all levels of the signal processing or reach the system after the process after it passes through one or two levels depending on the operational faults and sensory data.

4.3 Supervisory control system

The procedures for the fault detection and isolation are data measurement, features extraction, and recognition of the features (supervision) as shown in Figure 4.2. The supervisory control system monitors the generated symptoms, and recognizes the symptoms to determine the occurrence of faults. After a fault occurs, the supervisory system classifies the fault, and decides a proper recovery strategy for the fault. In general, the FDI system generates residual, limit value or symptoms, which represent faults, from the sensory data using the advanced signal analysis or system model. A typical methodology for supervisory control is checking the limit value or residual whether they

exceed the tolerance or not. In this method, not only the uncertainty, but also the change of the operating condition may result in false alarm [31, 39, 134]. Many researchers are interested in the adaptive threshold, which varies the level of the threshold according to the operating condition of the system, and adaptive residual, which becomes insensitive to unknown inputs [26]. This limit value or residual comparison with regard to tolerance is appropriate when the number of sensory data and the number of faults are small. If the complexity and uncertainty in the system is much that the FDI system cannot generate a unique residual or limit value corresponding to the fault, then this method is useless. In such a complex and uncertain system, the supervisory system is required to have inference which can make a decision based on the rule based knowledge much like a human does.

Expert systems make it possible to use the sophisticated expertise of human being in a certain area to solve the problems at the level of the human expert. The basic elements of expert systems are: (1) knowledge base, (2) inference engine, (3) user interface. In the elements, the knowledge base is a collection of facts and rules, which represent the knowledge of expert, and the inference engine draws logical conclusions using the knowledge. This inference ability using the knowledge makes the expert systems appropriate to diagnostic systems. Some of the most popular uses of expert systems are monitoring systems, diagnostic systems, and planning systems [60, 74, 81]. However, the ambiguity in the knowledge base and the uncertainty in the system make the rules become more complex and tend to cause them to conflict with each other. In such systems, the traditional expert systems are inefficient since the number of the rules in the knowledge base increases drastically as the complexity of the system increases. The efforts to

overcome the ineffectiveness and inefficiency of conventional expert systems lead to the creation of fuzzy expert systems. Fuzzy expert systems use fuzzy logic in the expert systems, and have been applied to complex systems successfully. The fuzzy expert systems replace the crisp knowledge base and inference engine with fuzzy data and fuzzy inference engine. In fuzzy expert systems, the knowledge is captured in natural language which has ambiguous meaning, and the membership function embodies all fuzziness [74, 75]. One of the prominent differences between the conventional expert systems and the fuzzy expert systems is in the expression of their *If-Then* rules. If the conventional expert system is applied to the supervisory control system for the operational fault detection of the pipe cutting task using the band saw of Chapter 3, one of the possible *If-Then* rules may be

Expert system:

IF (dominant frequency of oscillation is higher than 10 Hz) *AND* (amplitude of oscillation is higher than 20mm) *AND* (cutting acoustic signature is lower than 10 dB)

Then (blade is worn out) *AND* (task must be stop)

In this study, the *If-Then* rule of the fuzzy expert system for the task is proposed as follow:

Fuzzy expert system:

IF (oscillation is severe) *AND* (cutting acoustic signature is small)

Then (possibility of blade worn out is high) *AND* (the need of task pause is high) *AND* (the need of task stop is medium)

The first term in the consequent presents the possibility of the fault. The second and third

terms present the priority of the fault recovery strategies. Therefore, the output of the fuzzy expert system is quantitatively expressed possibilities and priorities of each possible faults and recovery strategies. The human operator and finite state machine use this quantitative information to make a decision. The example of the rules shows that the conventional expert system, which based on the Boolean logic, provides only “True/false” about the occurrence of the fault. Thus, if the uncertainties in the task and environment change the dominant frequency in the spectrum analysis, the conventional expert system cannot detect the fault. In case of the fuzzy expert system, the little change of the input variable may little lower the possibility of the fault, but it still provides useful information about the occurrence of the fault. Furthermore, fuzzy expert systems inherently make it easy to change the knowledge and data.

4.4 Summary

A FDI framework and supervisory control system concept for operational faults of telerobotic systems are proposed. The proposed FDI framework focuses on the integration of various different data processing techniques, which are used for FDI of operational faults, to improve the FDI efficiency and simplify the system configuration. The supervisory control concept using a fuzzy expert system is proposed to overcome the uncertainties in tasks and environments, and ambiguities in the conditions of the operational faults. The integration of the proposed modular framework and the supervisory control system improves the ability to adapt to varying operating environments resulting from variable task condition. And, it can be easily applied not only to different

tasks, but also to different telerobotic system as a generalized methodology for operational FDI. In the next chapter, specific signal processing techniques for FDI of operational faults are discussed and proposed. The emphasis of the development will be not only on the particular techniques, but also on the procedures for the selection of representative operational faults and generalization of the techniques.

Chapter 5

Operational Fault Detection Strategies

In this Chapter proposed methodologies for the operational fault detection (OFD) in telerobots are discussed. For the generalization of the proposed methodologies, the sensors considered in this study are confined to the sensors which are usually installed in the standard or general configuration of telerobots, such as joint position sensors, acoustic sensors, and inputs to actuators. Thus, OFD schemes do not require any additional sensors. Also, the common characteristics and limitations of telerobot are considered in the development of the algorithms for the generalization of the proposed methodologies. Thus, even though the basic task considered in this study is pipe cutting using a band saw, the algorithms are applicable to other task and tools. The methodologies can be applied to other telerobots and tasks with minimal changes. For example, the microphone for the acoustic data, which is imbedded in a digital camcorder, is installed near the hydraulic pump instead of near the task object or tool. The position data of end-effector in Cartesian space is calculated using the joint angular position data. The sampling frequency of the position data is 100 Hz, which is the sampling frequency of the control system. The sampling frequency and recording format of the acoustic data is 8 kHz mono sound.

These sampling frequency selections minimize the software routine for data acquisition and amount of data to be processed in the CPU. The proposed methodologies use: (1) signatures in the frequency domain of the acoustic data sampled at 8 kHz, (2) signatures in the time domain of the position data of end-effect sampled at 100 Hz.

5.1 Power spectrum analysis of acoustic data

Before analyzing the acoustic data in the frequency domain, two important features of the acoustic data in a telerobot system are compared to that of an industrial process. First, the acoustic data has relatively large environmental noise in which the manipulator noise and tool consist of two dominant components. The manipulator noise includes hydraulic pump noise, hydraulic fluid flow noise, hydraulic isolation valve noise, and joint servo actuator noise. The tool noise is usually electric motor noise. In this study the hydraulic Titan 2 manipulator is used for the band saw pipe cutting tests. In the test environment, the hydraulic pump noise and tool noise are the most significant noise, and the microphone is installed near the pump in this research to develop a scheme with more noise data. Figure 5.1 is the power spectrum of the acoustic data when only the manipulator is turned on. It shows that the dominant components are a dc component and an ac component at around 500 Hz. Another dominant noise source is motor noise of the tool which usually has a high rotational speed. Figure 5.2 shows the power spectrum of the acoustic data when the manipulator and the band saw are turned on in the idle state. The power spectrum includes both the spectrum signatures of the manipulator noise and tool noise. It shows that the tool makes the component at 1600 Hz become dominant, and generates a

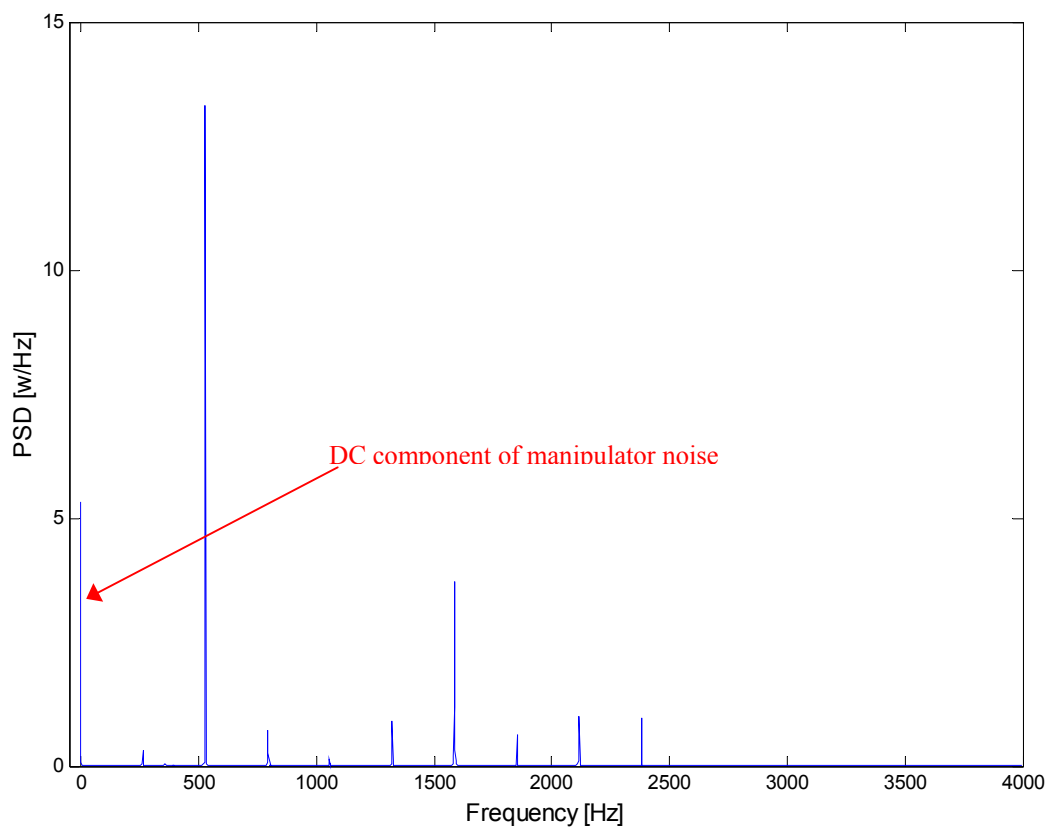


Figure 5.1 Power spectrum of acoustic data for the manipulator.

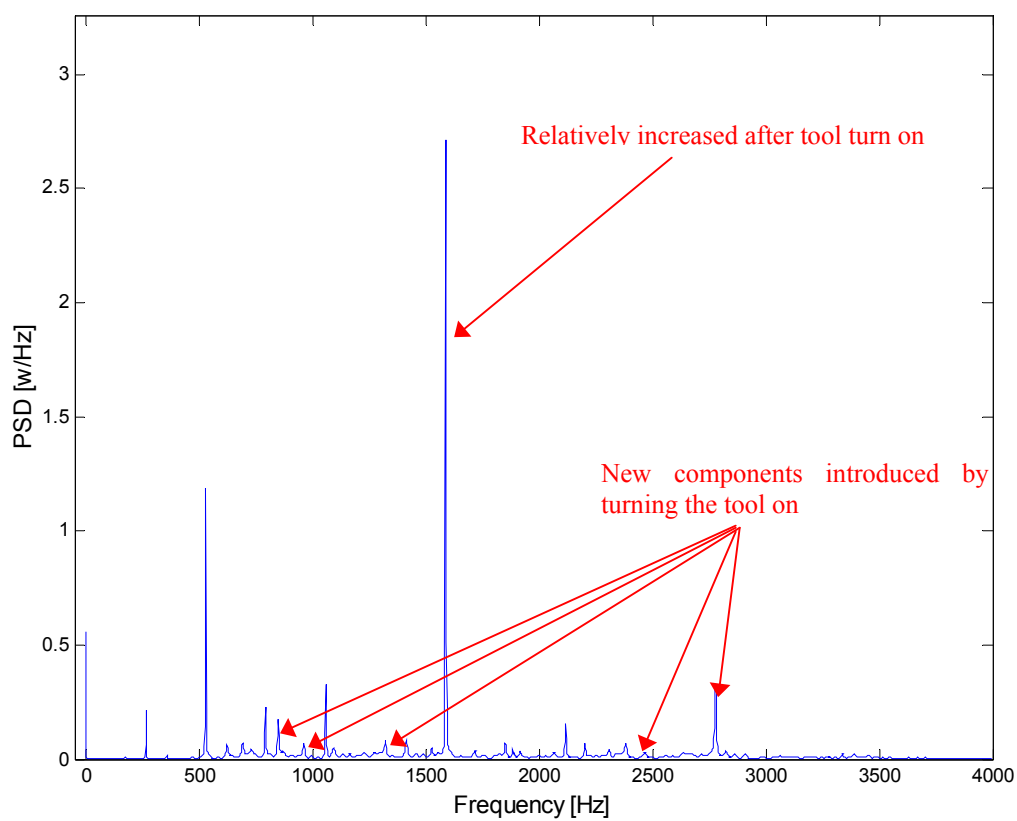


Figure 5.2 Power spectrum of acoustic data for the manipulator and band saw.

new component at 2800 Hz. Thus, the dominant frequencies of the tool noise are 1600 Hz and 2800 Hz. These components relate to the operation of the manipulator and the tool. These components are defined as fundamental system noise in this study.

Secondly, the uncertainties in the task space and the task process cause anomalies during the task process that can generate noises different from the fundamental noise. However, the appearance of the anomalies or the appearance and disappearance of specific signatures in the power spectrum does not always mean the failure of the task. Therefore, the FDI system cannot simply identify the operational faults or task failures by spectral analysis. For example, the uncertainties in the workpiece and tooling, the effects of different materials, loosening of the workpiece, and variation of tool feed-rate, cause the tool to oscillate and change the spectrum signatures. The oscillations can make the guide of the band saw bump on the workpiece causing noise. The variation of the tool feed-rate temporarily changes or removes the signatures, which is related to the number of teeth per inch on the band saw blade and the band speed. However, after a while, the oscillation and variation of the feed-rate dissipate, the cutting process returns to a normal condition. Figure 5.3 shows some of power spectrums of band saw pipe cutting, when the cutting operation was successful. It shows that the uncertainties cause a lot of variation in the signatures of the power spectrums during task execution even though the task was finished successfully. Therefore, the decision of operational fault or failure of the task must consider not only the appearance of the signature in the frequency domain, but also other system parameters, such as manipulator vibration. These complex system behaviors suggest decision processes need the intelligence and experience of human operators.

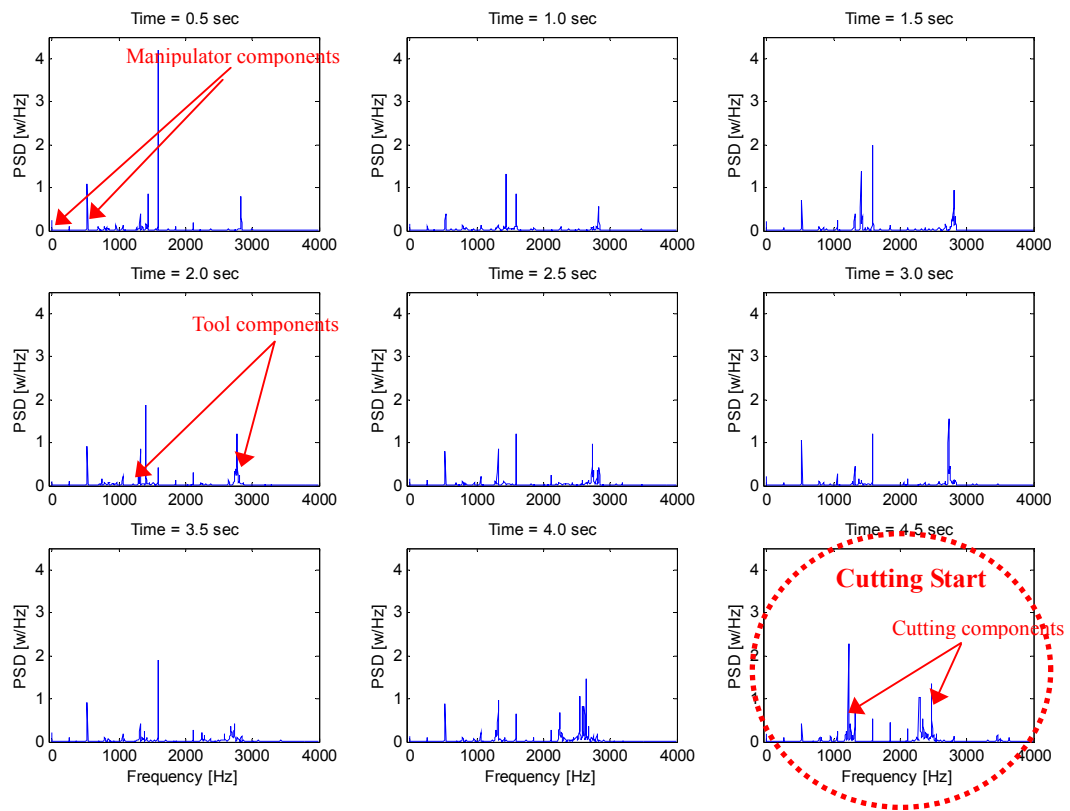


Figure 5.3 Series of power spectra of acoustic data during the pipe cutting.

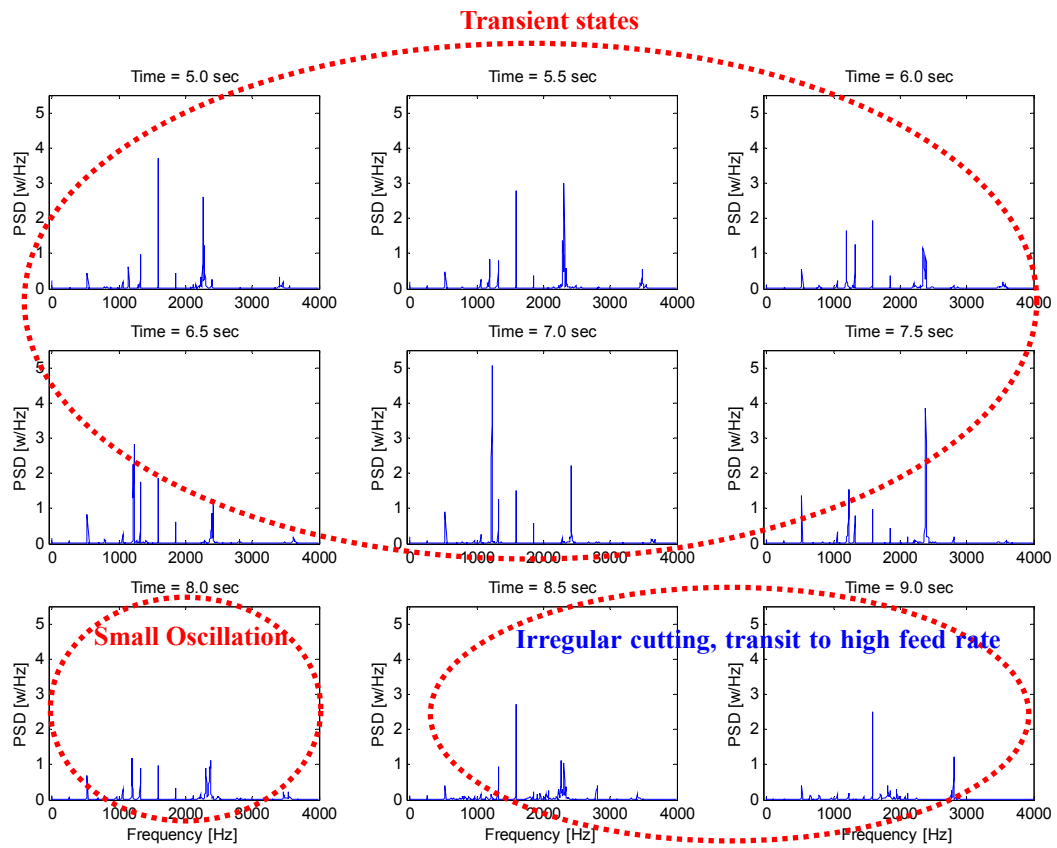


Figure 5.3 Series of power spectra of acoustic data during the pipe cutting (continued).

Abnormal cutting process (high feed rate)

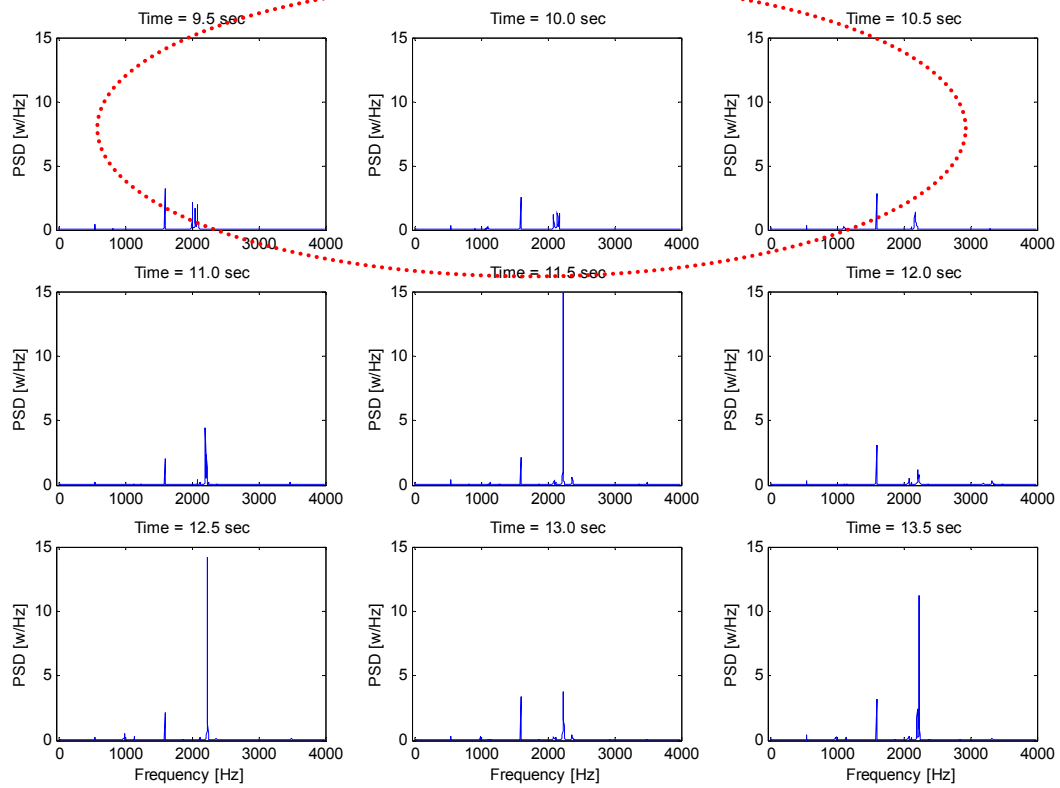


Figure 5.3 Series of power spectra of acoustic data during the pipe cutting (continued).

In this study a methodology is proposed to decide the severity of the anomalies and help the human operator in understanding the task failure.

5.1.1 Extraction of the signatures in the spectrum of the cutting noise

Figure 5.1 shows that large variations of the complicated spectrum signatures make it difficult to classify normal cutting. In this study, the selected fundamental system noise, which is emitted in the idle state of system, are removed from the spectrum of the cutting process to simplify the spectrum even though the components may be produced by not only the idle state of system, but also the cutting process. The selected fundamental system noise components are summarized in the Table 5.1, and Figure 5.4 shows the fundamental system noise components which are extracted from the Figure 5.2.

Table 5.1 Selected system noise of the manipulator and tool (band saw).

Manipulator	Band saw
0~9.7 Hz	830~870 Hz
240.2~291 Hz	908.2~980.5 Hz
500~560.5 Hz	1378.9~1439.5 Hz
771.5~820.3 Hz	1548.8~1621.1 Hz
1039.1~1070.3 Hz	2418.0~2468.8 Hz
1298.8~1341.8 Hz	2722.7~2820.3 Hz
1808.6~1890.6 Hz	
2050.8~2140.6 Hz	
2367.2~2390.6 Hz	

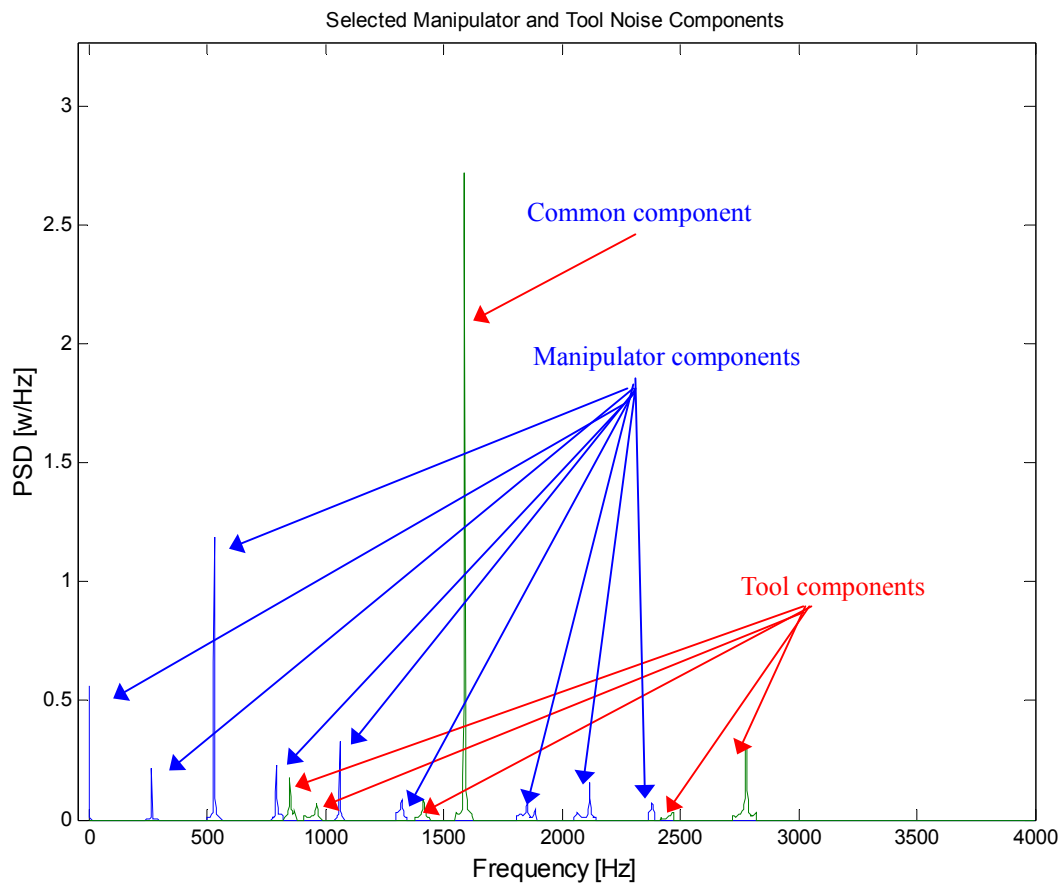
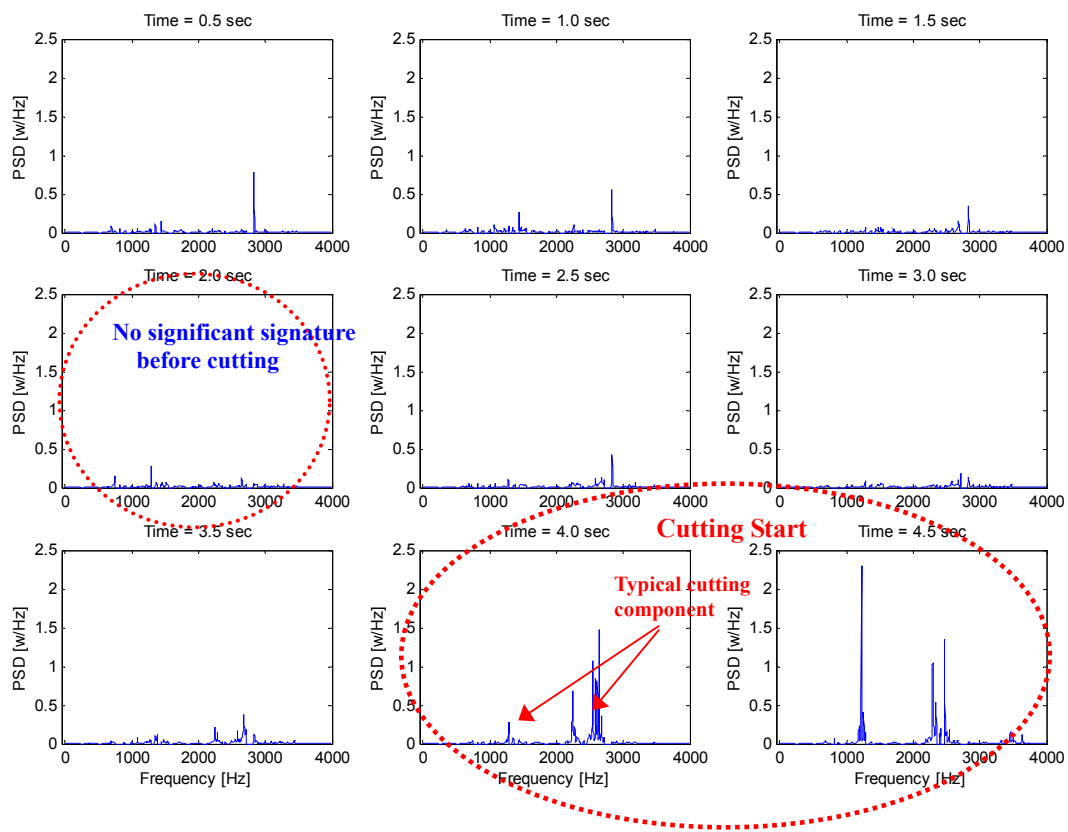


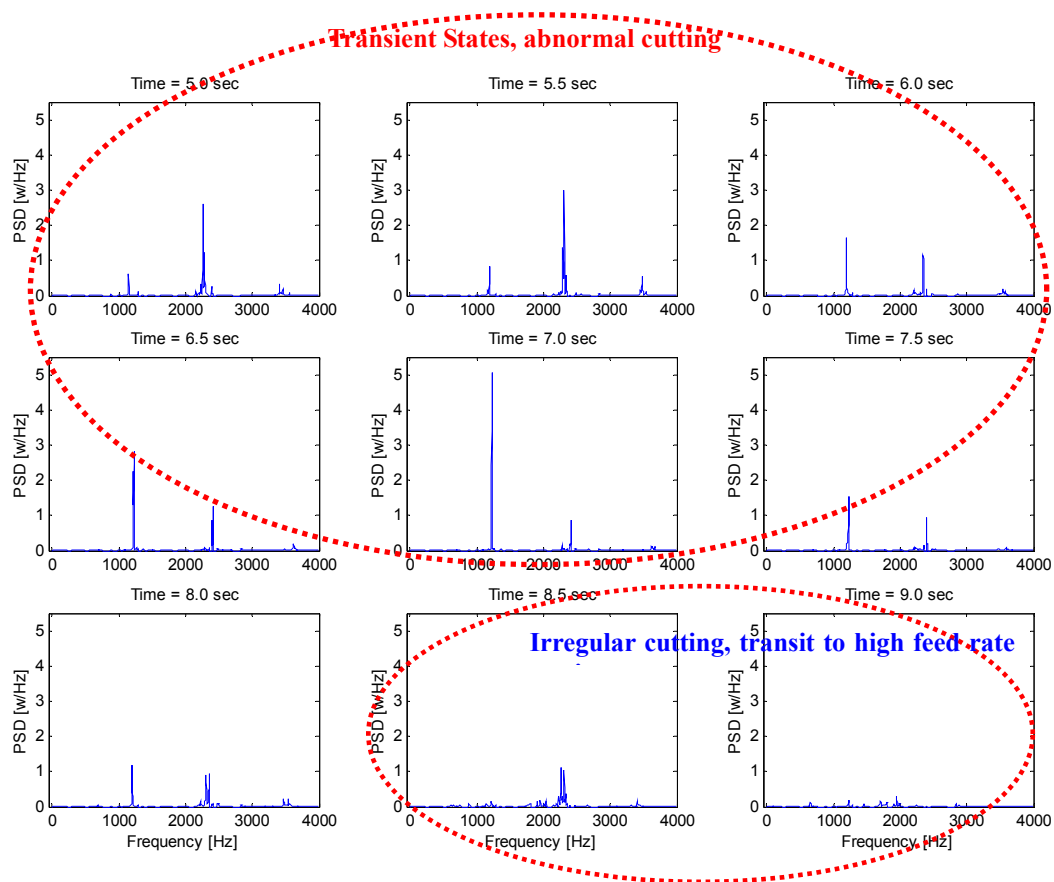
Figure 5.4 Selected noise components of the manipulator and band saw.

In this study, the power spectral density (PSD) of the acoustic data is calculated every 0.5 second using the Matlab toolbox (Yule-Walker method of the DSP blockset) [137, 138]. The sampling frequency of the acoustic data is 8000 Hz, and thus 4000 samples and 96 overlap samples are used for the PSD calculation. After the power spectrum of the cutting process is calculated, the selected fundamental system noise is removed from the power spectrum. Power spectrum examples, in which the system noise is removed, are shown in Figure 5.5. For the analysis and identification of the signatures in the power spectrum of acoustic data, the recorded video is also used for the observation of the anomalies. Figure 5.5 (a) shows that the pipe cutting starts at around 4 seconds since the signature before 4 seconds is almost negligible. Figure 5.5 (b) is the PSD in the early period of the cutting. It shows that the cutting in the beginning (5~7.5 sec) is close to normal cutting, but, later, uncertainties in the process cause the oscillation of the end-effector (8~9 sec), which impedes the proper cutting process. The proceeding of the end-effector with the temporary retardation of the proper cutting causes high feed-rate in the next few seconds (9.5~15 sec). In this period, there are two dominant components in the beginning at 1150 and 2300 Hz, and one small component at 3500 Hz. The small component at 3500 Hz will disappear in the normal cutting condition. Figure 5.5 (c) is the power spectrum of pipe cutting with a high feed-rate and shows that cutting with a high feed-rate has one significant component. The frequency of the dominant component is around 2000 Hz in the beginning (9.5~10 sec) and moves to 2200 Hz as the cutting proceeds. Figure 5.5 (d) shows how the spectrum transits to the normal condition, and Figure 5.5 (e) shows the typical power spectrum of normal cutting process. In the normal cutting process, the



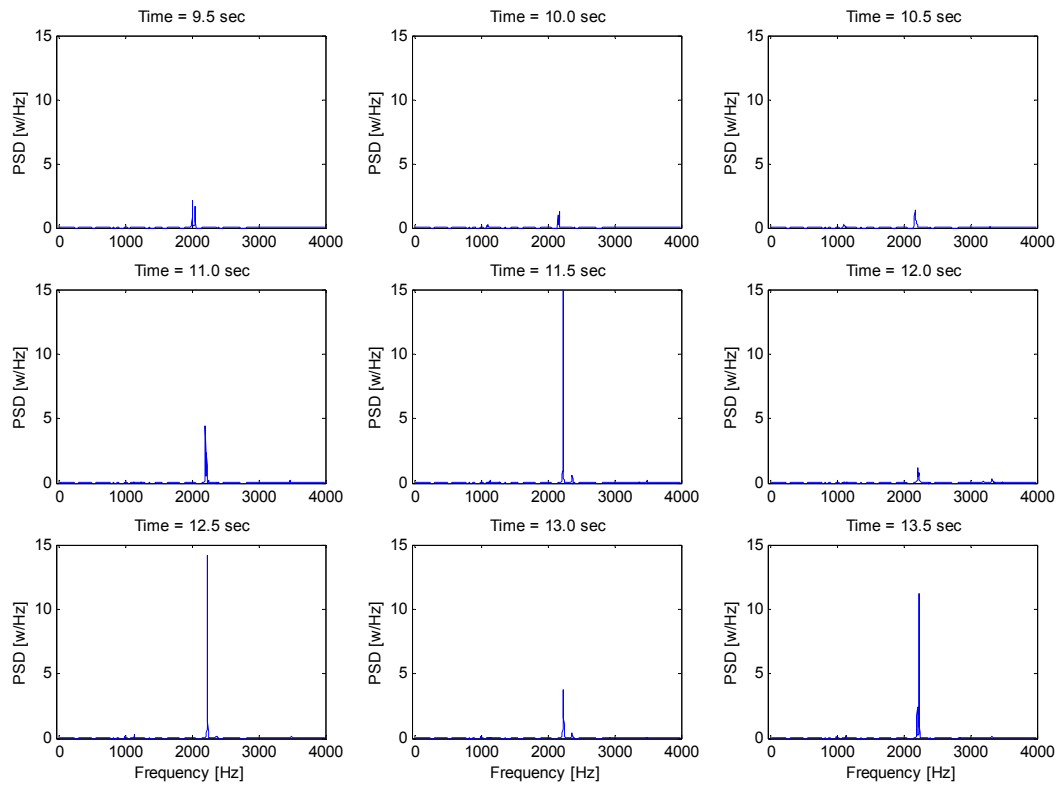
(a) Starting of the cutting

Figure 5.5 PSD of pipe cutting noise after the system noise is cancelled.



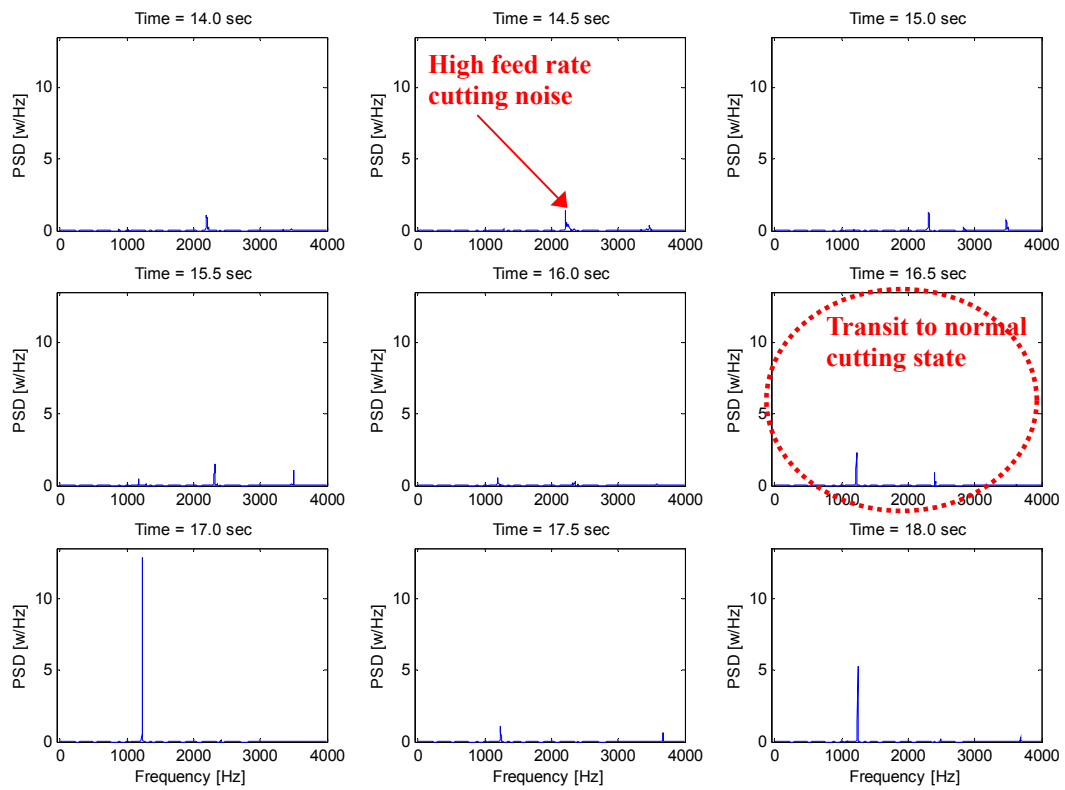
(b) Early period of cutting

Figure 5.5 PSD of pipe cutting noise after the system noise is cancelled (continued).



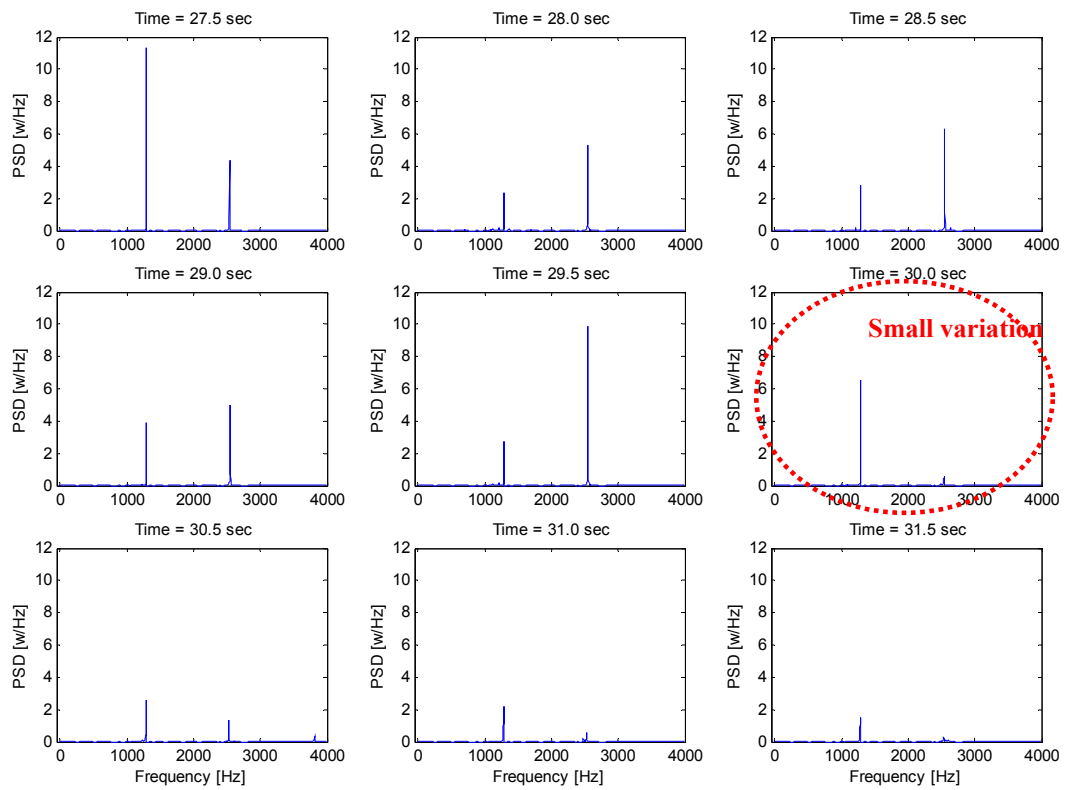
(c) Cutting with high feed-rate

Figure 5.5 PSD of pipe cutting noise after the system noise is cancelled (continued).



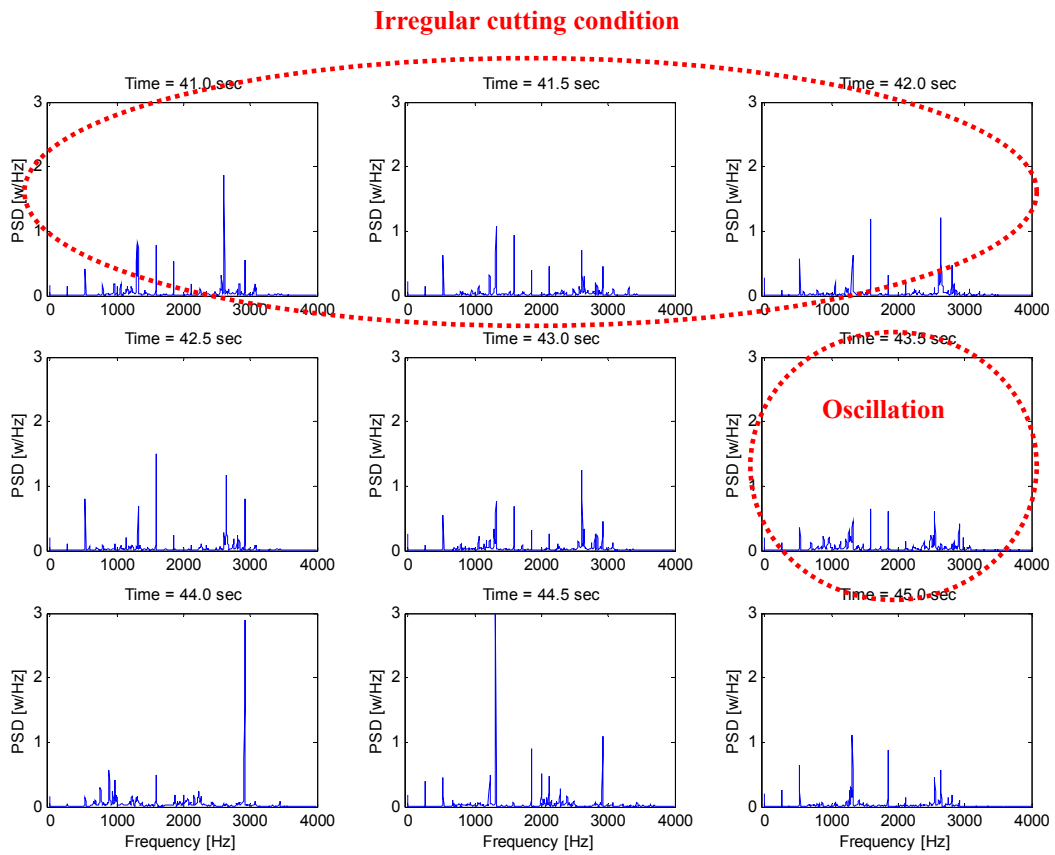
(d) Transition state to normal cutting

Figure 5.5 PSD of pipe cutting noise after the system noise is cancelled (continued).



(e) Normal cutting

Figure 5.5 PSD of pipe cutting noise after the system noise is cancelled (continued).

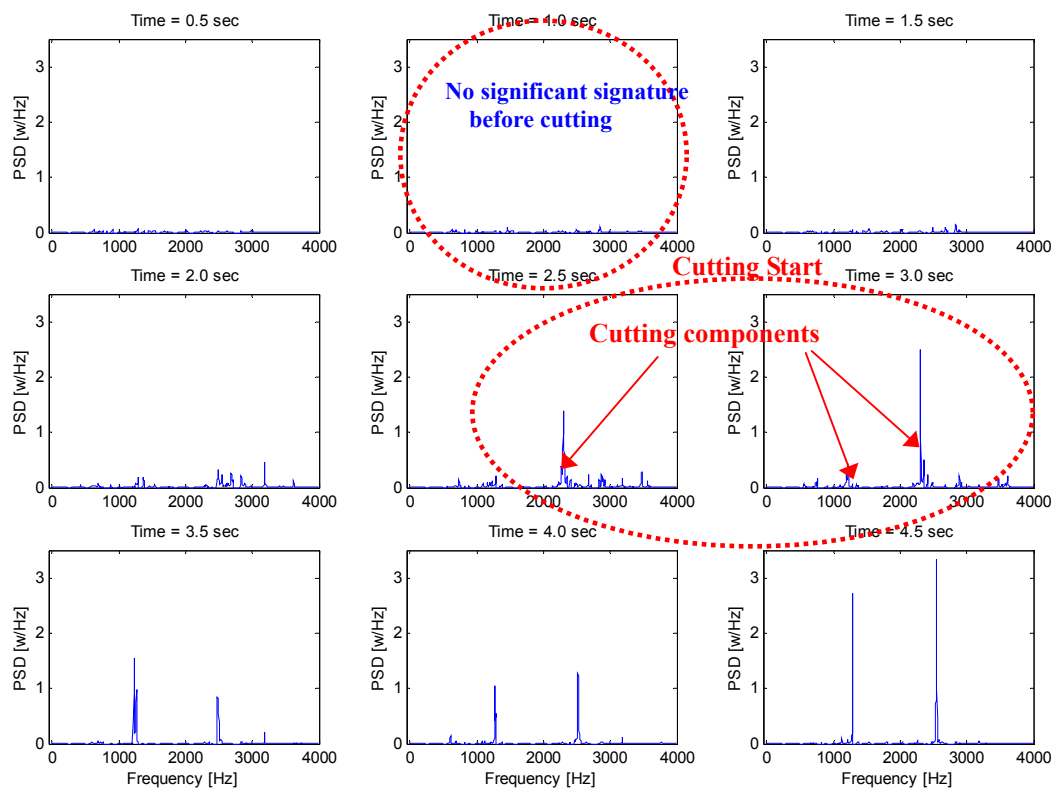


(f) Oscillation during cutting

Figure 5.5 PSD of pipe cutting noise after the system noise is cancelled (continued).

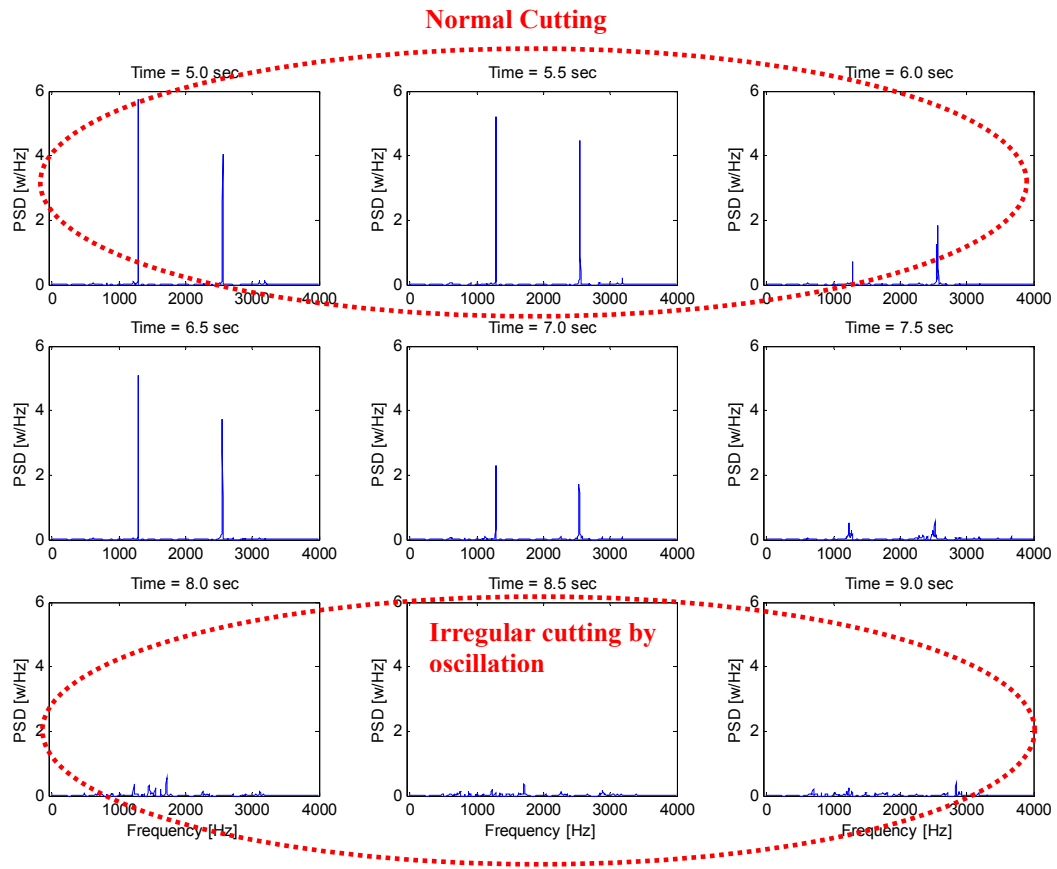
frequencies of the dominant components are 1290 and 2550 Hz. Figure 5.5 (f) is the power spectrum with an oscillation of the end-effector (42~45 sec). It shows that the oscillation of the end-effector increases noise, but the dominant frequencies are 1265 and 2550 Hz. This means that, in this period, the cutting can proceed normally with the oscillation.

The power spectra of other cutting process, which uses a softer and coarser blade, are shown in Figure 5.6. The phenomena and effects of the uncertainties in this cutting are very similar to the former test (Figure 5.5). The uncertainties in the beginning of the cutting cause the oscillations of the end-effector and high feed-rate in the next few seconds after the oscillation. After the feed-rate has recovered to a normal speed, the cutting proceeds normally for a while. As the cutting progresses, the teeth made of soft material are worn away and end-effector starts oscillating. Figure 5.6 (a) shows that the cutting starts around 3 seconds, and Figure 5.6 (b) shows that there is a period of normal cutting before the start of the end-effector oscillation at around 7.5 seconds. The frequencies of two dominant components in the normal cutting process are 1295 and 2555 Hz, which are very close to that of the cutting with a harder blade (Figure 5.5). Figure 5.6 (c) is the power spectrum of the cutting with a high feed-rate after the oscillation, and shows that there is a dominant component in the period in the range of 1950~2050 Hz in the beginning and the frequency moves to around 2200 Hz as the cutting proceeds. Figure 5.6 (d) is the power spectrum of the normal cutting condition, and the two dominant frequencies are around 1280 and 2530 Hz. Figure 5.6 (e) is the power spectrum after the teeth were worn away and the end-effector is oscillating. It shows that the cutting process with a worn



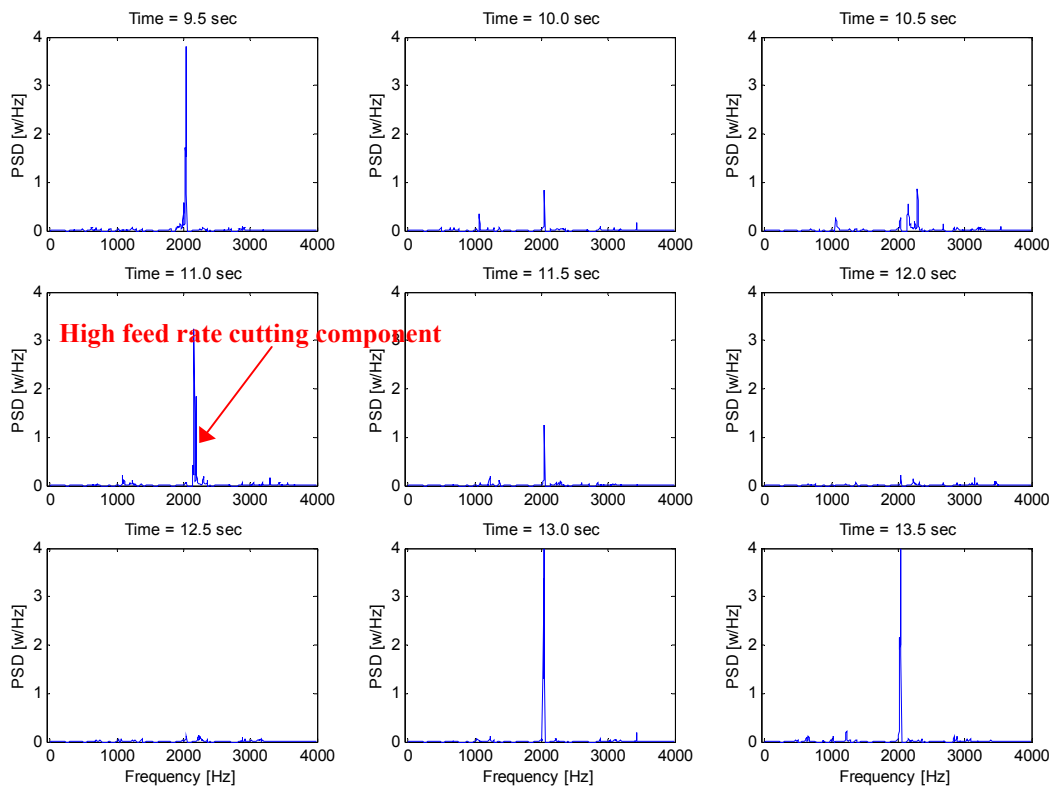
(a) Starting of the cutting

Figure 5.6 PSD of pipe cutting noise (with soft blade) after the system noise is cancelled.



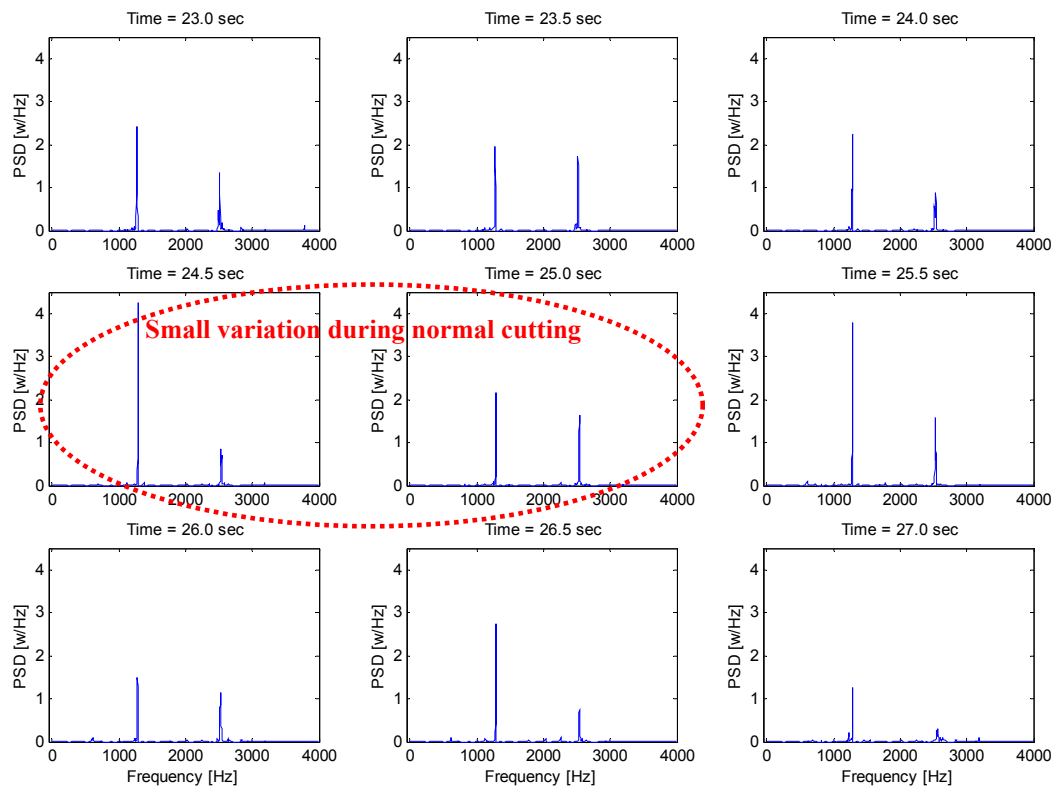
(b) Oscillation during the cutting

Figure 5.6 PSD of pipe cutting noise (with soft blade) after the system noise is cancelled (continued).



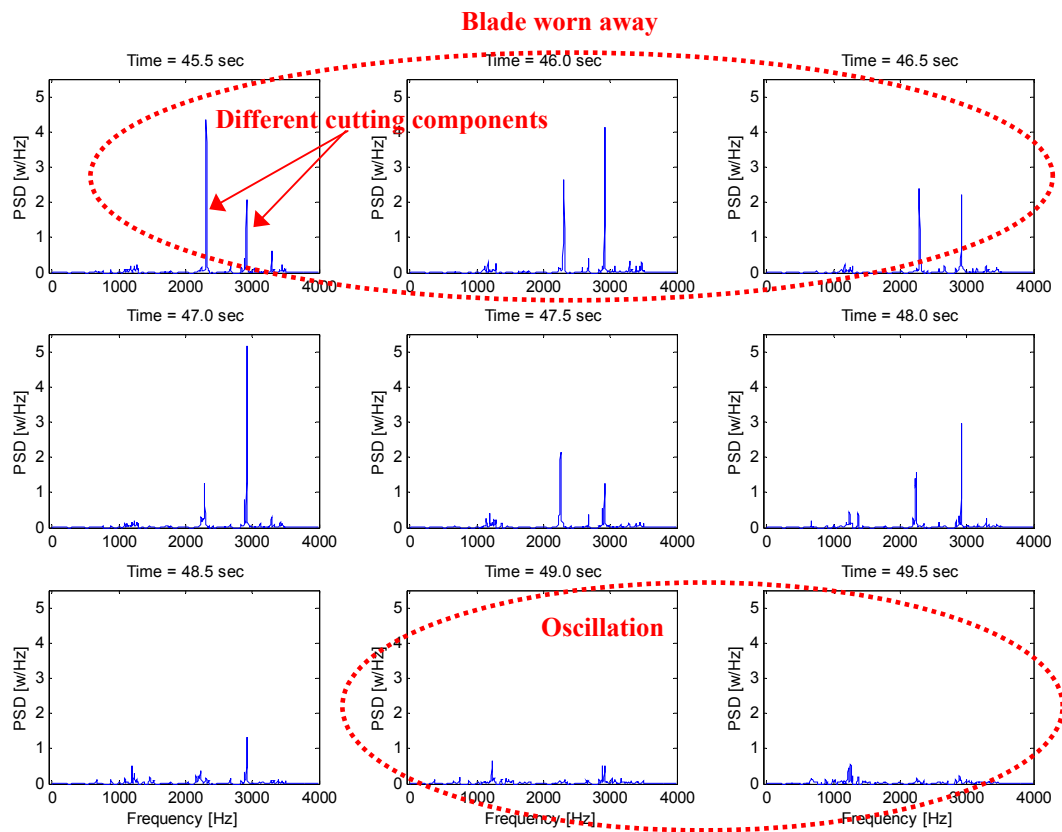
(c) High feed-rate

Figure 5.6 PSD of pipe cutting noise (with soft blade) after the system noise is cancelled (continued).



(d) Normal cutting

Figure 5.6 PSD of pipe cutting noise (with soft blade) after the system noise is cancelled (continued).



(e) The blade worn away and oscillation

Figure 5.6 PSD of pipe cutting noise (with soft blade) after the system noise is cancelled (continued).

blade generates two significant frequency components at 2300 and 2910 Hz. The existence of the component at 2910 Hz is the prominent feature compared to other PSDs, and it can be used for classification of tool condition.

5.1.2 Analysis

The spectrum analysis using the roughly sampled acoustic data shows that the analysis cannot provide sufficiently detailed information about the tool and task conditions. The frequencies of the dominant components have large width and vary in the steady state, and relatively high noise makes it difficult to classify the components which have small amplitudes. However, the proposed methodology, which cancels some fundamental system noise (hydraulic pump noise and tool noise in this test), makes it possible to distinguish and concentrate on a few dominant components in the tooling process. The test results show that the remaining components after cancellation relate to cutting conditions and they are not affected by blade and workpiece material changes. This robustness to the change of work material is an important attribute for the telerobotic applications. Therefore, the methodology used in this study is practical and useful for the operational fault detection during telerobotic operations, and the fault tolerant system will need automatic pattern classification ability to utilize the results of this spectrum analysis to assist a human operator.

5.2 Time based monitoring of end-effector position data

The position data of the end-effector in Cartesian space is acquired by the

transformation of the joint position data using the direct kinematics. The joint position data is usually measured by a shaft position sensor such as a resolver and used as a feedback in the control system. Even though, as mentioned earlier, the errors in each joint sensor and the errors in the parameters of the kinematics deteriorate the accuracy of the position data and therefore the quality of the analysis, the low sampling frequency of the control system imposes even more limitations on the analysis of the data. As is well known, the sampling frequency must be at least two times higher than the input frequency. Usually, the sampling frequency is much higher than the input frequency to get clear signatures in the spectrum analysis and to get high frequency information. For example, in the case of tool condition monitoring in industrial applications, the interesting frequency of the input signal, which is a function of motor revolution speed and number of tool teeth, is in the range of a few hundred Hz, and the sampling frequencies of the FDI systems are above 1 kHz.

However, the usual sampling frequency of the control system for manipulators is in the range of 100~200 kHz, and the sampling frequency of the control system used in this study is 100 Hz. The low sampling frequency nature of the data limits the utility of the spectrum analysis as inappropriate for monitoring tool and task conditions in telerobotics. For example, the 100 Hz sampling frequency of the system used in this study limits the maximum frequency of the spectrum analysis to 50 Hz. Thus, the spectrum analysis of the position data provides information about the low frequency oscillations, which are visible, but, it cannot provide information about higher frequency oscillations, which relate to the tool and task condition. Another important feature of the position data is that the position

data has a large time varying dc component. The large dc component hides the ac components and obstructs the analysis of the data. Figure 5.7 is the position data in time domain and Figure 5.8 is the power spectrum of the position data. The definition of the x-y-z coordinate in the world frame is shown in Figure 5.9. In this pipe cutting test, the x-axis of the world frame points the same direction as the cutting proceeds. The z axis is perpendicular to the x axis and upward, and the x-axis and z-axis define the cutting plane. The y axis is perpendicular to the cutting plane and toward left side of the cutting plane. The power spectrum shows that the maximum frequency is 50 Hz and the dc component in the position data overwhelms the other components. Thus, the dc components must be removed before the spectrum analysis

In this study, the end-effector oscillations caused by perturbations from the cutting process are analyzed using the end-effector position data in the time domain. First, two methods for the extraction of the ac components from the position data are compared, and the characteristics of the extracted ac components are discussed. Secondly, wavelets are used for the qualitative analysis of the oscillations. For analysis and comparison, three tests, which are shown in Figure 5.10 ~ 5.12, were selected. Test 1 used the blade which has coarse teeth made of soft material. The blade was worn away during the cutting process, and the cutting process was stopped by the operator around 70 sec. Test 2 used different blade, which has fine teeth made of hard material. In the case of test 2, the cutting process was successfully finished. Test 3 used the blade, which has hard material and fine teeth, but the blade was broken by manipulator control instabilities in the early process of the cutting.

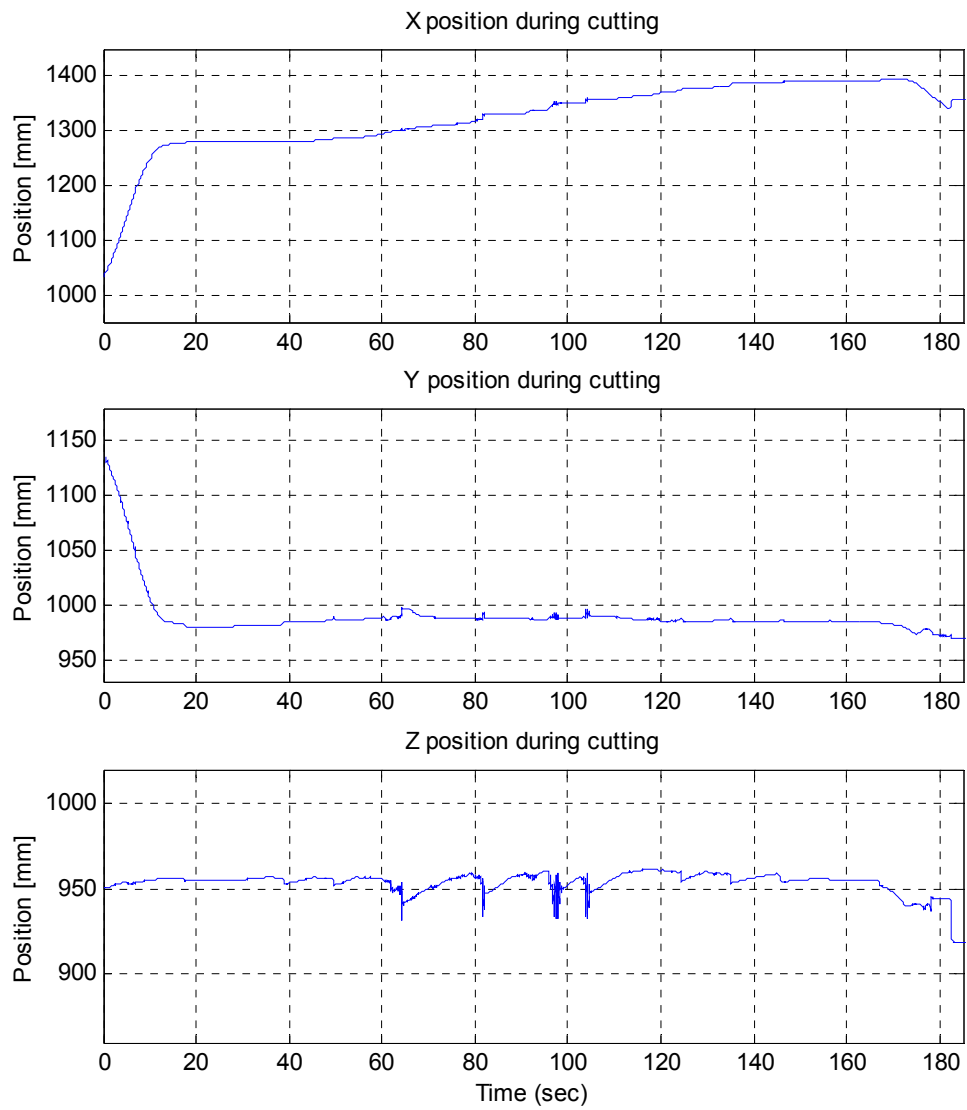


Figure 5.7 Position data of end-effector during the pipe cutting task.

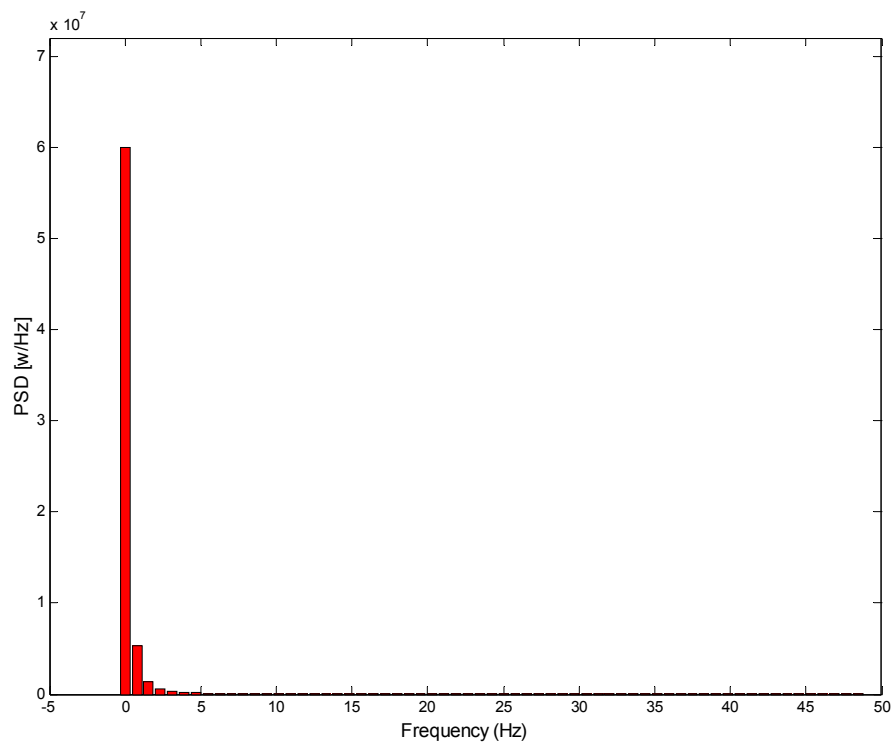


Figure 5.8 Power spectrum density of position data (z-axis) during oscillation.

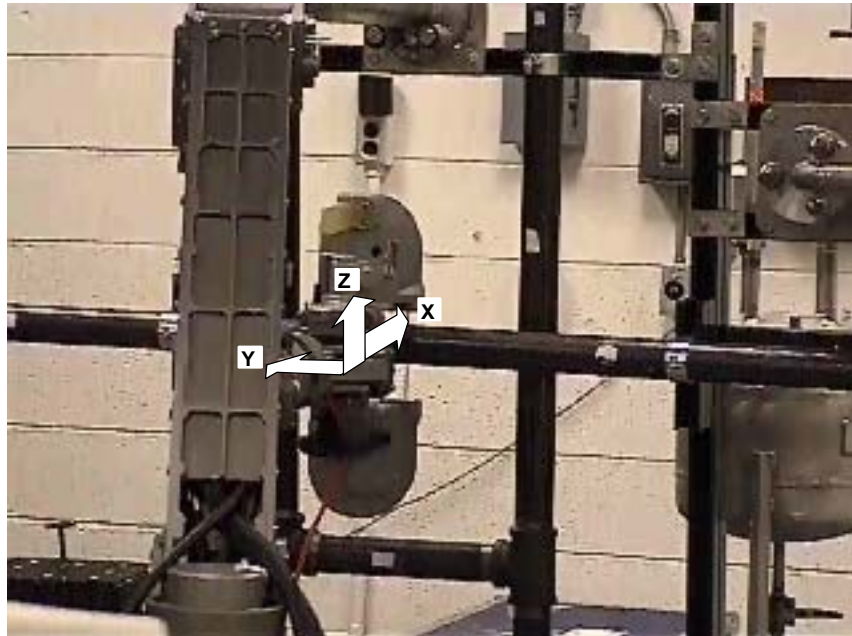


Figure 5.9 Pipe cutting task and definition of the x - y - z coordinate frame.

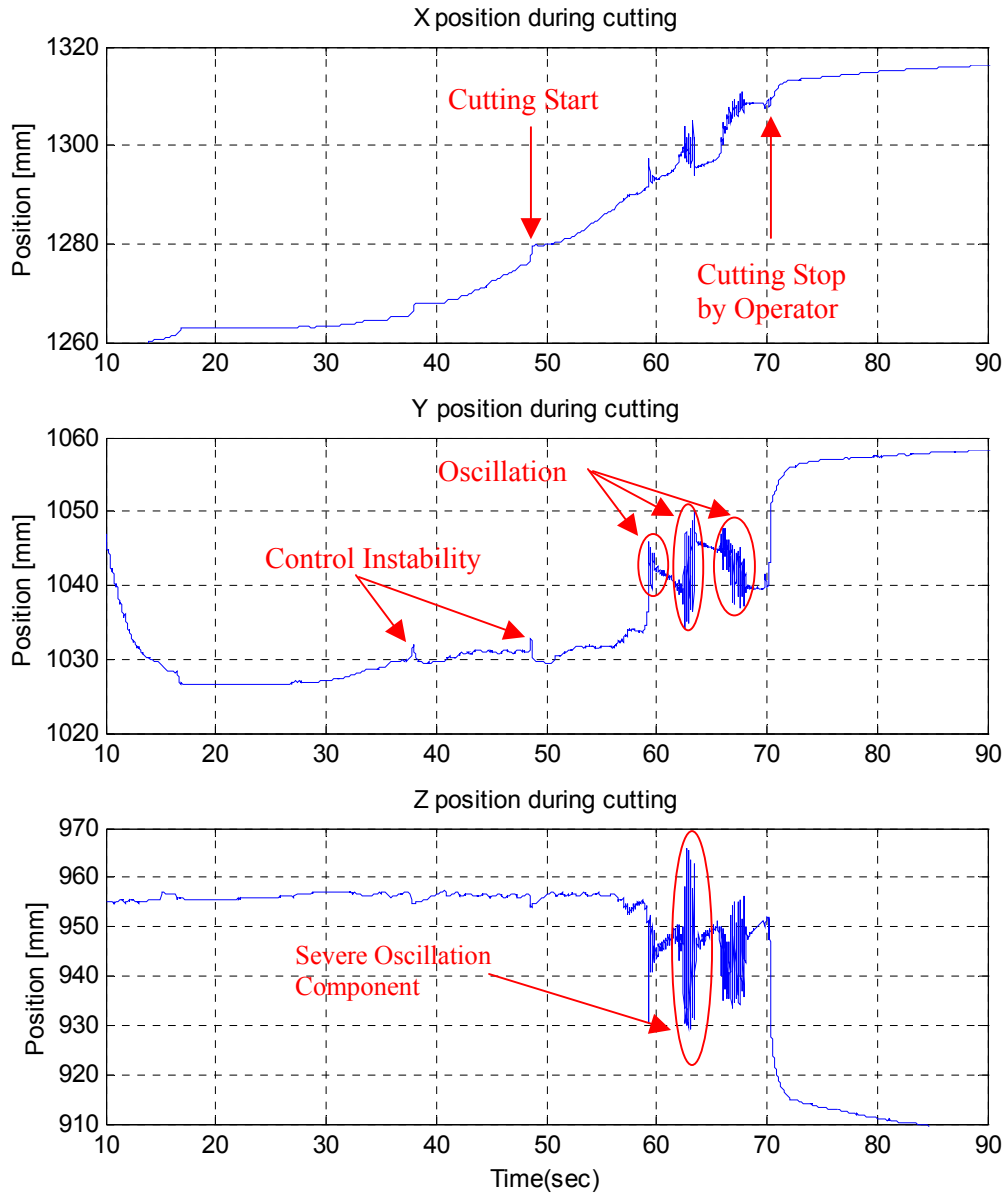


Figure 5.10 Position data of end-effector during the pipe cutting (Test1).

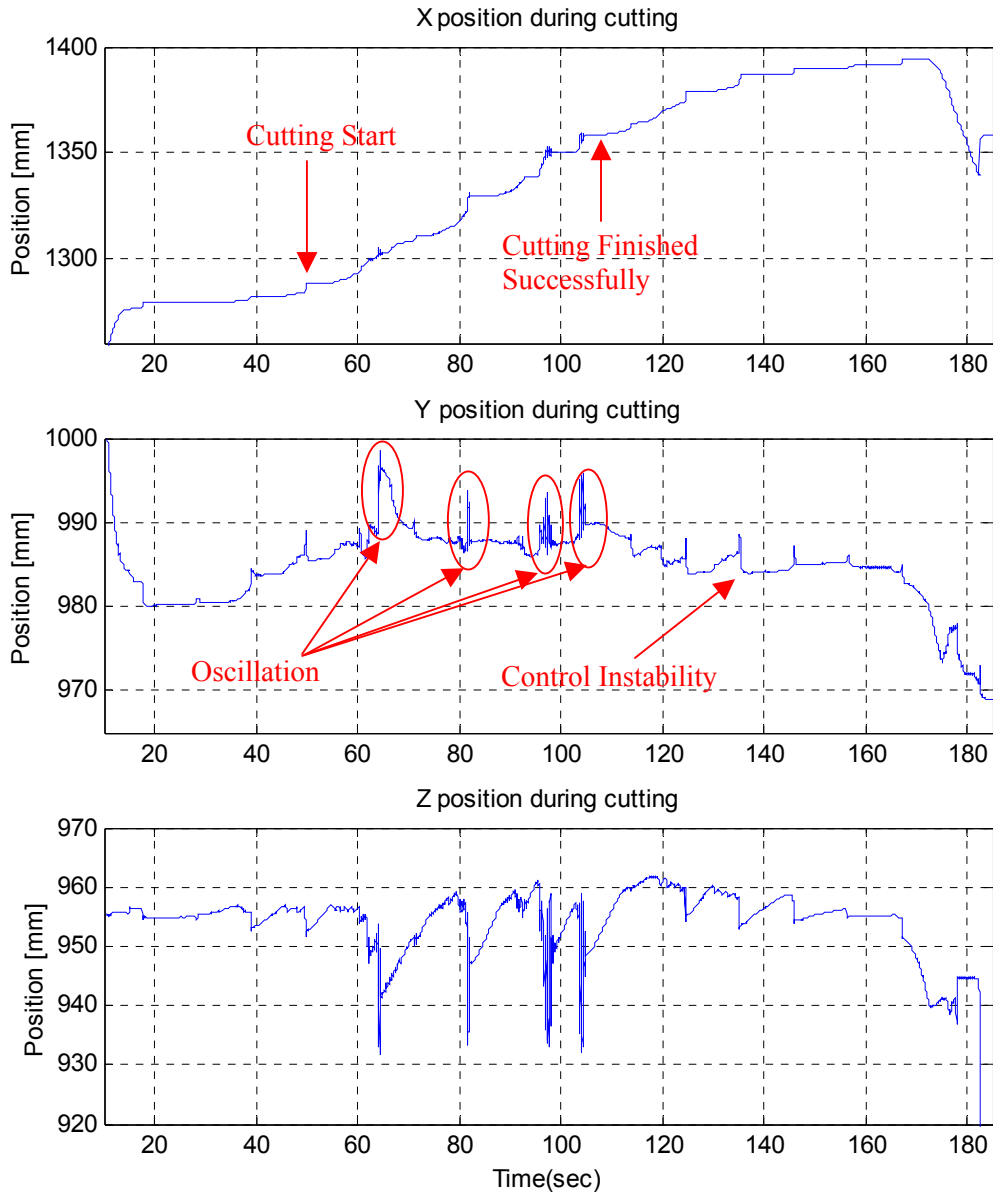


Figure 5.11 Position data of end-effector during the pipe cutting (Test 2).

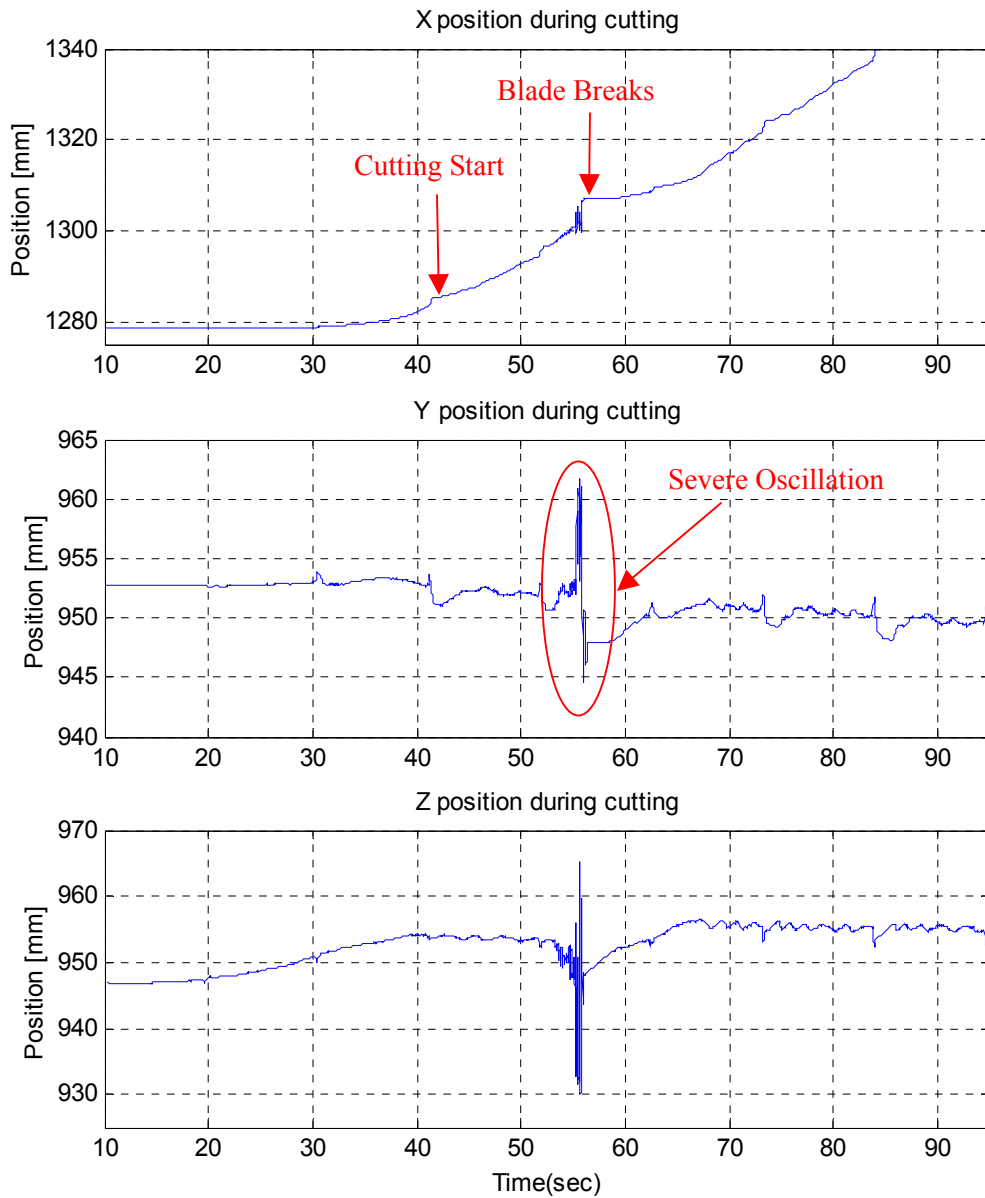


Figure 5.12 Position data of end-effector during the pipe cutting (Test 3).

5.2.1 Time based monitoring of the ac components

Figure 5.10 ~ 5.12 shows that the joint sensors can measure the oscillation of the end-effector caused by the instabilities in the cutting process. It also shows that the dc component must be removed for the analysis of the oscillation. If the end-effector is not moving during a task, the dc component is the average of the signal value. So, subtraction of the average value from the signal value provides the ac component of the signal. However, the end-effector is not suspended and moves along the position profile in the cutting plane for cutting (only the x position profile is changed in this test), and the planned trajectory for the task causes a relatively slow movement of the end-effector. These movements of the end-effector make the inclined trend in a certain interval in the position data as shown in Figure 5.13. When the data has incline, the subtraction of the mean values from the data does not provide correct ac components even though the result has zero average as shown in Figure 5.14 (a). It shows that the subtraction of the mean value shifts down the signal to the zero average, but the signal still has the incline. If the signal has incline, the deviation of the data from the slope provides more correct information about the oscillation than the subtraction of the mean value. Figure 5.14 (b) is the result of the slope subtraction of the data using the first order linear slope which fits the data in a least square sense, and it shows that the results provide more correct information about the oscillation. However, this method has two problems: (1) it needs a time interval for the calculation of the slope and this time interval introduces a time delay in the results by the amount of the time interval, (2) it provides incorrect ac components like the mean value subtraction when the signal has higher order incline or abruptly changes, as is shown in

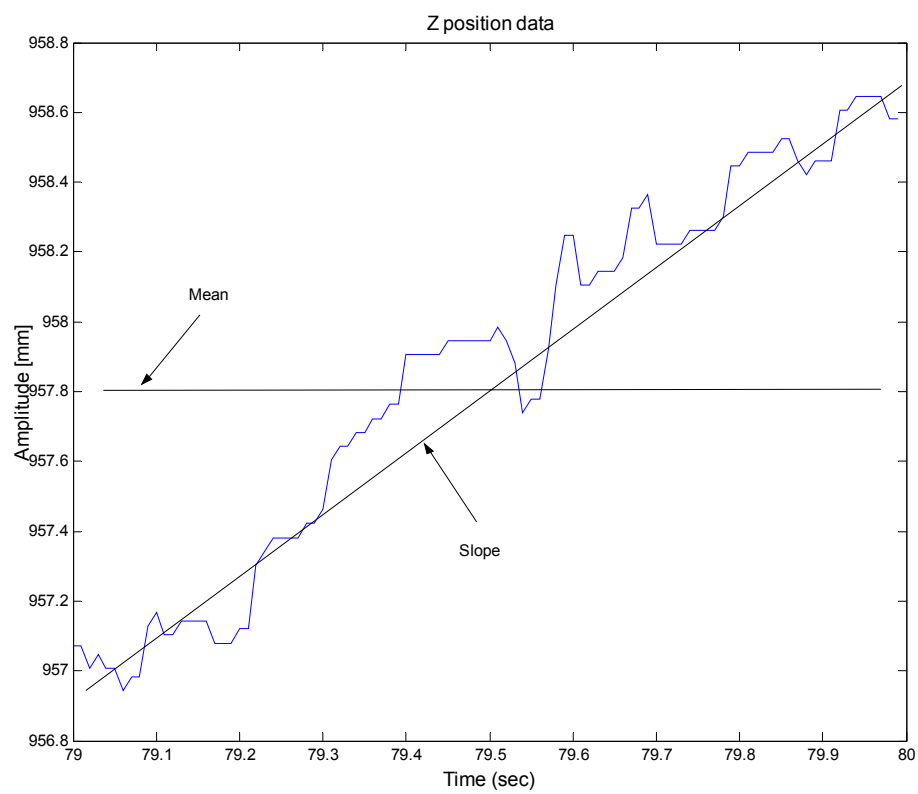
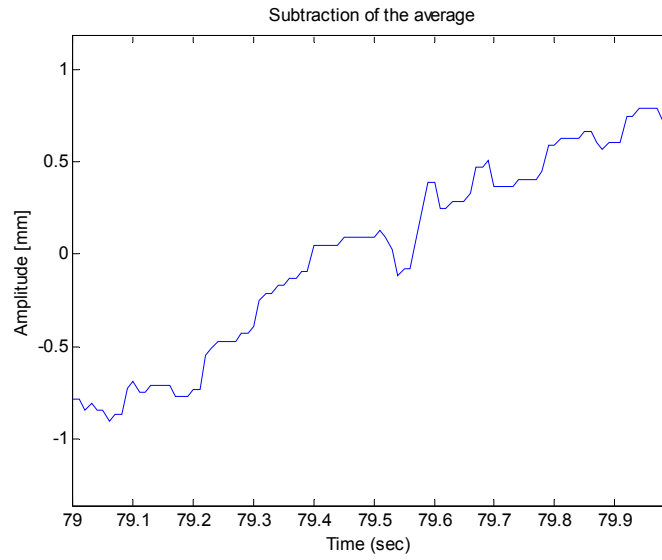
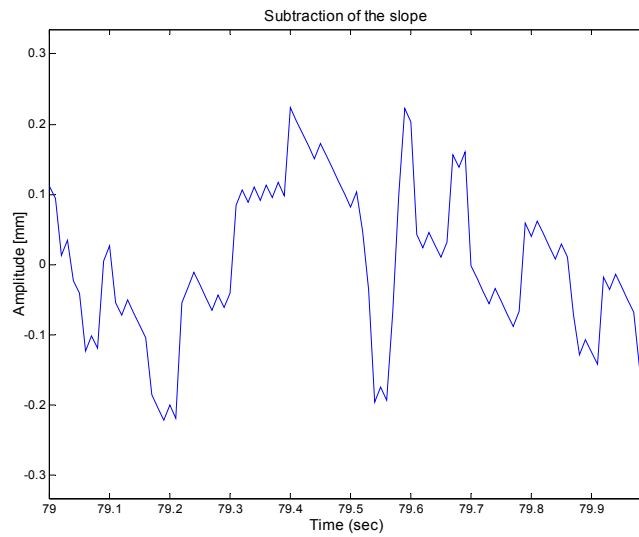


Figure 5.13 Mean and slope of the position data.



(a) Subtraction of the mean values



(b) Subtraction of the slope

Figure 5.14 Comparison of the dc component removal methods.

Figure 5.15. For the minimization of these effects, the time interval must be minimized or optimized, and the slope must be a higher order when the data has a complicated incline. In this study, only the first order linear slope is used to get the ac component from the end-effector position, and the “detrend” blockset of Matlab is used for the calculation [137]. The time interval for the calculation is selected as 0.5 sec by test.

Figure 5.16 ~ 5.18 show the ac components of the position data, which is acquired by the cancellation of the slope every 0.5 sec. They show that the method extracts the ac components effectively, and the amplitude and frequency of the ac component are proportional to that of the position. For example, test 1 was stopped by the operator since there was severe oscillation during the cutting. The ac components of test 1 (Figure 5.16) shows that the duration of the oscillation is longest and the amplitude is relatively high compared to other tests. However, as mentioned earlier, the method has problems when the signal changes abruptly as shown in Figure 5.15 and it cannot provide correct information about the abrupt change. For this reason, even though the sudden change of end-effector position breaks the blade causing a halt in the cutting process shown in test 3 (Figure 5.18), the ac components of the position data generated by the subtraction of the slope cannot provide a prominent signature to detect tool breakage, as shown in Figure 5.18. Therefore, the ac components can be used to quantitatively express the severity of the oscillation by the time duration, amplitude, and frequency of the oscillation. However, it cannot provide useful information about the sudden change of position data which has a great effect on the performance of the task execution.

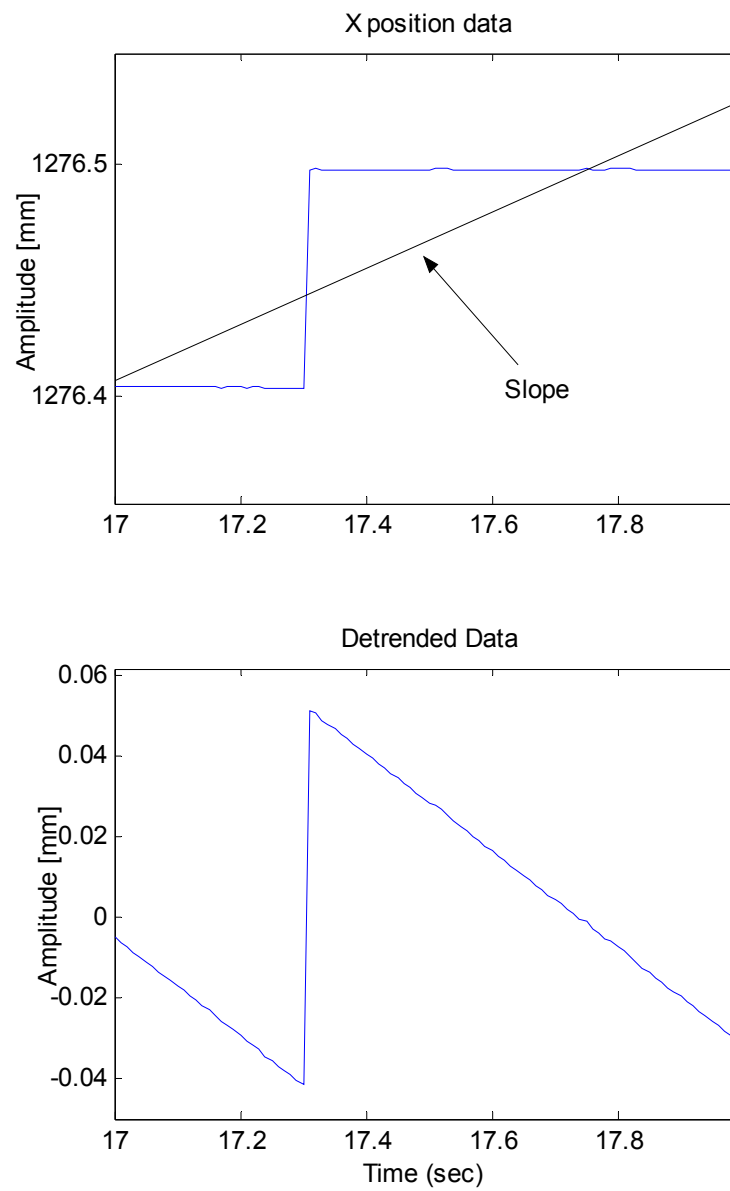


Figure 5.15 Subtraction of the linear slope when the signal changes abruptly.

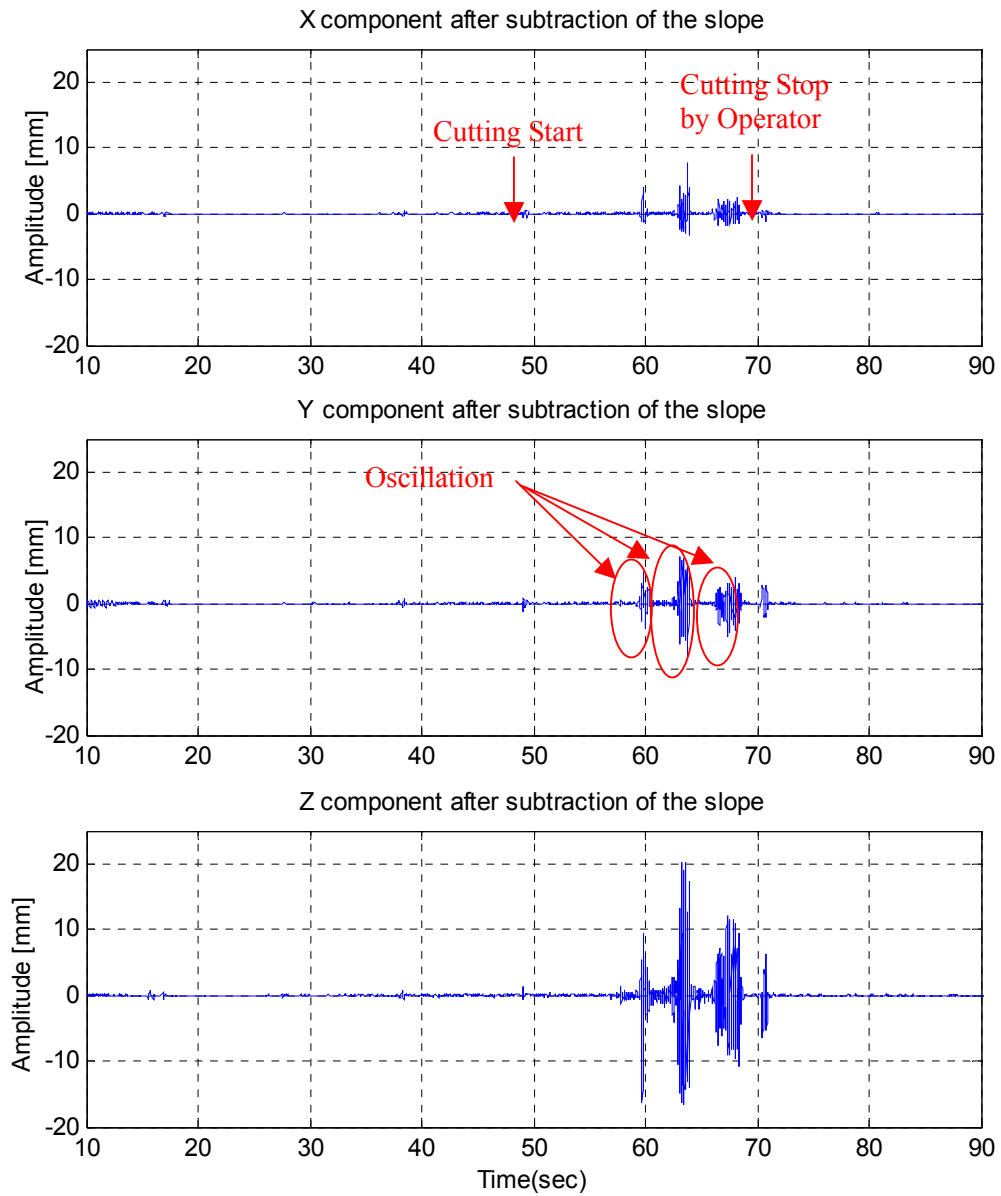


Figure 5.16 AC component of the position by the subtraction of the slope (Test 1).

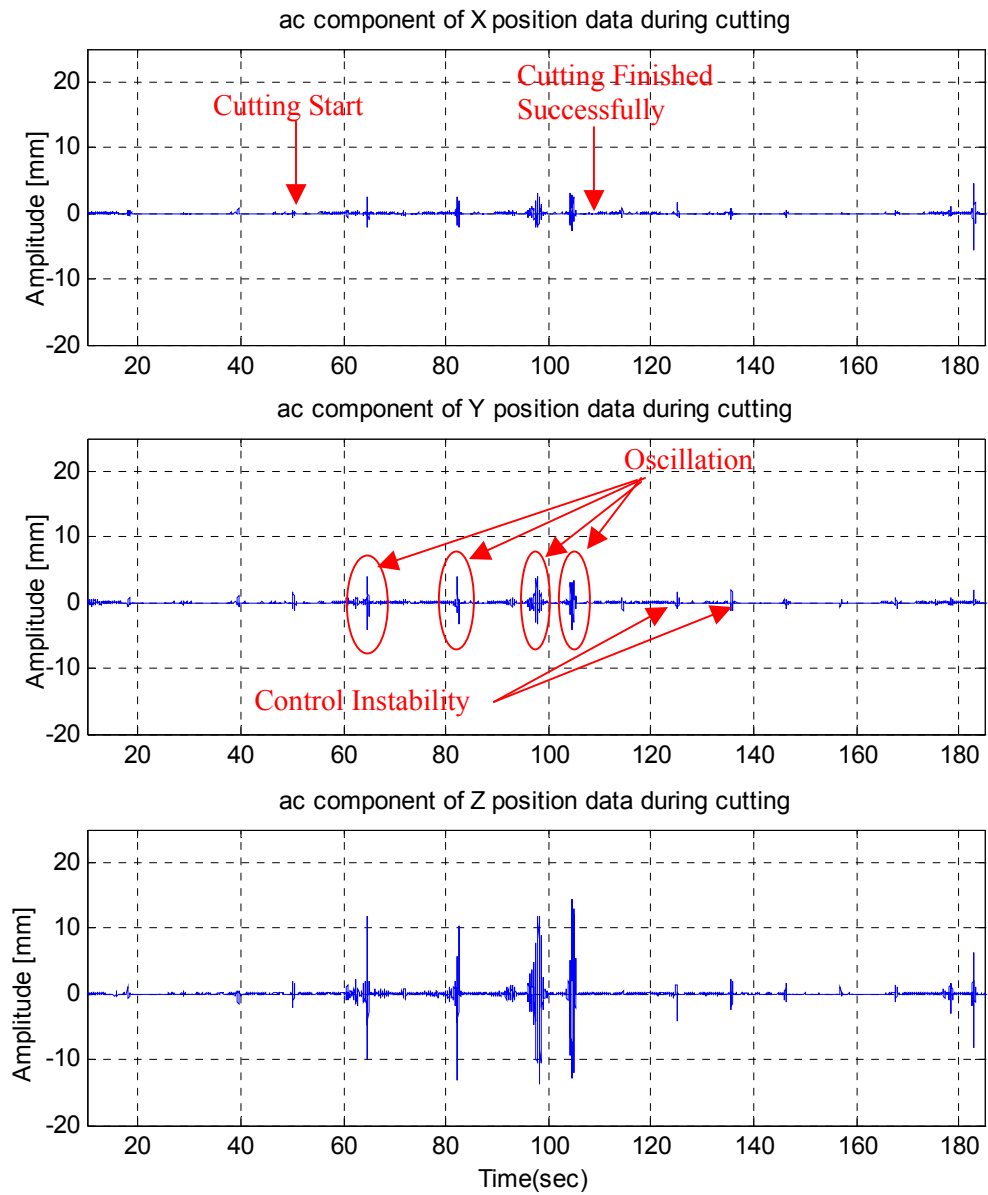


Figure 5.17 AC component of the position by the subtraction of the slope (Test 2).

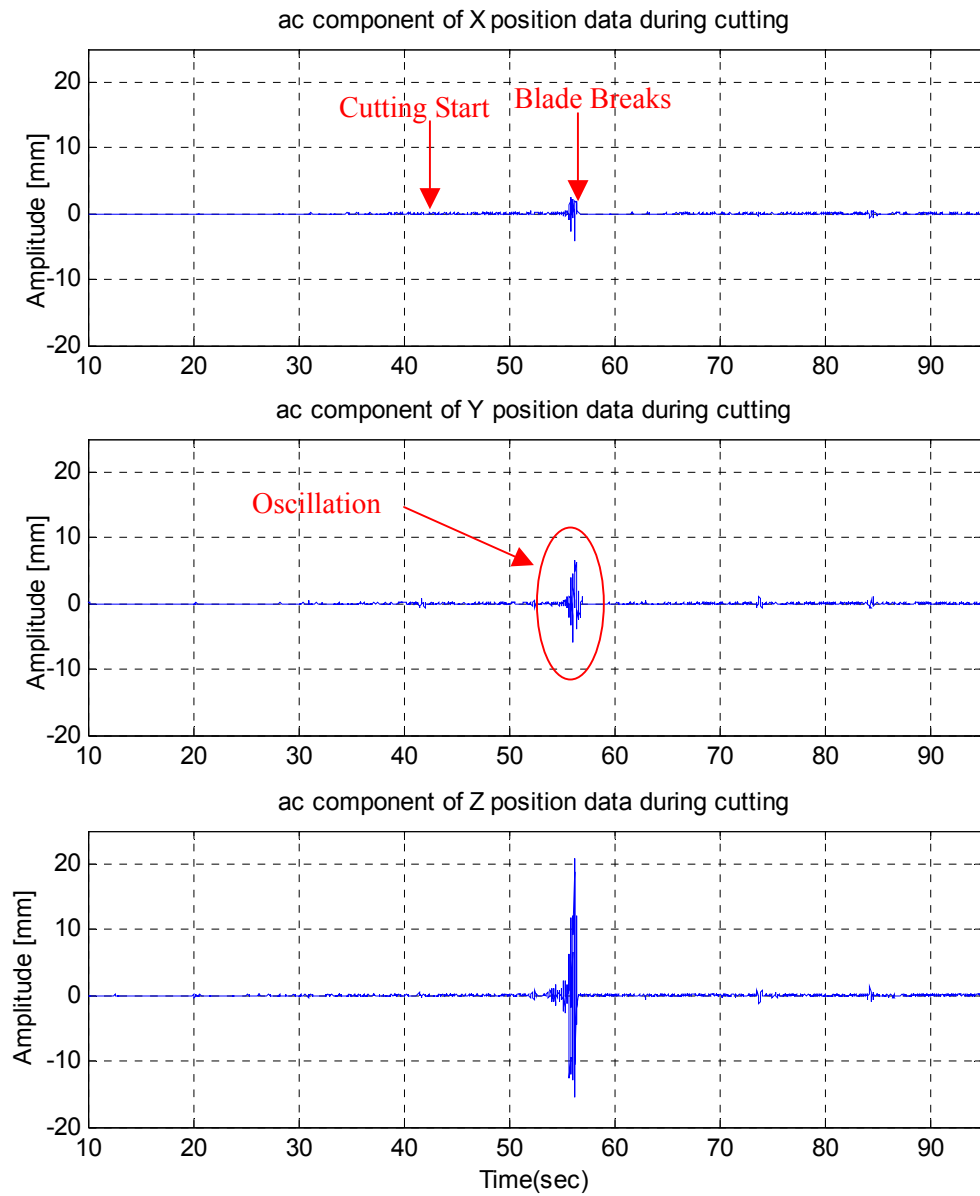


Figure 5.18 AC component of the position by the subtraction of the slope (Test 3).

5.2.2 Time based monitoring using wavelets

In this study, wavelet analysis is proposed and tested for the detection and analysis of the sudden movement of the end-effector, and the results of the discrete wavelet transform (DWT) of the test 1~3 are shown in Figures 5.19~5.21. The wavelet used in this analysis is “db3” in Matlab Toolbox [137], and the numbers of levels in the DWT are 4. Unlike the results of the ac component extraction in section 5.2.1 (the amplitude of the ac component is the displacement of the end-effector), the output of the wavelet analysis is not the displacement of the end-effector, but is related to the amplitude and frequency of the input signal (the displacement of the end-effector in this test). The parameters of the DWT (type, order, and level) determine the frequency and amplitude of the input signal to which the output of the DWT responds. Thus, the parameters for the DWT are adjusted so that the output of the DWT is proportional to the amplitude of the abrupt large movement of the end-effector. The wavelet analysis of the tests show that the output of the wavelet analysis has peak values in the beginning of the oscillation of the end-effector with a time delay of approximately 0.5 sec, and the amplitude of the peak corresponds to the amplitude of the abrupt change of signal at the starting of the oscillation. Figure 5.19 shows that the wavelet analysis of test 1 has larger amplitude in the x and y direction than those of test 2 at the onset of the oscillation. The peaks of the wavelet analysis in z direction of test 1 and test 2 at the onset of the oscillation are almost the same. The wavelet analysis shows that test 1 has a more abrupt movement in the x and y direction than test 2 at the onset of oscillation, but they are almost the same abrupt movement in the x direction. Actually, the movement in the z direction of the end-effector is confined by the guide of the band saw, so

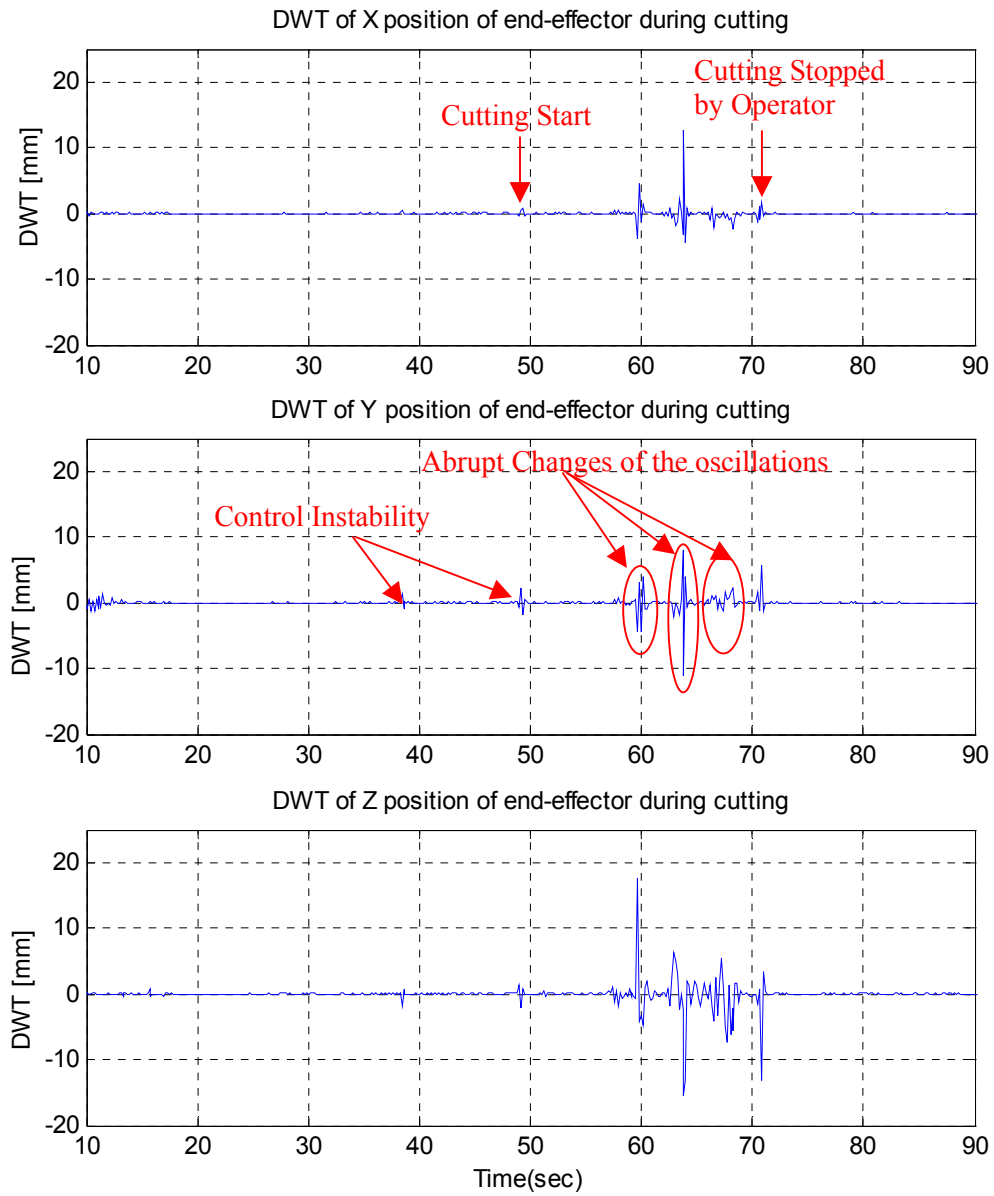


Figure 5.19 DWT of the position data of the end-effector during the cutting (Test 1).

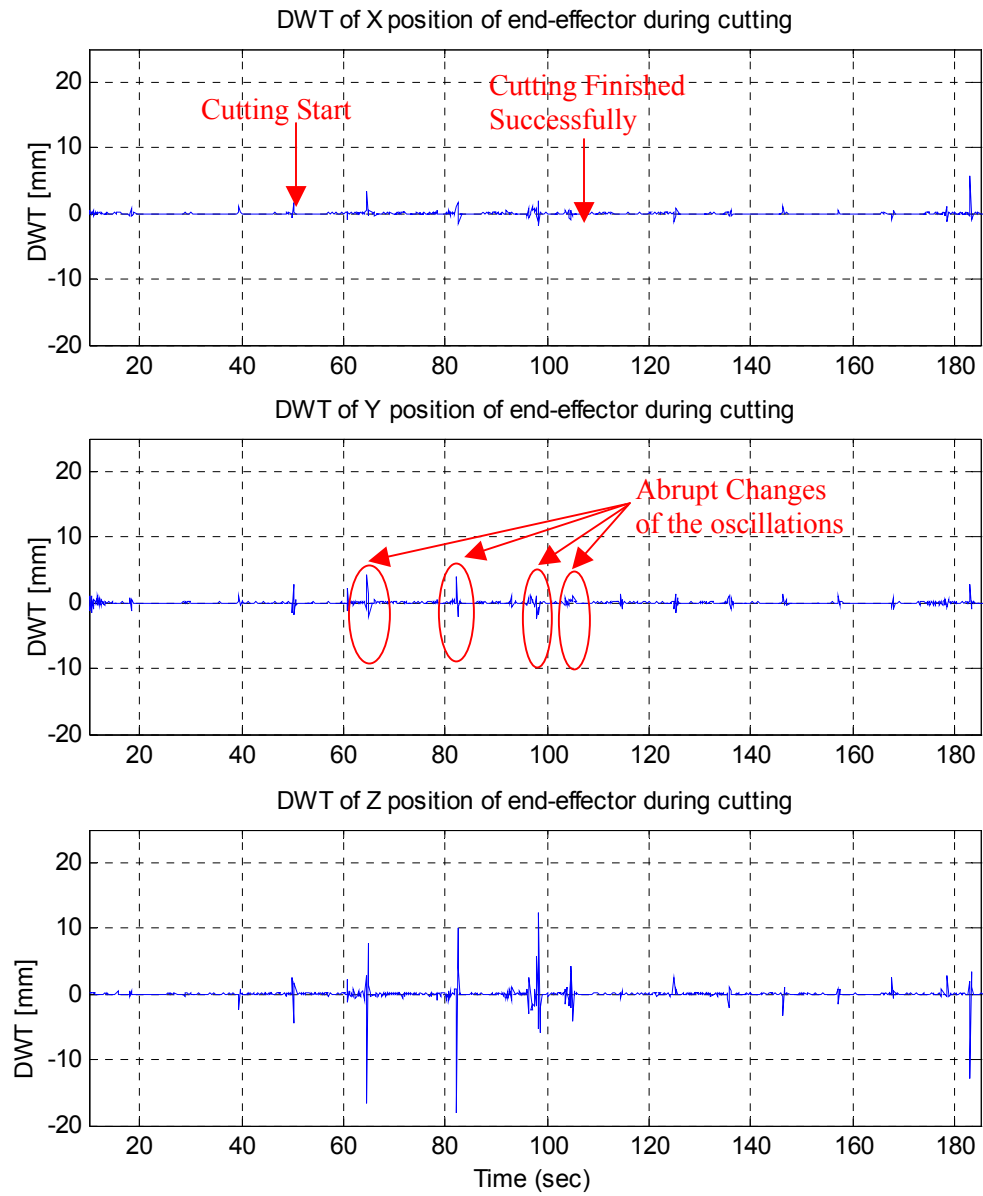


Figure 5.20 DWT of the position data of the end-effector during the cutting (Test 2).

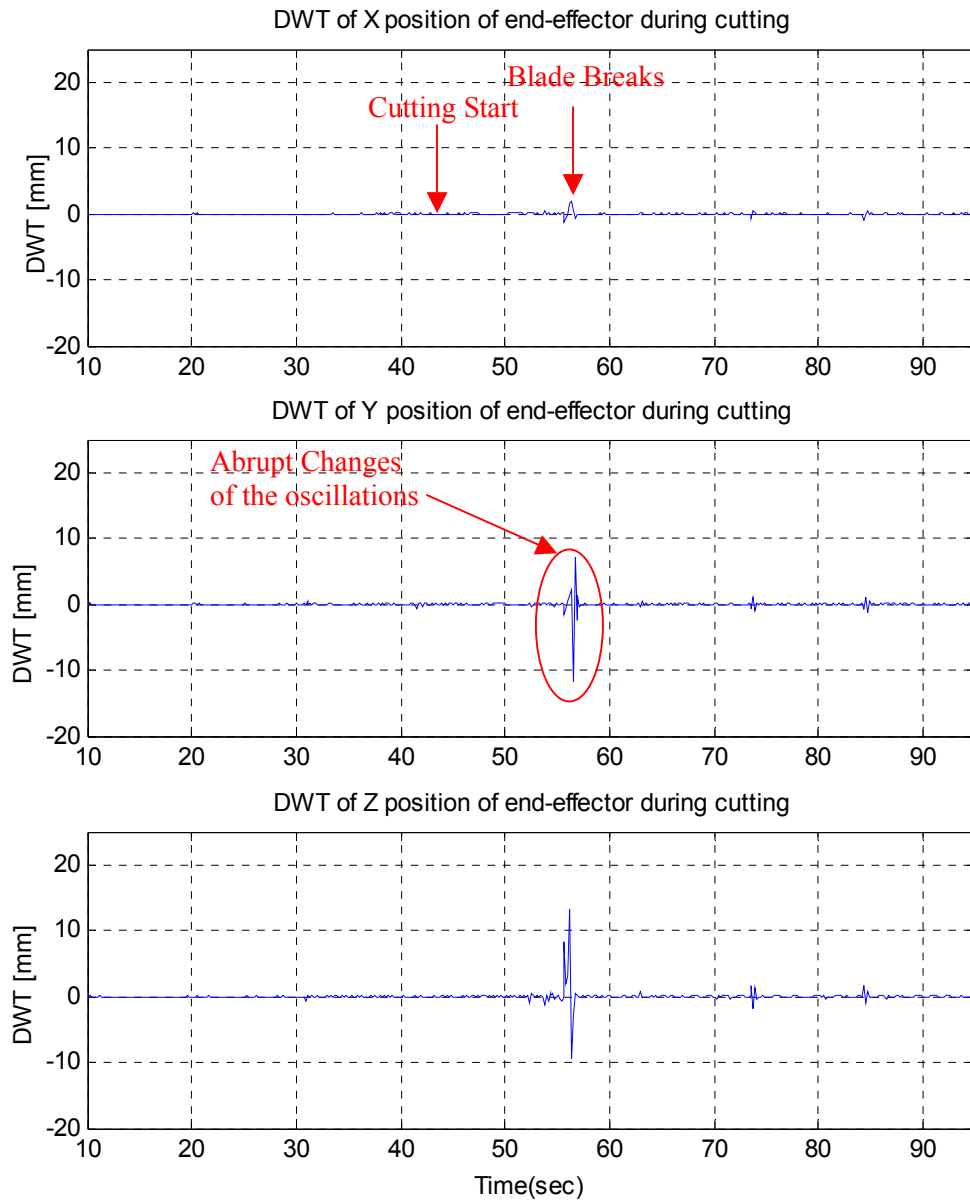
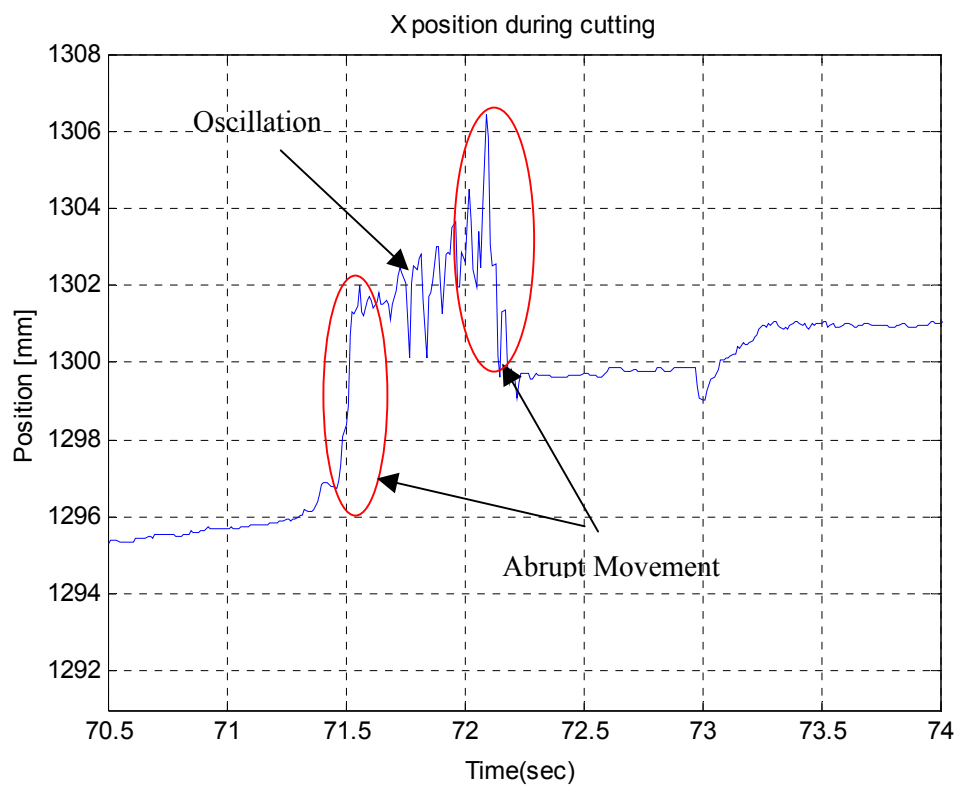


Figure 5.21 DWT of the position data of the end-effector during the cutting (Test 3).

the maximum value of the movement in the z direction is limited. Figure 5.21 is the wavelet analysis of test 3, in which the blade broke, and it shows that the peak value of the x, z direction is similar or smaller compared to those of the other tests, but the peak value in the y direction is the largest (-11.6) compared to peak values in the y direction in the other tests. This leads to the assumption that the large abrupt movement of end-effector caused the blade to break. However, a simple threshold, like ± 11 is inappropriate to detect tool break since the peak value in the y direction in test 1 is -11.1 and is close to the peak value of test 3. Instead of defining a simple threshold for the detection, the absolute peak values of the wavelet analysis and the relative amplitude of the peak value in the critical direction compared to the other directions (for example, in this test, the y direction is the critical direction compare to the x and z directions since large movement in the y direction can easily break the blade) can be used as a qualitative expression of the oscillation of end-effector and task condition.

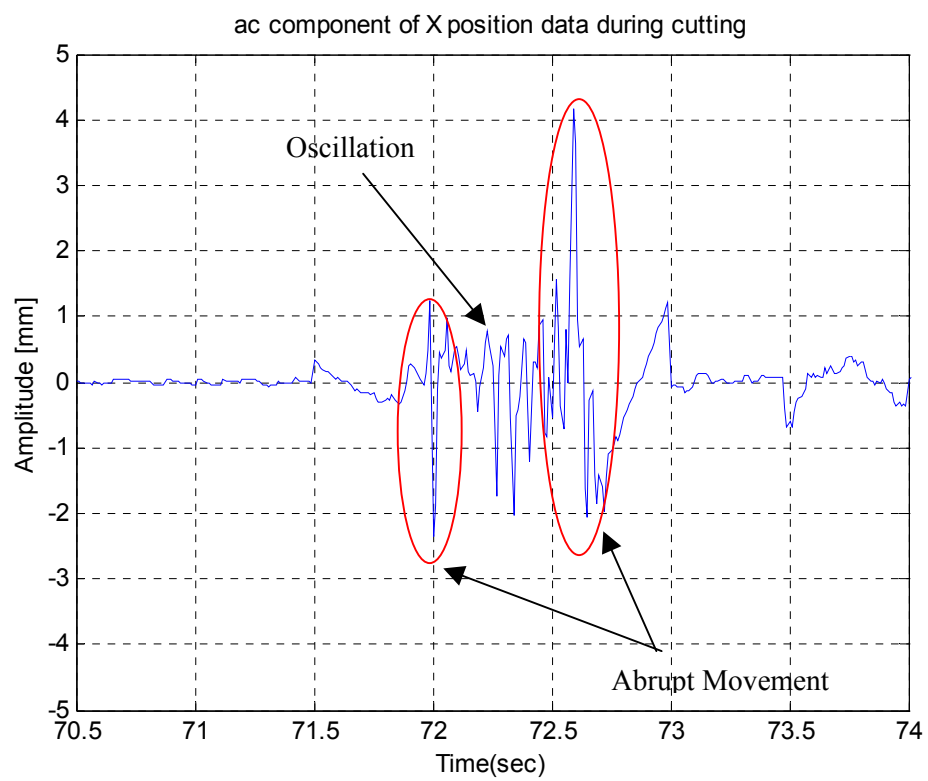
5.2.3 Analysis

For the time based analysis and monitoring of the end-effector position data, two methods are proposed: 1) subtracting of the slope of the signal and 2) wavelet analysis. One of the typical oscillation patterns shows that there is a large abrupt movement at the beginning and end of oscillation (Figure 5.22 (a)). In the case of the test, the abrupt change at the beginning of the oscillation and at the end of the oscillation has the same amplitude (6 mm). The ac components of the oscillation acquired by the subtraction of the slope (Figure 5.22 (b)) show that the method extracts the ac components effectively and



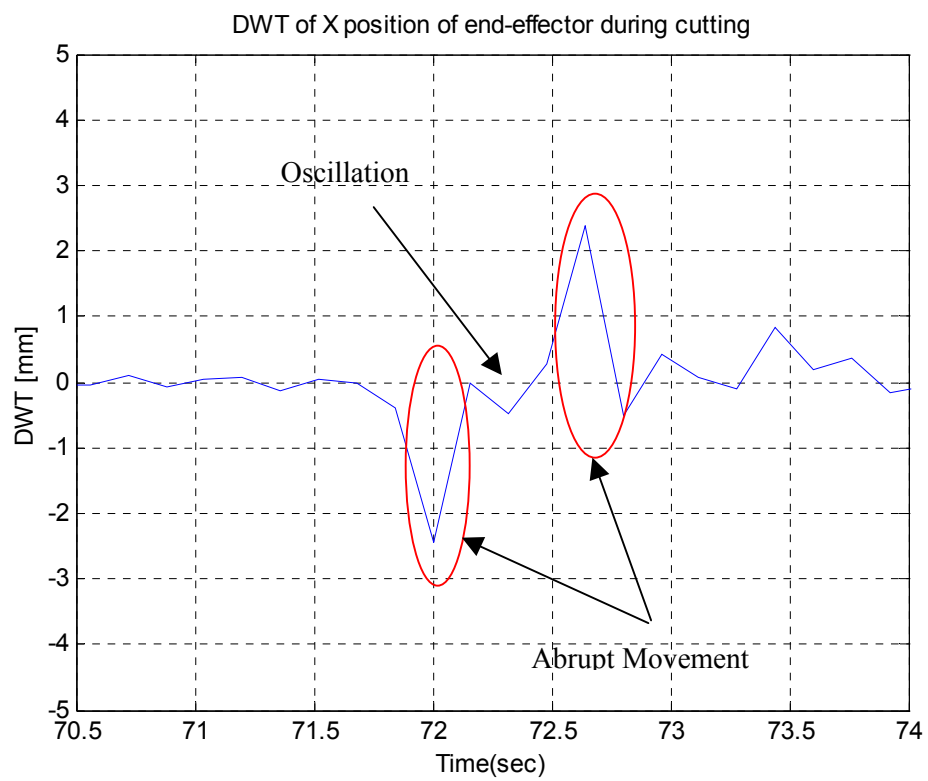
(a) Position data

Figure 5.22 Comparison of the results.



(b) AC component of the position data

Figure 5.22 Comparison of the results (continued).



(c) Wavelet results of the position data

Figure 5.22 Comparison of the results (continued).

correctly during the oscillation, but the extracted ac components at the beginning and end of oscillation have some errors. The amplitude of the abrupt change at the beginning of the oscillation is 1~2 mm, which is 4 mm lower than the amplitude of Figure 5.22 (a), and the amplitude of the abrupt change at the end of the oscillation is 2~ 4 mm, which is 2 mm lower than the amplitude of Figure 5.22 (a). These results show that the subtraction of the first order linear slope can extract ac components effectively and correctly when the oscillation is continuous, but it provides incorrect results at the beginning and ending of the oscillation or when the position moves abruptly. The second method uses wavelet analysis. The order of wavelet and number of levels are selected to detect the abrupt change of the position data, including the changes at the beginning and end of the oscillation. Figure 5.22 (c) shows that the DWT clearly distinguishes the two abrupt changes since the DWT do not respond to the stationary signal. The DWT results show the abrupt changes have the same amplitude and this coincides with the observation in Figure 5.22 (a). Thus, DWT not only can detect the abrupt change of the input signal, but also provides information about the size of the change. Therefore, the wavelet analysis is more effective in the detection and evaluation of the abrupt motion of the end-effector than the ac components acquired by the subtraction of the slope. However, the uncertainty in the task and task space makes the wavelet analysis unable to determine the tool condition, like blade breakage, and also the analysis does not provide any other information about oscillation. Thus, both methods are needed to evaluate the oscillation. The ac component of the oscillation provides quantitative information of the oscillation and the wavelet analysis provides qualitative information of the oscillation. This information is selectively

used with other information, like acoustic analysis or the position errors, to detect the operational faults in the supervisory system.

5.3 Tool grasping fault detection using neural networks

The uncertainty in the task and task space affects the tool or load grasping states of the end-effector, and the errors in the grasping manner, such as improper orientation of tool and dropping of tool, are common operational faults not only in telerobots, but also in industrial robots. The tool and load of robot may have different meaning. The load can be confined to the objects which are delivered and moved by robot, and the tool can be confined to the objects which are needed to execute a task. However, sometimes, the load means not only the load, but also the tool since they are described by the same parameters. In telerobotics, some researchers notice the importance of the detection of the tool grasping condition for critical application, and include the function, which can detect the operational fault, in their system configuration even though the practical techniques for the detection are not proposed [38, 50, 51]. In industrial robotics, many studies for the robust control of robots are interested in the accurate estimation of the parameters, which describes the load, to use the parameters in the control algorithm. A change of the parameters has load disturbance or parameter variation effects on the system, and deteriorates the system performance. One of the criteria for the robust control system is insensitivity to the parameter variation and load variation. Furthermore, most of the studies assume that a change of the parameters is caused by the intended or scheduled change of the tool or the load, not by an operational fault. Therefore, they are interested in the accurate estimation

of the parameters in the beginning of the change instead of the detection of the change, and there are some researches who utilize test motions, which are performed after picking up the tool, for an accurate estimation of the parameters. However, in telerobotics, a change of the parameters or an error in the grasping of the tools occur suddenly by the uncertainties in the task process, and the detection of the change and errors in a timely manner is more critical than the accurate estimation of the parameter. Therefore, in this study, a practical method, which can detect grasping faults especially the dropping of a tool, is developed using a neural network.

The characteristics or the grasping condition of the load and tool can be described by ten parameters: mass of load (needs one parameter), center of the mass (needs three parameters), and the inertia tensor (needs six parameters) of the load. The mass of the load can be used to detect the dropping of load, and the center of the mass and the inertia tensor can be used to detect the slipping and rotating of the load in telerobotics for operational fault detection. In industrial robotics, the accurate estimation of the parameter by the load identification is used in the control system to improve the control performance, and it also can be used to identify the load if the parameters of the loads are pre-known [114]. One of the methods for the load identification develops the load dynamic models and uses the model to calculate the parameters. Kozłowski [114] develops the model of load (Eq. (5.1)), and solves the equation to get the ten parameters using a least square method. In Eq. (5.1), the $F_{x,y,z}$ and $M_{x,y,z}$ are force and torque components measured by the sensor which is mounted between the wrist and end-effector, m is mass of load, $C_{x,y,z}$ are three coordinates of center of mass, and I_{xx} are six inertia tensor elements. The matrix K

has dimensions 6×10 , and the elements are functions of linear acceleration ($\ddot{P}$), angular velocity ($\dot{\omega}$), angular acceleration ($\ddot{\omega}$), and gravity (g). Even though, the method based on the load model can provide all parameters with high accuracy, it has problems: (1) higher the degree of freedom of the manipulator, more complicated calculation in the matrix K , (2) using least square method to solve the ill-condition equation in the inverse problem needs rich data to improve the accuracy of the results. Therefore, the algorithms take time to perform the data collection and calculations. For example, Slotine [115] precisely estimates the mass of manipulator and load within first half second 0.5 of a typical run in the system which has 200 Hz sampling frequency. Atkeson [116] uses 1000 samples for the static load estimation and 400 samples for dynamic load estimation in the system which has 200 Hz sampling frequency. Thus, the conventional approaches are not appropriate for use in operational FDI where real time response is required.

$$\begin{bmatrix} F_x \\ F_y \\ F_z \\ M_x \\ M_y \\ M_z \end{bmatrix} = K(\ddot{p}, \dot{\omega}, \ddot{\omega}, g) \times \begin{bmatrix} m \\ mc_x \\ mc_y \\ mc_z \\ I_{xx} \\ I_{xy} \\ I_{xz} \\ I_{yy} \\ I_{yz} \\ I_{zz} \end{bmatrix} \quad (5.1)$$

$$K = \begin{bmatrix} \ddot{p} - g & [\dot{\omega} \times] + [\omega \times][\omega \times] & 0 \\ 0 & [(g - \ddot{p}) \times] & [\dot{\omega}] + [\omega \times][\dot{\omega}] \end{bmatrix}$$

In this study, a time-delayed multilayer perceptron network is proposed for the estimation of the load mass in real time. The load mass estimation using the neural network is started from the hypothesis that there are functional relationships between the force/torque at the end-effector and the joint output torques and also there are functional relationships between the joint variables (such as joint accelerations) and the Cartesian variables (such as linear acceleration), and the functional relationships allow the neural network to estimate the load mass without the force/torque and Cartesian variables. Thus the neural network, using the joint variables and joint output torques, can estimate load mass faster than the algorithm using the Eq. (5.1). For the test and validation of the proposed hypothesis, the load mass estimator using the neural network with joint variables is applied to a two link manipulator simulation. Even if the method is effective for a two link manipulator, application of the method to higher order manipulators may not be possible. Increased training data and controller complexity of higher order systems often make this approach not practical, even though mathematical similarity between the lower order and higher order manipulator suggests applicability.

5.3.1 Control system of the two link manipulator

For the control of the manipulator, a joint space Proportional-Derivative (PD) control algorithm [118] is used, and the block diagram of the control system is shown in Figure 5.23. Even though the time step of the simulation is 1m second, the sampling frequency of the control system and data acquisition in the simulation is 100 Hz. Therefore, the sampling frequency of the system used in the simulation is 100 Hz, which is equal to the

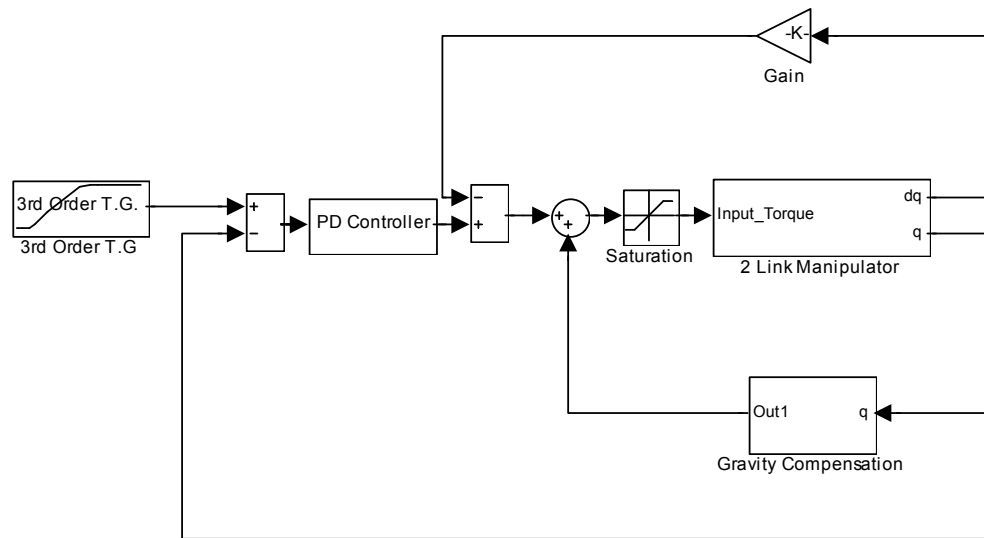


Figure 5.23 Joint space PD control scheme in Simulink.

sampling frequency of the system used in 3.1~3.2. This study assumes that the load is a concentrated tip payload and the selected load mass for the training of the neural network are 0, 5, and 10 kg. The position profiles of the two joints are generated by the third order trajectory generator. Joint 1 rotates from 0 to 60° and joint 2 rotates from 0 to 45°.

5.3.2 Development of NN with present data

The powerful functional approximation ability of neural networks have made neural network readily applicable to system identification, control, etc. It is also possible to replace the load parameter estimator, which is based on the solution of the numerical model of the load, by the neural network trained with well organized input and output data sets of

the model based parameter estimator. However, the neural network always provides less accurate results than the model based parameter estimator since the neural network is a functional approximation of the model based estimator. Also, the usage of the force/torque sensory data may lead to reduced reliability since force/torque sensors are generally more delicate and less reliable as mentioned earlier. The calculation for the angular velocity of end-effector is complicated and increases the computational load of the controller. These drawbacks lead to idea of a load mass estimator, which uses other sensory data and parameters as inputs. Based on the general features of neural networks: (1) nonlinear mapping, (2) drawing close match from partial input, this study proposes an estimator using a neural network to estimate load mass without a force/torque wrist sensor and angular velocity of the end-effector. Instead, the proposed neural network estimator uses joint torques, joint angular positions, joint angular velocities, and joint angular accelerations as inputs. These parameters have implicit relationships to force/torque at wrist and angular velocity of end-effector, and neural network incorporate these implicit relationships in the mapping. This approach does not need the development of complicated equations for the end-effector variables using the joint variables, and it can be applied to manipulators which do not have a wrist force/torque sensor.

Some important parameters used for the development and training of the neural network load estimator are as follows: The selected error goal for the training is 0.005 Mean Squared Error (MSE) to make the average error lower than 0.1. The number of hidden layers is one, and the number of neurons in the hidden layer, which is determined by experimentation, is four. The activation function for the hidden layer is the Hyperbolic

Tangent Sigmoid (Tansig), and the activation function for the output layer is the linear function (Purelin). The Levenberg-Marquardt algorithm is used for fast training, and the cross validation training method is adopted to reduce the overfitting of the network. Then, out of the total of 1053 data points of each input variable for each load, 3/5 of them (632) are used for training, 1/5 of them (210) are used for cross evaluation, and the remaining 211 patterns are used for test. The time step for simulation is 1 msec, and the data are sampled at 100 Hz. A neural network used in the training is shown in Figure 5.24.

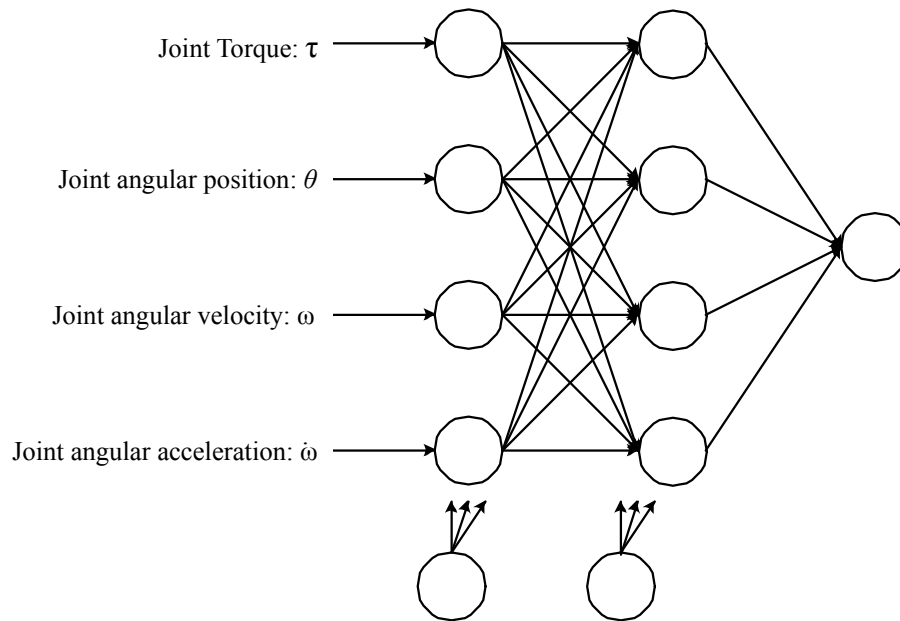


Figure 5.24 Neural network used in the development with present data.

The training results for the neural network for the load mass identification of the two-link manipulator are shown in Figure 5.25. It shows that the training is successful, and the MSE of the neural network is 0.00418. This particular neural network was selected for load mass identification. Figure 5.26 is the joint position data including the command profiles of the joints. It shows joint 1 reaches the final position at around 1.7 seconds, and joint 2 reaches the final position around 1.2 seconds. The tracking error of the control system is under 0.02° . Figures 5.27 and 5.28 show the test results of the neural network with 5 and 10 kg loads, which are used in the training. It shows that the neural network can detect and estimate the change of the load mass immediately whether the change occurs in the transient state or steady state, and Figure 5.29 shows the neural network can detect the change within the sampling time of 10 ms. The test results show that the accuracy of the neural network in the transient state is somewhat poor, and the accuracy is improved in the steady state. The higher non-linearity of the relationships between the input and output of the neural network in the transient state deteriorates the accuracy of the estimation. However, the response time of the neural network to the abrupt change of the load mass is not affected by the operating state (transient or steady state) of the manipulator. The result of the generalization test, which uses 2, 6, 8, and 9 kg instead of the 5, 10 kg used in the training, is shown in Figure 5.30. The result shows that the neural network correctly estimate and detect the mass of the loads whether the manipulator is in the steady state or in the transient state when the loads are inside the training space (0~10kg). The generalization test validates the approach using neural network for the online estimation of the load mass and online detection of the change of the load mass without the sensory data,

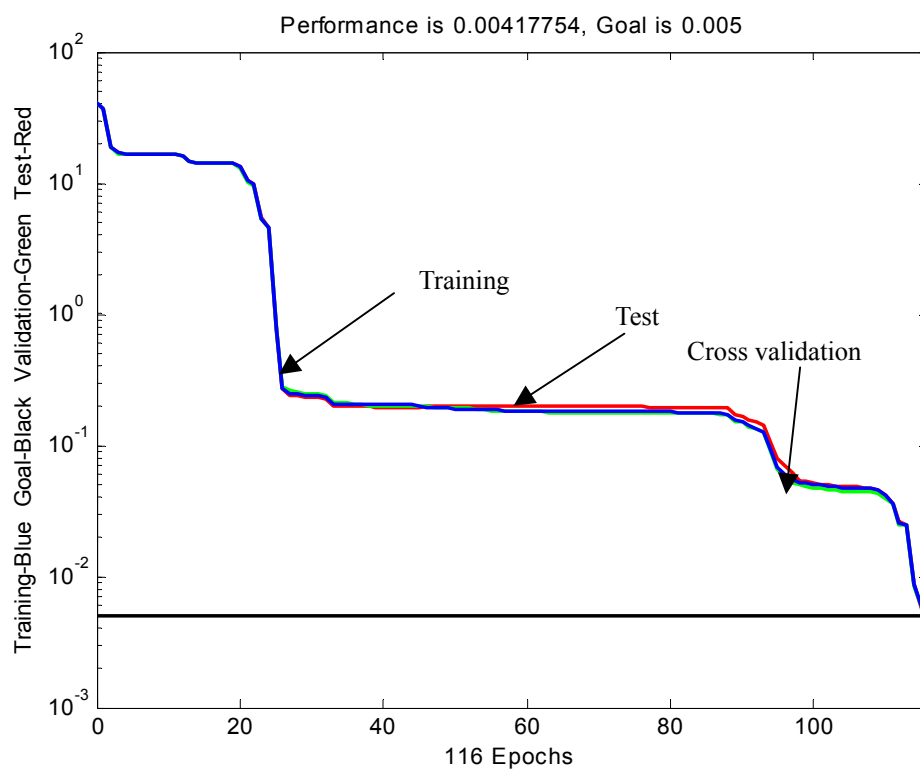


Figure 5.25 Training result of the NN.

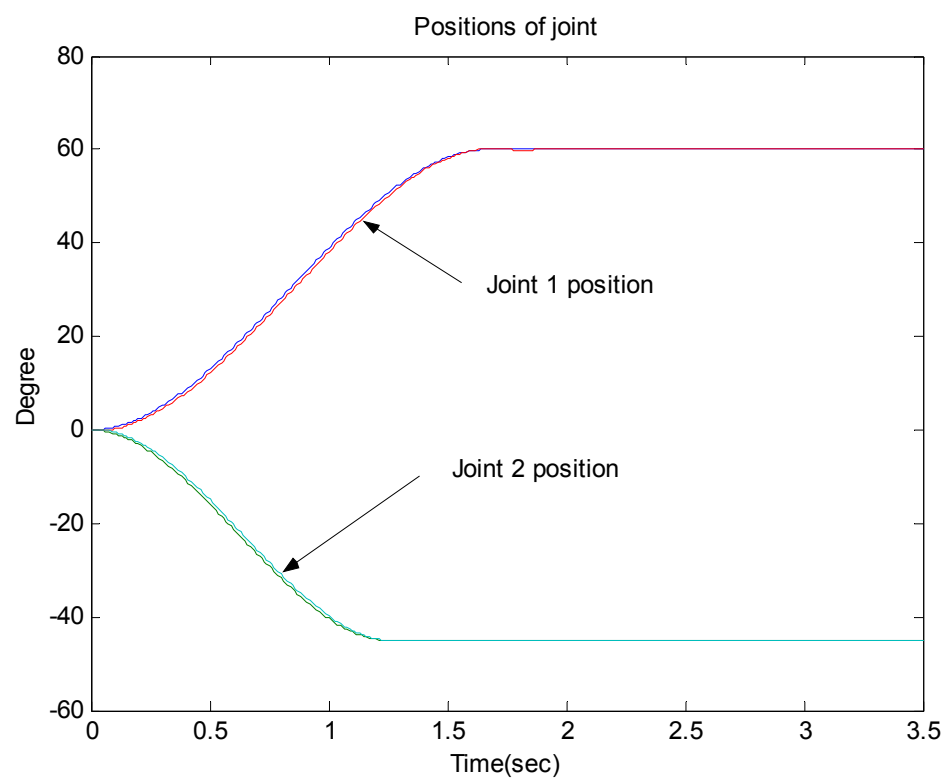


Figure 5.26 Position data of the joint 1 and 2.

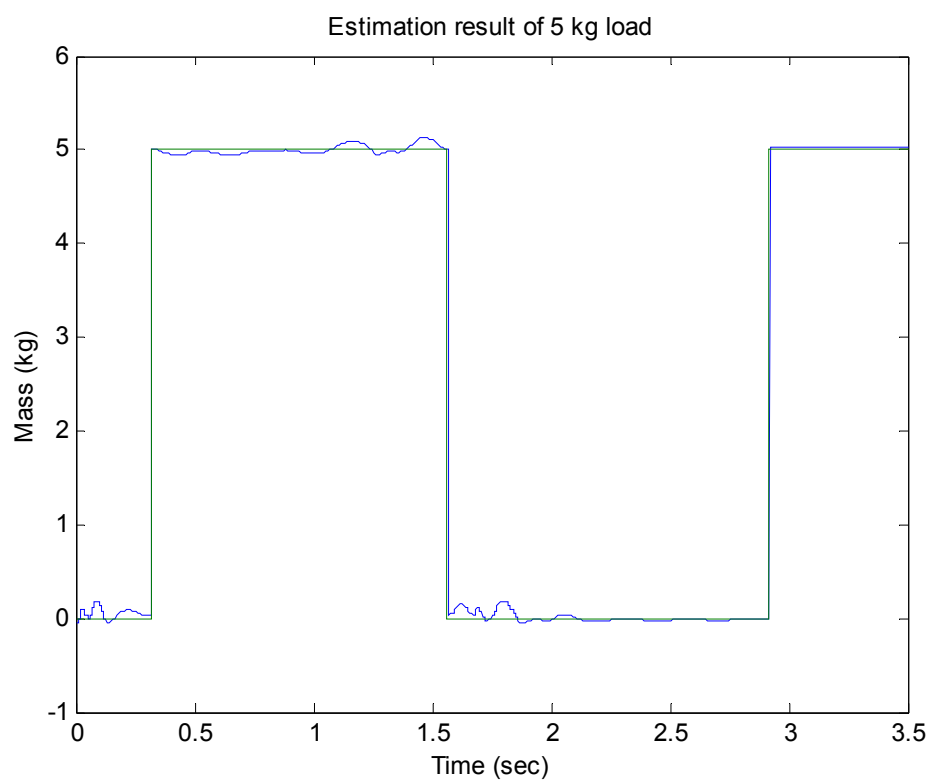


Figure 5.27 Test results of the NN with 5 kg load.

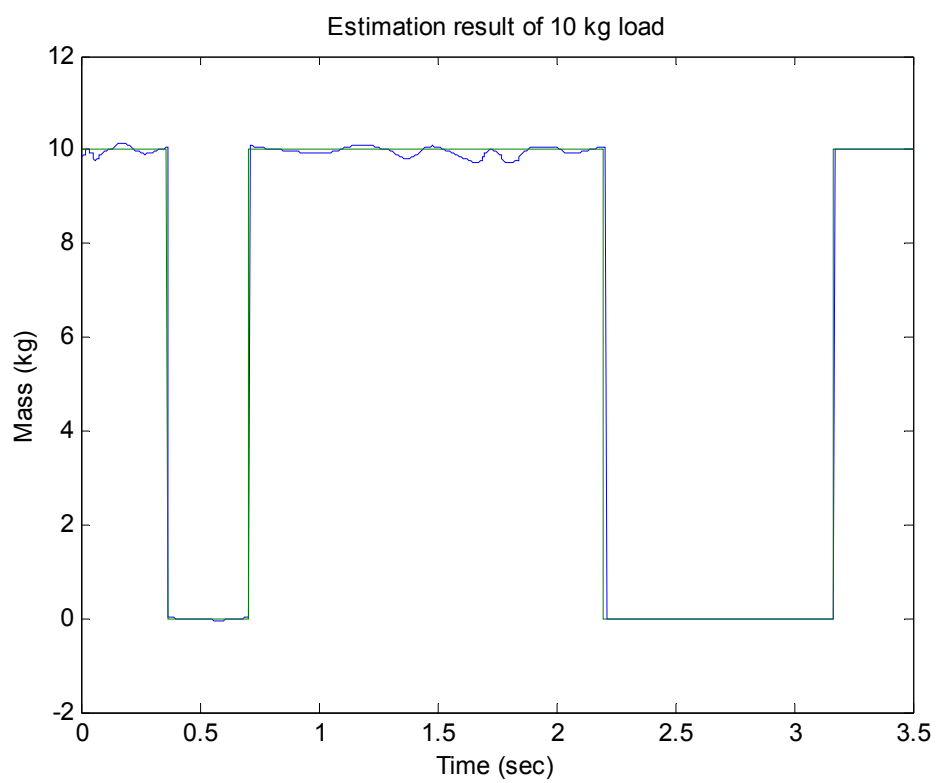


Figure 5.28 Test results of the with 10 kg load.

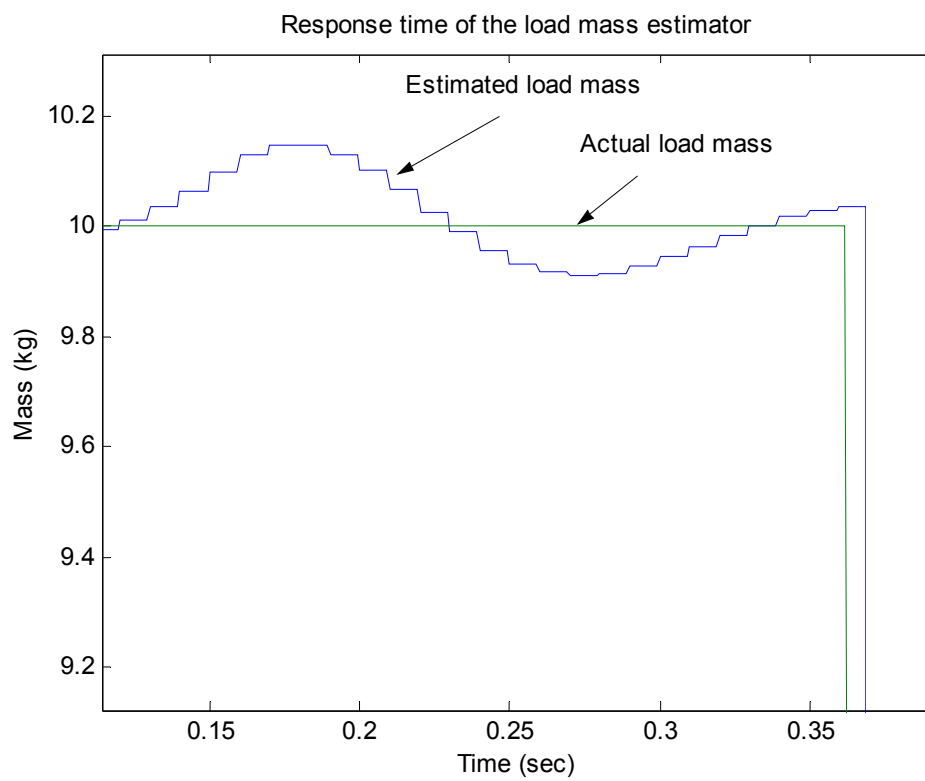


Figure 5.29 Response time of the neural network.

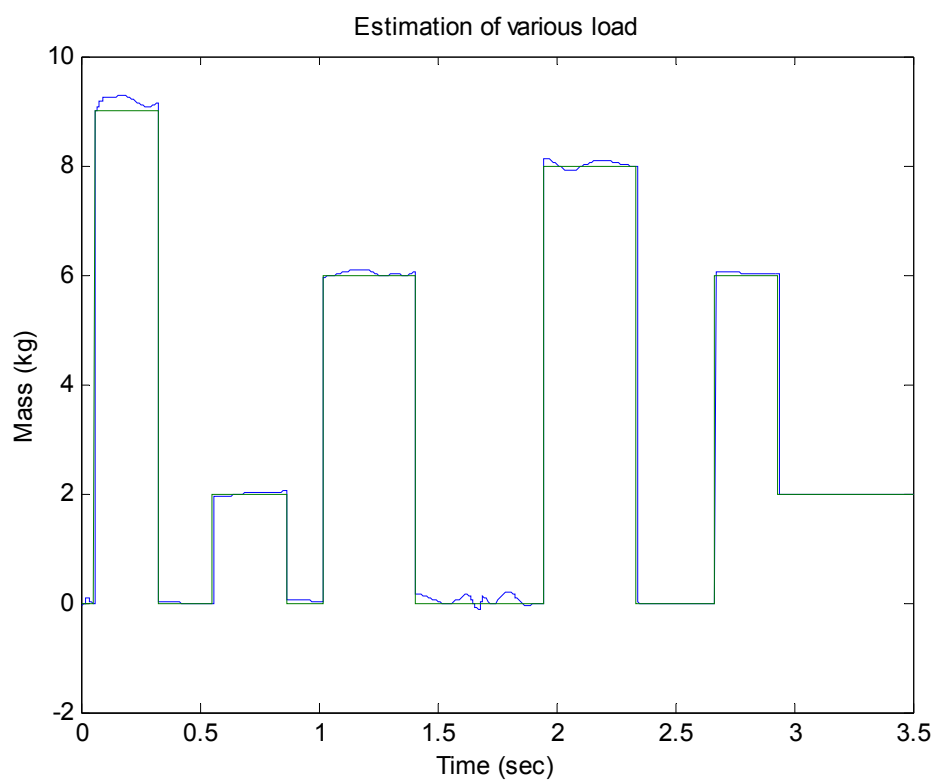


Figure 5.30 Generalization test of the NN.

which is required in the Eq. (3.1), such as, force/torque, end-effector angular velocities, etc. From these features, this approach will be also useful for the control of industry robots since many control systems require load estimator for robust control of systems. However, the training data of the neural network will tremendously increase as the work space of the manipulator and the number of degree of freedom of manipulator increase. Actual application of the proposed scheme needs the optimization of the neural network parameters and the optimization of the training data, which can represent the overall work space of the manipulator with a minimum data set.

5.3.3 Development of NN with time delay data

The developed neural network using sensory data shows that it can detect the change of load mass online, but the requirement of angular acceleration as input makes the actual implementation difficult. This leads to the investigation of time delay neural networks, which use time delay data as shown in Figure 5.31, to estimate load mass without the need of angular acceleration. The angular position, angular velocity, and angular acceleration have explicit relationships: derivative and integration, and one of them can be derived or estimated from the time series data of the others. The nonlinear mapping ability of neural network avails such relationships, and makes the neural network with series of time delayed data able to estimate the acceleration or velocity. One of the significant factors, which effect the performance and accuracy, is the sampling time or time step of the data. Thus, the three angular input variables of the developed neural network can be replaced with series of time delayed data of one angular variable.

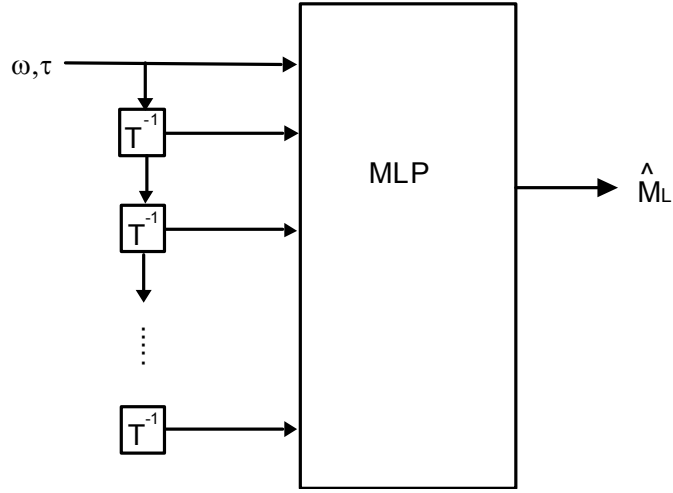


Figure 5.31 Time delay neural network.

This study attempted to train neural networks with the data, which was used in 5.3.2 (100 Hz sampling frequency), but a useful neural network for load mass estimation has not been trained. It was supposed that the low sampling frequency of the data causes the training failure. Thus, new data having 1 kHz sampling frequency was generated under the same conditions and used for training. With these data, the Mean Squared Error (MSE) of training has not reached the goal, and the least MSE in training is 0.027087 when the neural network has five consecutive time series data of angular velocities and joint torques. The training result is shown in Figure 5.32, and the test result of the neural network including generalization test is shown Figure 5.33. The test result shows that the accuracy of the estimation is poorer than that of the neural network having all three angular variables as input. However, it can detect the abrupt change of the load mass rapidly like the former neural network, and the need of only angular velocities and joint torques will be

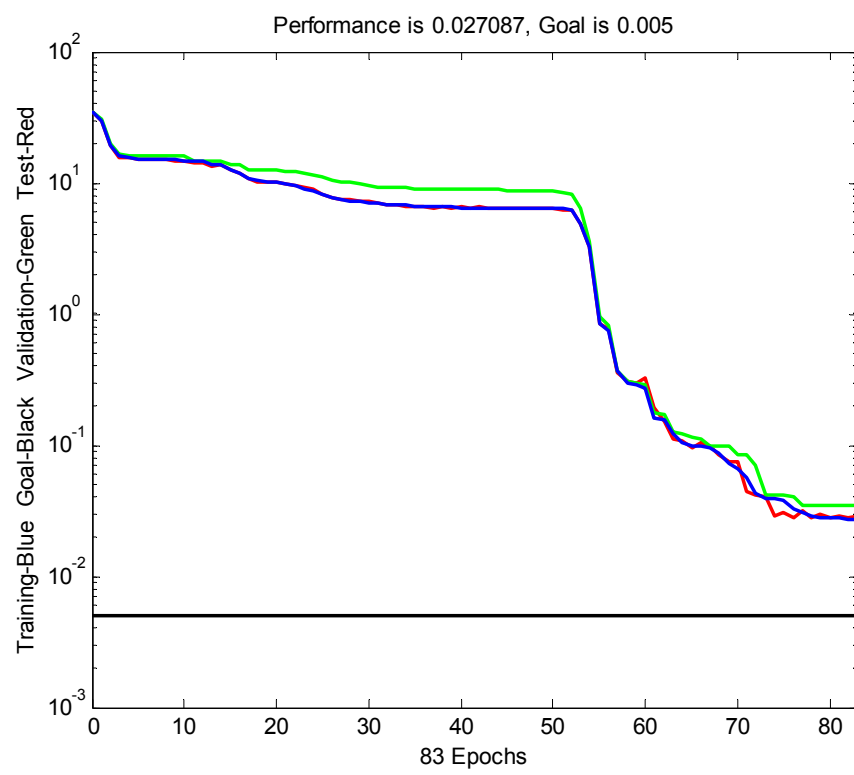


Figure 5.32 Training result of the time delayed neural network.

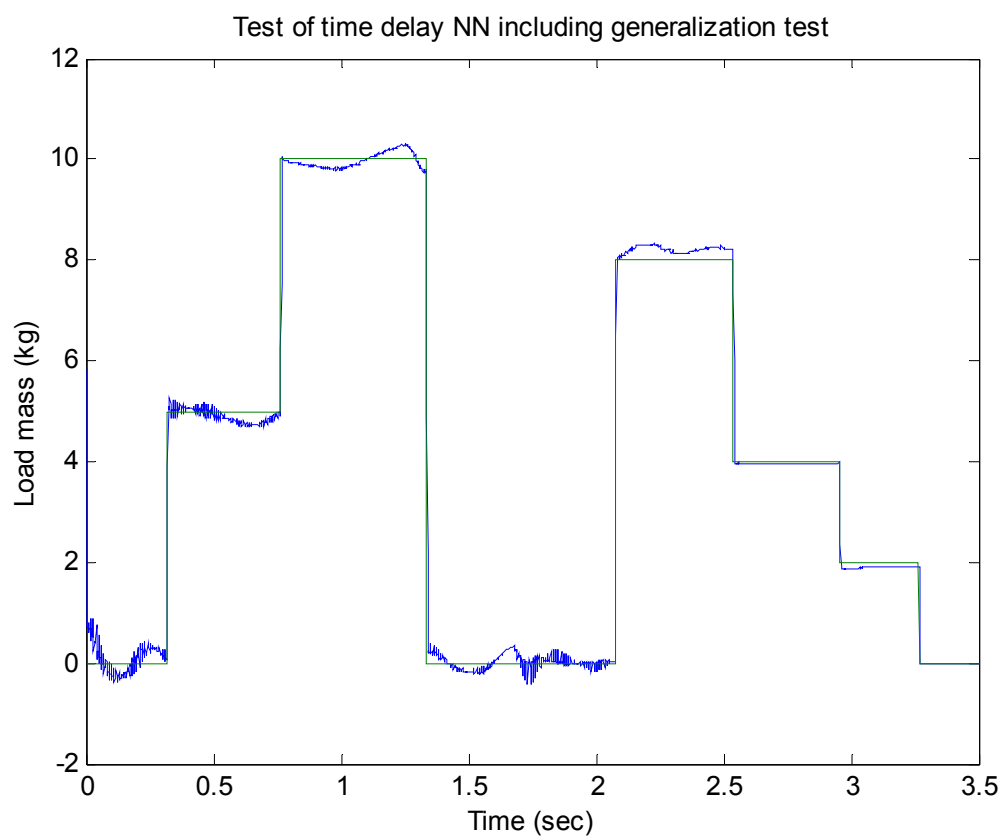


Figure 5.33 Test results of time delay NN including generalization test.

a great benefit in actual implementation.

5.4 Summary

In this chapter, specific signal processing techniques for operational fault detection are developed. For the generalization of the techniques, some representative operational faults are selected based on the subspace, the frequency characteristics of the signal, and the sampling frequency of the signal. The selected representative operational faults are used in the development of the signal processing techniques. The developed signal processing techniques have concentrated on the extraction of features which are related to identify operational faults. The signal processing techniques for feature extraction are placed in the level two of the proposed FDI framework. The recognition of the extracted features is executed in the level three of the proposed framework, but fault recognition is not included in this research and left for future work. In the next chapter, general characteristics of the operational fault recovery are discussed and a fault recovery scheme is proposed. The integration of the proposed framework, feature extraction techniques, and fault recovery scheme comprise the fault tolerant control system for operational faults of telerobotic systems.

Chapter 6

Fault Recovery Strategies

6.1 Introduction

In fault tolerant control, which includes fault detection, fault identification, and fault recovery, fault recovery is the most challenging area. The practical strategies, which can eliminate the faults or make the system operates with degraded performance without the help of a human operator, is a final aim of the fault tolerant control. The recovery strategies, which can eliminate all possible faults or make it possible for the system to operate in a degraded condition in the presence of faults, will not be available in the near future [1]. Furthermore, the detection of the failures, which cannot be recovered, is also an important issue for the improvement of the system reliability. Thus, many researchers are interested in the development of a practical fault detection technology, and there are a few interested in the development of practical recovery strategies. Many researchers working on fault recovery strategies are interested in not the operational faults, but the internal faults. A general fault recovery strategy for the internal faults is disconnecting the parts, which include the fault, from the system, and the system is operated in the degraded performance conditions. For example, in robotics, when a joint has failed and cannot

provide torque for operation, the joint is locked by the brake, and the control system including the path planner is modified to correspond to the deformed configuration of the manipulator. In the case of an ac drive system, when a power device in the power supply is broken, the phase, which includes the broken device, is disconnected, and the power supply operates with reduced number of phases. The drive system then provides at least 33 % of its rated power after the fault [12, 45, 118, 125].

In case of operational faults, the development of practical fault recovery strategies is broader and more complicated than those for the internal faults since the operational faults and the recovery strategies are highly dependent on the tools and tasks. It is possible that a slight change in the tool, task, or workpiece may require a totally different recovery strategy. Sometimes the operational fault recovery strategy requires a high intelligence level for a simple operational fault. For example, tool dropping is one of the most common operational faults in robotics, and the recovery strategy, which is picking up the tool and resuming the task, is a simple task for humans. But, it is difficult to implement in autonomous mode since the recovery strategy involves a high intelligence level in the process such as the recognition of the location and orientation of the tool, and deciding on the proper path to grasp the tool correctly. On the contrary, even in a complicated task, simply stopping and restarting of the task can be a good recovery strategy. In other cases the simple stop and go cannot remove the fault, such as the high contact force caused by an incorrect insertion angle in the peg in a hole task.

Even though the variety and uncertainty of the tasks and task space make it difficult to develop generalized fault recovery strategies for operational faults, one of the most

common features in the tasks is that the contact force must be constrained properly, and inappropriate contact force is caused by or may lead to the operational faults. Based on this observation, this study proposes a recovery strategy, which constrains the individual contact force components, as a generalized fault recovery strategy, which can be applied to various tasks with a minimal change of the strategy. The proposed strategy is used as the force assistance function in the teleoperation mode of Human Machine Cooperative Telerobotics (HMCT), which is being developed at University of Tennessee in Knoxville [41,124]. The assistance function compares the actual contact force components with the reference values of the components, and changes the input position command of the manipulator when the actual contact force deviates from the reference value to keep the force component within a safe level [119]. The functional configuration of the force assistance function is very similar to that of the fault tolerant control. The comparison of each contact force to the reference values corresponds to the fault detection, the evaluation and decision of the dominant component of the error corresponds to fault isolation, and the change of the position command corresponds to fault recovery. In section 6.2, the concept and the simulation test result of the force assistance function using fuzzy logic are introduced.

6.2 Contact force control using fuzzy logic

6.2.1 Computer assistance functions

The Robotics and Electromechanical Systems Laboratory at the University of Tennessee has developed a telerobotic architecture which consists of the Robot Task Space Analyzer

(RTSA) and Human Machine Cooperative Telerobotics (HMCT). The RTSA introduces robotic modeling and task planning techniques into the teleoperation. It generates the 3-D model of the robot task space by using either an automated reasoning process or interactive manual operation. The task planner in the RTSA builds the task plan file, which describes the execution of the tasks including the manipulator and tooling motion, using the 3-D model. The HMCT interprets the task plan file and executes the tasks defined in the task plan file. These autonomous abilities during the modeling and task execution phase increase the system efficiency. They also improve system reliability by allowing the operator to review the planned operations after the 3-D models and task plan file have been generated. However, if the environment is highly unstructured, the tooling tasks cannot be executed in the autonomous mode due to the increased complexity of the task and unavoidable errors in the model. In such cases, the telerobotic system operates in the teleoperation mode, and it is necessary to assist the human operator to improve overall work efficiency [4, 9, 119].

The HMCT introduces robotic control techniques, which are called assistance functions, in the teleoperation mode to help the human operator, and the control scheme is shown in Figure 6.1. The HMCT consists of a finite state machine (FSM), an interpreter, and assistance functions. The FSM selects the operating mode, and the interpreter activates the functional blocks corresponding to the operating mode. In the autonomous mode, the HMCT transforms the commands, which are listed in the task plan file, from Cartesian space to joint space and sends them to the low-level controller. In the teleoperation with assistance function mode, the human operator generates the commands, which are

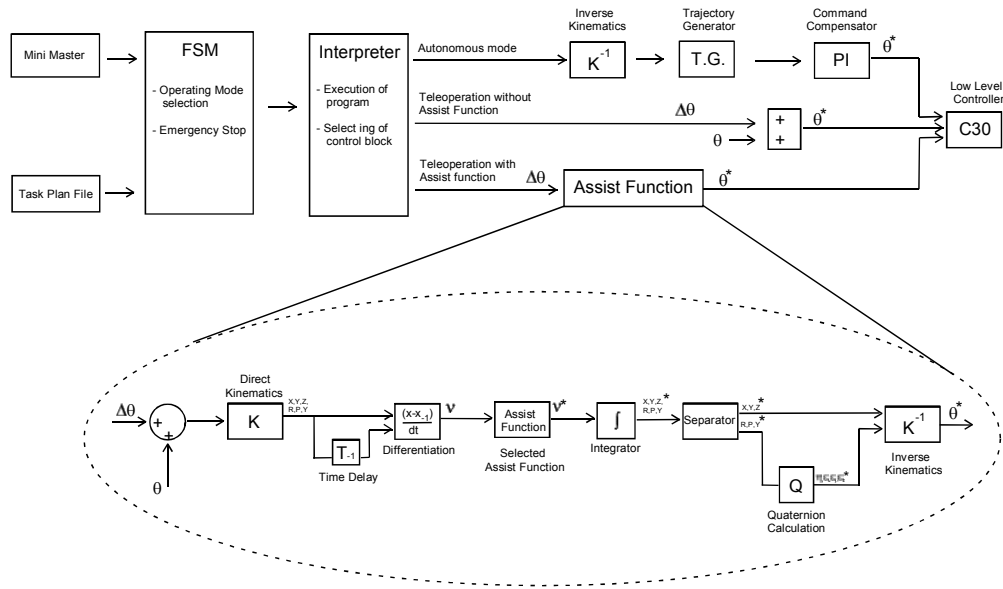


Figure 6.1 Human machine cooperative telerobot control scheme.

increments of joint angles, using the mini-master. The assistance functions modify the commands to limit the actions of the end-effector of slave, and thereby satisfy the predefined constraints on the end-effector of slave. The assistance functions consist of a linear assistance function, which keeps the end-effector in the line, a planar assistance function, which keeps the end-effector on a plane, and a force assistance function, which controls the contact forces to follow the set points of the contact forces [41,119].

The force assistance function modifies the commands of the human operator and limits the individual contact forces within the constraints, which are pre-defined in the constraint frame. For example, in a drilling task, the operator sets the force component in the approach direction of the tool at 10 Nm and the other forces and moments at 0 Nm. Thus,

if the approach force component varies from 10 Nm, the force assistance function modifies the corresponding position and rotation commands from the human operator. Also, if the other contact forces and moments deviate from zero, the force assistance function modifies the corresponding position and rotation commands. Therefore, the force assistance function allows the operator to execute a tooling task without concern of damaging the manipulator, tool, or environment.

When the robot task requires interaction with the environment, a pure position control is not sufficient to fulfill the task and it is necessary to control not only the position of the end-effector, but also the contact force simultaneously. Many researchers have devoted efforts to force control, and effective strategies have been developed [117, 120~123]. However, many strategies require a precise model of environment and manipulator, and it prohibits the application of the strategies for force assistance function since such a precise environmental model is not available in the teleoperation mode. Thus, for teleoperation, adjustable damping and impedance strategies based on motion, and force scaling for a bilateral feedback system and have been developed [9, 124]. However, the strategies cannot control a contact force to a desired value and cannot be applied to a unilateral control system.

In this study, parallel force/position control [117, 120] using fuzzy logic is proposed for the force assistance function. The fuzzy logic scheme removes the need for detailed geometric information about the task space. The inference ability of the fuzzy logic decides the input pattern and selects proper rules to reduce the contact forces and complete the task. For the verification of the proposed scheme, the developed control concept is

applied to a two-link manipulator.

6.2.2 Control strategy

The proposed control scheme for the force assistance function in the HMCT is shown in Figure 6.2. The force assistance function changes the position command from the human operator when the contact forces and moments deviate from the reference value. In this study, the proposed force assistance function is tested with a two-link manipulator, and the block diagram for simulation is shown in Figure 6.3. The trajectory generator in Cartesian space is used instead of the human command and generates the reference trajectory of the end-effector based on the predetermined environment model. The position command, modified by the force assistance, is the input of low level controller. This is operational

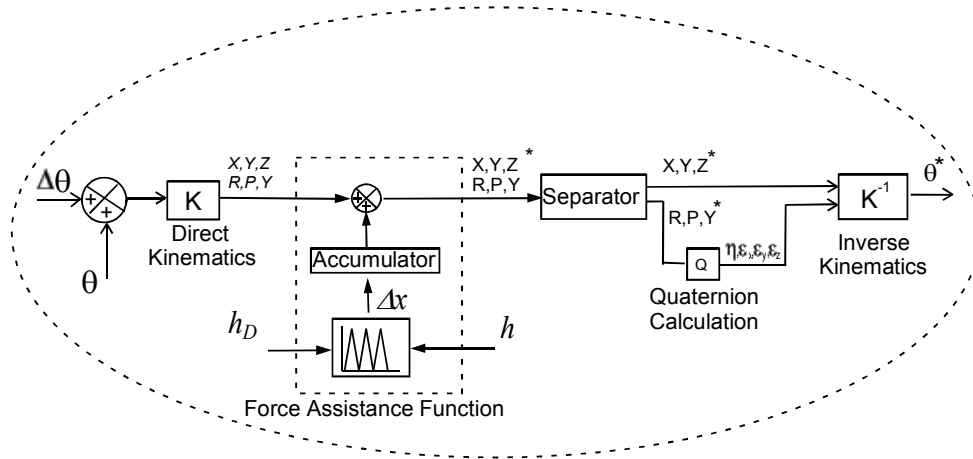


Figure 6.2 Force assistance scheme for the HMCT.

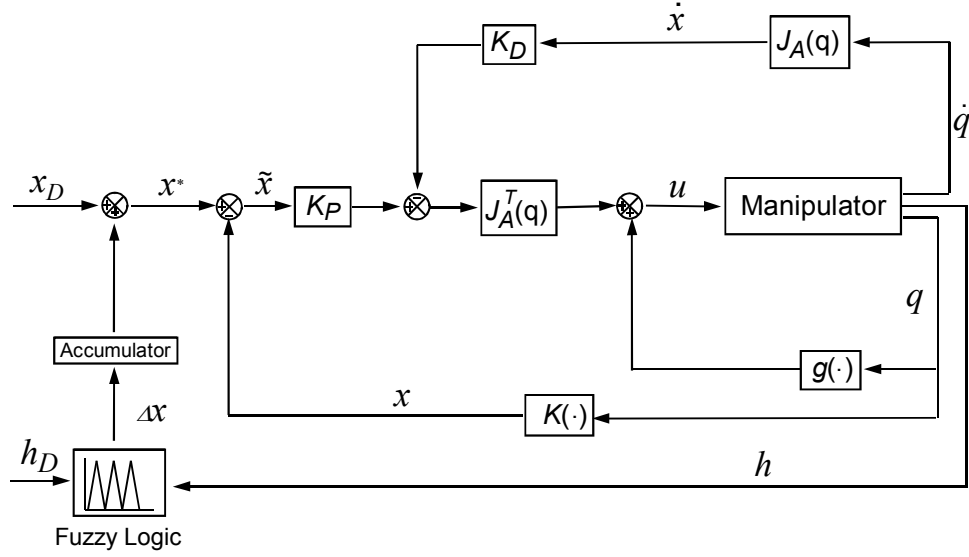


Figure 6.3 Simulation block diagram.

space PD-control with gravity compensation. It is assumed that the manipulator generates enough torque to overcome the contact force. The sampling time is 1 ms and the total simulation time is 10 sec for each test.

6.2.3 Contact force and task environment modeling

For the simulation test of the proposed force assistance function, it is assumed that the contact forces can be modeled by a simple mass-spring system as shown in Figure 6.4 and that the contact force is the spring force of the system. The definition of the displacement of X and Y for the calculation of the contact force is shown in the Figure 6.5.

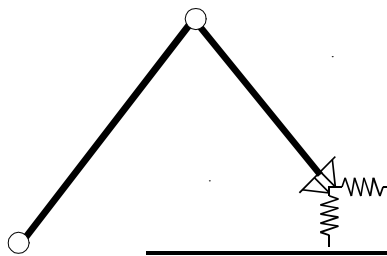


Figure 6.4 Mass-spring model for contact force.

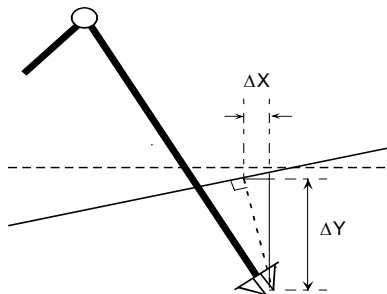


Figure 6.5 Definition of the displacement of x and y displacement,

Figure 6.6 shows the actual environment and environment model, which is used in trajectory generation. As shown in the figure, the environment model has errors. If the reference trajectory of the end-effector is generated based on only the model, the system must face unexpected contact forces during task execution. The contact force is proportional to the size of the error and may damage the manipulator and the environment when the error causes a large contact force. The selected task for the test of the proposed scheme is surface tracking of the wall, which is shown in Figure 6.6. In this case, the force assistance function not only reduces the unexpected contact forces, but also improves the task performance of the system. In this paper, the trajectory generator generates the trajectories based on the modeled wall, and it generates 4-moving patterns out of the total 8-moving patterns of the 2-D space. The contact forces and surface tracking ability of the system with the force assistance function using fuzzy logic are compared with those of the system without the force assistance function.

6.2.4 Fuzzy logic controller design

When the end-effector moves toward the wall at a right angle, there is only one contact force component, which is perpendicular to the wall. In this case, the control strategy to reduce the contact force is reduction of the increment of movement or withdrawal of the end-effector. However, if the contact angle of the end-effector and the wall is not a perpendicular angle, there are two contact force components and the control strategy is more complicated. For example, when the end-effector moves along the x-axis as shown in Figure 6.6, the contact causes not only the x component contact force, but also the y

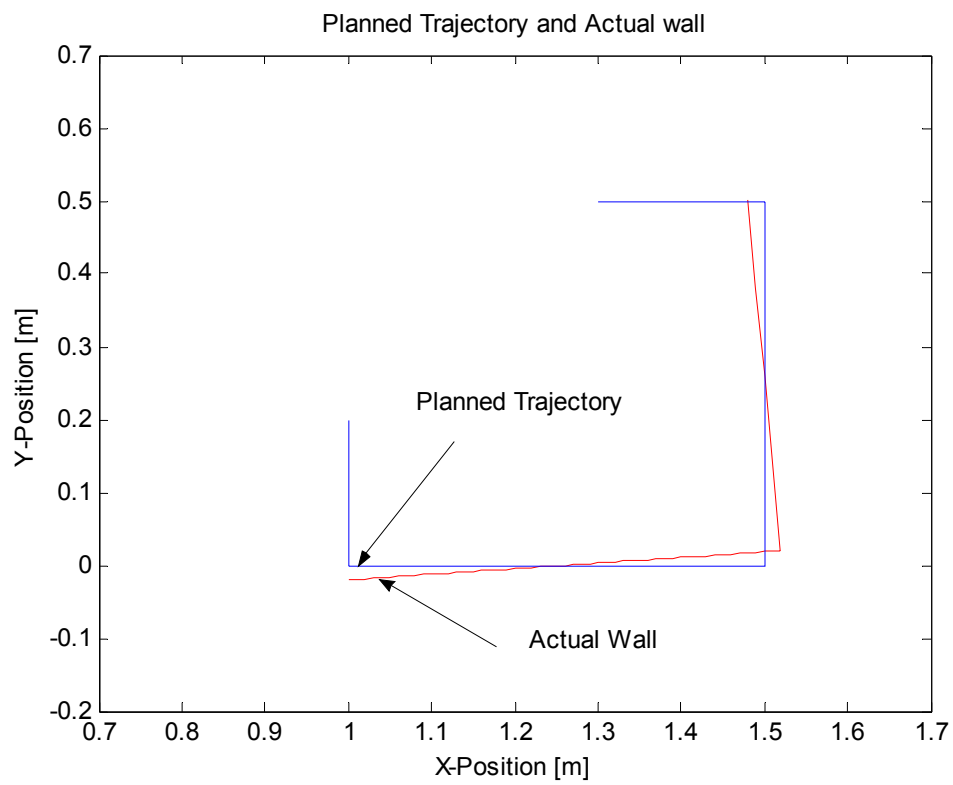


Figure 6.6 Planned trajectories and actual environment.

component contact force, and the control strategy must change the y position command instead of the x position command even though the y position command is constant. The control strategy is strongly affected by the characteristics of the environment and the task, and the scheme can use analytical methods if an accurate environment model is available. However, in the teleoperation mode, such an accurate environment model is not available, and the knowledge-based approach is more effective. In this paper, the proposed fuzzy logic control strategy modifies the input command based on the system status, and the system status parameter (fuzzy variables) and fuzzy rules are determined heuristically.

The developed fuzzy system has 10 input variables: (1) increment of input reference ($\Delta X_r, \Delta Y_r$), (2) increment of actual position ($\Delta X, \Delta Y$), (3) preceding increment of actual position ($\Delta X(t-1), \Delta Y(t-1)$), (4) contact force (F_x, F_y), and (5) error of absolute values of references and actual position ($E_x = |X_r| - |X|, E_y = |Y_r| - |Y|$), and two output variables (O_x, O_y). The meanings and purposes of the variables are as follows. First, the increment of input reference is used to decide the direction of reference motion of the end-effector. Secondly, the present and preceding increments of actual position decide the directions of actual motion of the end-effector at a current and former time step. Thirdly, the error of absolute value is used to decide whether the current position is smaller or larger than the reference value. Finally, the output variables are added to the reference position command to limit the contact force. The membership function for the fuzzy variables and output variables is shown in Figure 6.7. In this paper, forty-one fuzzy rules have been developed for the environment model of Figure 5.6, which has four moving patterns for a total of eight possible moving patterns in the two degree of freedom system. Table 6.1 shows.

Table 6.1 Some of the fuzzy rules for the moving pattern.

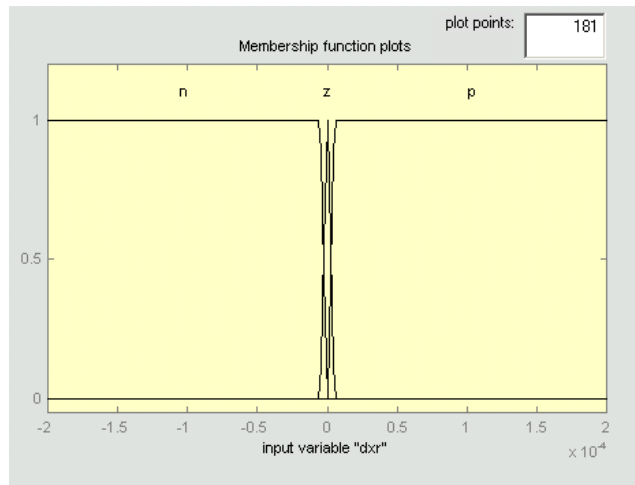
ΔX_r	ΔY_r	ΔX	ΔX^{-1}	ΔY	ΔY^{-1}	F_x	F_y	E_x	E_y	O_x	O_y
P	Z	P	P	P	P	P	P	P	X	Z	BP
P	Z	P	P	P	P	Z	Z	P	X	Z	SN
P	Z	P	P	N	P	Z	Z	P	X	Z	SN
P	Z	P	P	N	N	Z	Z	P	X	Z	BN
P	Z	P	P	N	N	P	P	P	X	Z	SP
P	Z	P	P	P	N	P	P	P	X	Z	SP
P	Z	P	P	N	P	P	P	P	X	Z	SP
P	Z	P	P	P	N	P	P	P	X	Z	SN

P: positive, N: negative, Z: zero, X: not concern, BP: big positive, SN: small negative, SP: small positive.

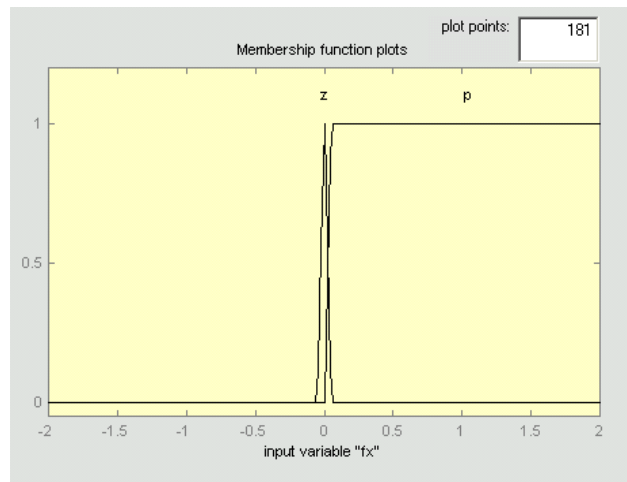
some of the fuzzy rules developed

6.2.5 Results

The system simulation results without the force assistance function are shown in Figure 6.8. It shows that the operational space PD controller precisely drives the manipulator to follow the planned trajectory or the modeled wall exactly. The error of the model causes an unexpected contact force when the end-effector reaches the wall, and the system without the force assistance function cannot follow the wall surface. Figure 6.9 is the simulation results with the force assistance function. It shows that the contact force is reduced to almost 20%, and trajectory is changed to follow the actual wall surface with some oscillation around the wall. The reduction of contact force and the degree of the

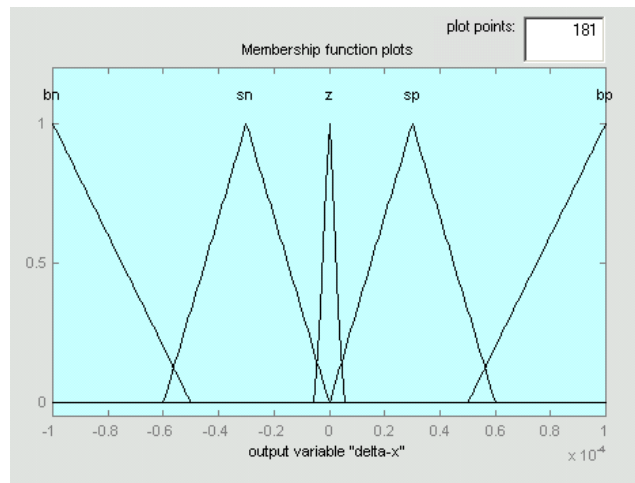


(a) Membership function for input variables.



(b) Membership function for contact force.

Figure 6.7 Membership functions.



(c) Membership function for output variables.

Figure 6.7 Membership functions (continued)

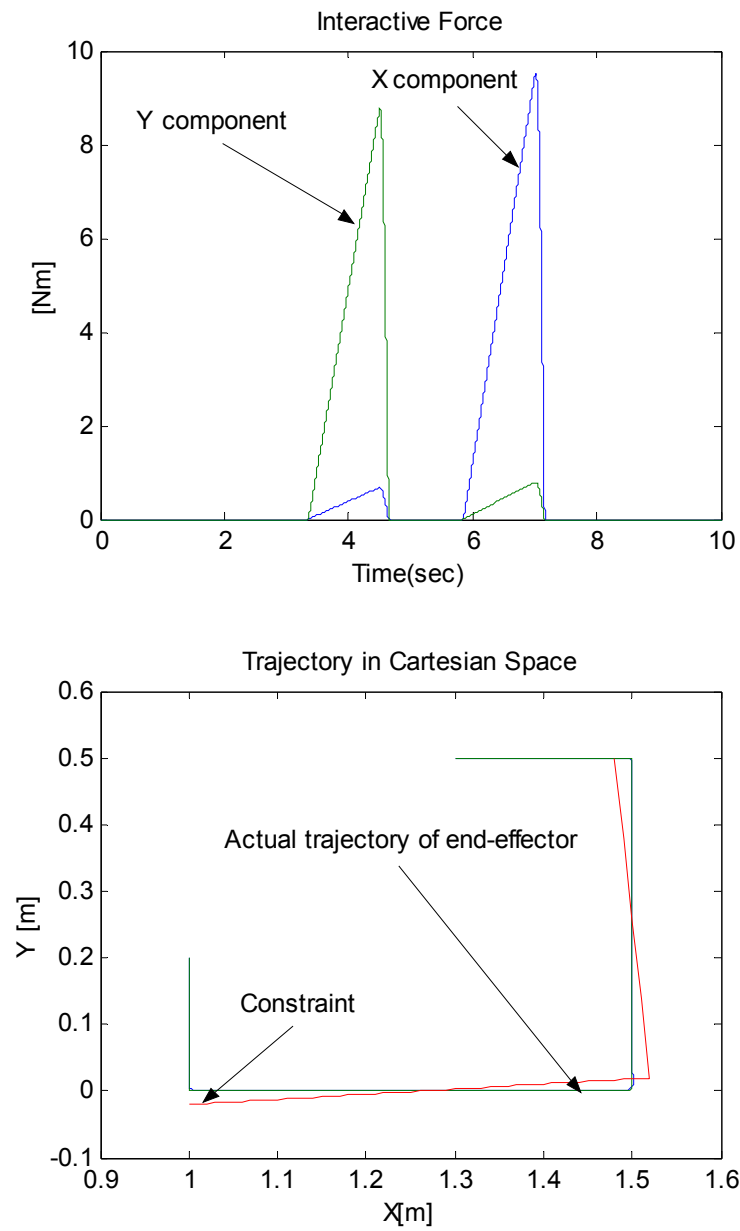


Figure 6.8 Simulation results without the force assistance function.

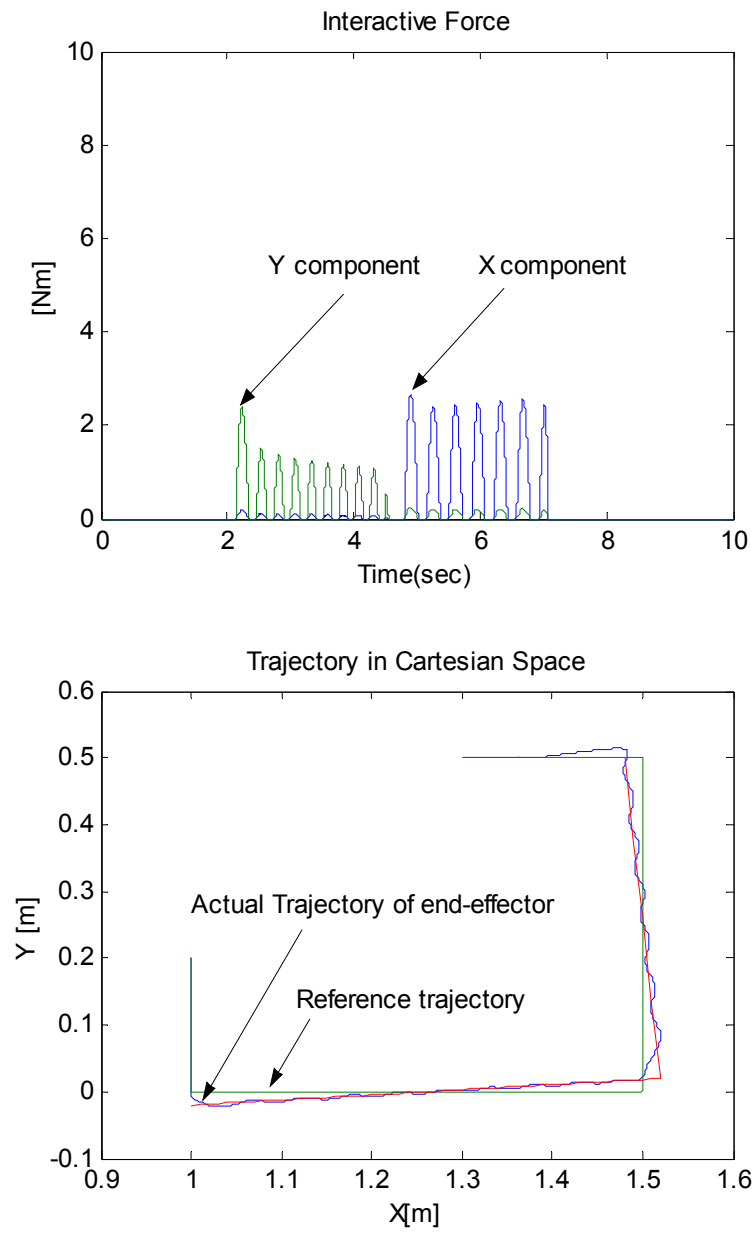


Figure 6.9 Simulation results with the force assistance function.

oscillation is affected mainly by the membership function of the output variables.

6.3 Summary

In this chapter, a fault recovery scheme using fuzzy logic is proposed. Although the proposed scheme was tested using a surface tracking task, it is also useful to other tasks, such as band saw cutting. In the case of band saw cutting, the proposed scheme constrains the cutting force within a pre-defined level by changing the feed rate of the saw. This makes it possible for the proposed scheme to adapt the feed rate to varying cutting conditions, and to reduce the occurrence of operational faults. Thus, if the proposed scheme is applied during normal task execution, it is close to fault preventing scheme rather than fault recovery scheme. However, this study uses “fault recovery” since the scheme is activated only when the contact force exceeds the limit values it is considered an operational fault. In next chapter, some practical problems relating to actual implementation of the proposed fault tolerant control scheme are discussed.

Chapter 7 Implementation Issues

In this chapter, the HMCT control system and Finite State Machine (FSM) are introduced, and some issues, which have to be considered for actual implementation of the FDI, are discussed.

7.1 Related control system issues

The control system of HMCT has been developed using ControlShell of Real-Time Innovations (RTI). ControlShell is a graphical user interface (GUI) based development tool for real-time control systems and supervisory control systems. It allows the developer to use flow diagrams graphically and to link them with finite state machines. Based on the flow diagram and state flow, the developer writes code using C++ for specific strategies and uses some blocks provided by RTI for general purposes, such as trajectory generation. ControlShell compiles the program and generates the system controller for real-time applications. Figure 7.1 shows the state flow diagram for the finite state machine, and mode selection control blocks. The current finite state machine has emergency shutdown (E-Stop) and model selection functions. Figure 7.2 is the high level controller block for the autonomous mode, and it transforms the commands from Cartesian space to joint space using inverse kinematics. The system parameters used in the control scheme are also used

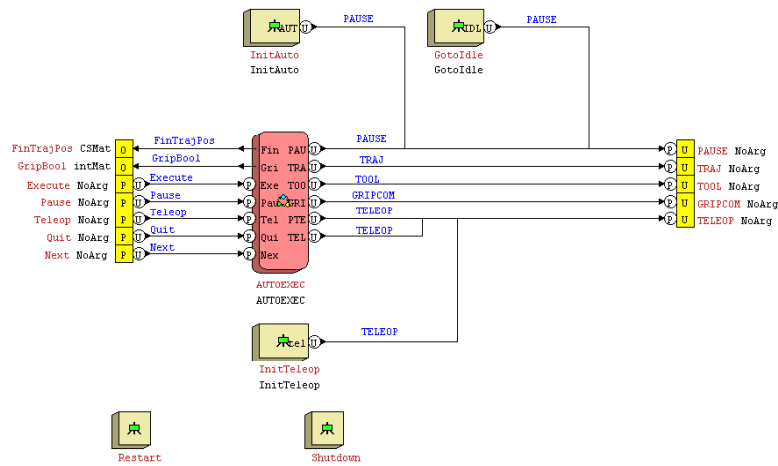
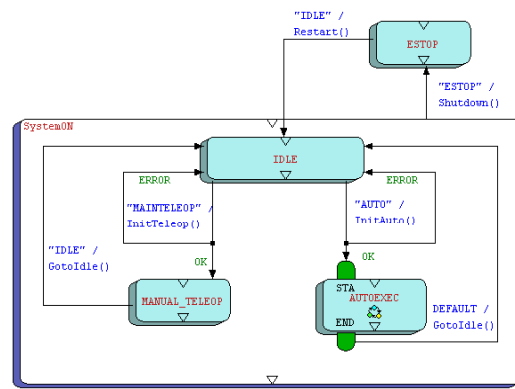
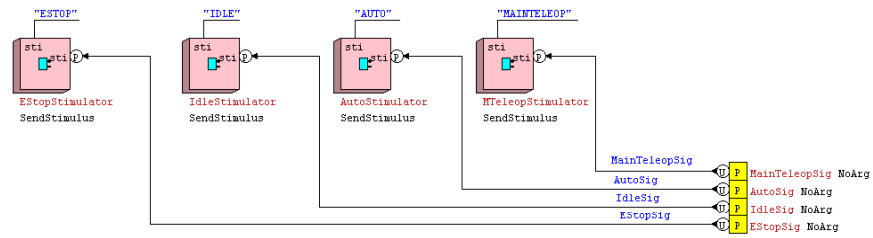


Figure 7.1 Finite state machine and mode selection blocks.

in the signal processing for FDI.

7.2 FDI implementation issues

The proposed fault tolerant control schemes essentially represent generalized methodologies, and have been developed under worst-case conditions. For example, the proposed methodologies were developed for implementation within the manipulator control system, which has a 100 Hz sampling frequency. An 8 kHz sampling frequency was used to acquire acoustic noise data although most robot control systems and acoustic noise data acquisition systems have higher sampling frequencies. This situation enables the proposed methodologies to be applied to other telerobotic systems with minimal modifications since higher sampling frequency improves signal quality and performance of the proposed methodologies. Also, the low sampling data is helpful for real-time execution of any possible FDI schemes. However, the ranges and uncertainties of operational faults increase the number of signal processing techniques to be processed simultaneously, which makes FDI difficult to be implemented in real-time. For example, the PSD analysis of acoustic noise sampled at 8 kHz, or the neural network having 4~7 neurons can be executed in real-time. However, parallel execution of some PSD analyses and some neural networks increases the computational load of controller and they will not be executed in real-time. In such a case, the FDI system must use a faster processor, such as Digital Signal Processor (DSP), or the signal processing techniques must be distributed to separate processors.

In the proposed FDI schemes, the load mass estimator using neural networks and

contact force controller using fuzzy logic have been applied to a two link manipulator to show the feasibility of these approaches. The application of the approaches to a 6 D.O.F. manipulator will increase the number of training data or the rules enormously, and this ultimately limits the application of the approaches. However, instead of considering the whole workspace of the manipulator, if the training data and rules are limited to a specific subspace where the manipulator has enough dexterity to execute task, the approaches will be practical and effective for this 6 D.O.F. manipulator.

Another important issue for the implementation of the FDI is to collect all information and knowledge related to operational faults, and build rules for the fuzzy expert systems.

A design procedure is as follows:

- i) Collect all information and knowledge related to operational faults.
- ii) Analyze the knowledge and find symptoms-clause relationships.
- iii) Write the fuzzy rules for each symptoms-clause relationship using natural language.
- iv) Determine the membership functions for fuzzification, and the fuzzy implementation.
- v) Test and adjust the membership functions

Chapter 8

Summary

8.1 Overall conclusions

The well organized work environments and predefined task procedures of typical industrial robots focus most current research for the fault tolerant control of robotic systems on internal system faults, improving system reliability, and increasing time between maintenance intervals. The extension of applications from the routine environments to complicated uncertain environments, and the unpredictable complicated task procedures in telerobotic systems make operational faults feasible and the successful execution of the tasks becomes an important issue. The very limited research in the detection and isolation of operational faults, which is paramount in telerobotics, was the motivation of this dissertation, and a generalized intelligent fault tolerant control system for operational fault of telerobotic systems was developed.

For the development of generalized FDI for operational faults, this dissertation classifies operational faults according to the subspace where they occur. The operational faults used in this dissertation to develop FDI methodologies are selected based on the classifications, and include all characteristics of operational faults and sensory data. Another important contribution of this dissertation is the development of a framework and

supervisory control scheme for operational FDI of a telerobotic system. The modular architecture of the proposed FDI framework and the inherent characteristics of fuzzy expert systems used in supervisory control enable the proposed fault tolerant control to easily expand the range of operational faults and type of telerobotic systems. This dissertation also produced operational FDI and fault recovery methodologies for the selected operational faults. The methodologies used signal processing technologies, (such as power spectral density (PSD), discrete wavelet transforms (DWT)), fuzzy logic control, and neural networks considering the characteristics of the selected operational faults and sensory data. It has been demonstrated that the proposed approaches can detect and isolate operational faults in uncertain environments, which restrict precise information about the task condition.

It should be mentioned that the limitation in this research, such as off-line analysis of the sensory data and the use of two-link model for simulation tests, must be investigated and improved in the future for truly generalized and applicable FDI system. However, overall the results of the experiments and computer simulations have shown the proposed operational fault tolerant control is applicable to other practical faults and systems, and has great potential as a generalized approach.

8.2 Future research

Some of the topics, which have not been explored in this dissertation and have to be studied further, are discussed as follows:

- **Pattern Classification:** Some outputs of signal analysis techniques may be inappropriate to be used in the supervisory system. In such cases, pattern classification techniques are needed as a post-process which qualitatively analyzes the outputs and represents the results by quantitatively. For example, the PSD analysis of the acoustic data provides a lot of information in the frequency domain, but the task condition is reflected on the change of a few frequency components. The pattern classification can recognize the change of the frequency components and identify the task condition as human does. Also, the ability, which can roughly estimate the degree of the oscillation or change of signals in time domain, is helpful to quickly estimate the task condition.

- **Time delay:** If the telerobot has long distance between the human operator and manipulator or the communication speed is relative slow, there will be a significant time delay between two sites. The time delay has large impact on the system performance, and there is much research time-delay system control aspect. The effects of the time delay on the fault tolerant control are not avoidable, and it can be critical constraint as the time delay increases.

- **Memory:** The mixture of the signal analysis techniques based on time domain and frequency domain makes the time difference between the outputs. Also, the different characteristics and sampling frequencies of sensory data make PSD analysis uses different time span for the sensory data. Therefore, the signal analyses usually

generates results at different times for the same fault, and the supervisory control system must have an ability to memorize precedence results and match the results to current outputs of signal analyses. Also, if the supervisory control system can memorize and utilize the process history, such as former faults, performed recovery strategies, and type of tasks, then the reliability of the FDI results will be improved.

- Fault preventing: Some operational faults are caused by the irregular working conditions. Thus, if the proper recovery or control action is applied in the irregular task condition before the operational fault occurs, the operational fault can be prevented unlike the internal faults. For example, if the oscillation or anomalies occur during the task execution and are amplifying by uncertainty, the fault tolerant control system implements some proper recovery actions before the operational fault occurs. Then the telerobot can continue and finish the task successfully.

- Tool input analysis: Analysis of tool input power or current in frequency domain using PSD or FFT has been used in many areas to detect motor or tool faults, such as rotor bar broken and tool breakage [83,85]. In industrial environments, the PSD or FFT results can provide detailed information about the tool and motor without further analysis of the PSD results. However, the uncertain environments and various tasks associated with telerobotic systems demand a more advanced tool for the further analysis of the results.

- Dynamic baseline in PSD analysis: For the feature extraction using the PSD of the acoustic noise, the system fundamental noise or baseline was subtracted from the PSD of task execution noise. The cancellation of the baseline from the PSD makes the features in the PSD distinct and the extraction of the feature easy. However, the baseline is not stationary since the different manipulator motions, task conditions, tools, and environments change the baseline not only before the execution of task, but also during the execution of task. The non-stationary or transitory baseline is one of important characteristics of telerobotic systems. Therefore, a “dynamic” baseline cancellation methodology which updates the information about the baseline online or periodically should be investigated.

Bibliography

Bibliography

- [1] William R. Hamel, "Sensor-Based Planning and Control in Telerobotics," in "Control in Robotics and Automation: Sensor Based Integration," edited by B. K. Ghosh, Ning Xi, and T.J. Tam, chapter 10, pp. 285~305, Academic Press, 1999.
- [2] T. B. Sheridan, "Telerobotics," *Automatica*, Vol. 25, No. 4, pp. 487~507, 1989.
- [3] M. B. Leahy Jr, S. B. Petroski, "Unified telerobotic architecture project program overview," *Proceedings of the IEEE/RSJ/GI International Conference on Intelligent Robots and Systems '94 'Advanced Robotic Systems and the Real World', IROS '94*, Vol. 1, pp. 240~244, 1994.
- [4] William R. Hamel, Reid L. Kress, "Elements of Telerobotics Necessary for Waste Clean Up Automation," *Proceedings of the 2001 IEEE International Conference on Robotics & Automation*, pp. 393~400, 2001.
- [5] Chuanfan Guo, Tzyh-Jong Tarn, Ning Xi, and Antal K. Bejczy, "Fusion of Human and Machine Intelligence for Telerobotic Systems," *Proceedings of the 1995 IEEE International Conference on Robotics & Automation*, pp. 3110~3115, 1995.
- [6] P. T. Boissiere, R. W. Harrigan, "Telerobotic operation of conventional robot manipulators," *Proceedings of the 1988 IEEE International Conference on Robotics & Automation*, pp. 576~583, 1988.

- [7] Markus Loffler, Nick Costescu, Erkan Zergeroglu, and Darren Dawson, "Telerobotic decontamination and decommissioning with QRobot, a PC-based robot control system," Proceedings of the 2000 IEEE International Symposium on Computer-Aided Control System Design, pp. 24~29, 2000.
- [8] A. R. Graves, C. A. Czarnecki, "A man-machine interface for an AI-based telerobotic system," International Conference on Humans Interfaces in Control Rooms, Cockpits and Command Centres, pp. 302~307, 1999.
- [9] Tomotaka Itoh, Kazuhiro Kosuge, and Toshio Fukuda, "Human-Machine Cooperative Telemanipulation with Motion and force Scaling Using Task-Oriented Virtual Tool Dynamics," IEEE Trans. on Robotics and Automation, Vol. 16, No. 5, pp. 505~516, Oct. 2000.
- [10] Robert L. Williams II, "Control Architecture for Telerobotic Systems," Proceedings of the Fifth National Conference on Applied Mechanisms and Robotics, Oct. 1997.
- [11] Philippe Even, Raymond Fournier, "Telerobotics Tasks Execution Based on 3D Geometric Modelling and Graphical Programming," Proceedings of the International Conference on Systems Engineering in the Service of Humans, Vol. 3, pp. 132~137, 1993.
- [12] Yung Ting, Sabri Tosunoglu, "A Comparison of Three Robot Control Algorithms in Fault Recovery," Internal Symposium on Robotics and Manufacturing, pp. 819~824, 1996.
- [13] Ron J Patton, "Fault-Tolerant Control Systems: The 1997 Situation," IFAC Symposium on Fault Detection Supervision and Safety for Technical Processes,

- Edited by R J Patton & J Chen, Vol. 3, pp 1033~1054, 1997.
- [14] Paul M. Frank, "Fault Diagnosis in Dynamic Systems Using Analytical and Knowledge-Based Redundancy- A Survey and Some New Results," *Automatica*, pp. 459~474, 1990.
 - [15] M. S. Visinsky, J. R. Cavallaro, and D. Walker, "Robotic Fault Detection and Fault Tolerance: Survey," *Reliability Engineering and System Safety*, pp. 139~158, 1994.
 - [16] Devakumar Sreevijayan, "On the Design of Fault-Tolerant Robotic Manipulator Systems," Master's Thesis, Science in Engineering, University of Texas at Austin, TX, 1992.
 - [17] K. P. Valavanis, C. A. Jacobson, and B. Gold "An Application of The 4-parameter Controller to The Robot Payload Variation Problem," *Proceedings of the 28th Conference on Decision and Control*, pp. 2658~2663, 1989.
 - [18] R. Isermann, "Integration of Fault Detection and Diagnosis Methods," *IFAC Fault Decisions, Supervision and Safety for Technical Process*, pp. 575~590, 1994.
 - [19] J. J. Gertler, "Survey of model-based failure detection and isolation in complex plants," *IEEE Control System Magazine*, pp. 3~11, Vol. 8, No. 6, December, 1988.
 - [20] Liu Wei, "An On-Line Expert System-Based Fault-Tolerant Control System," *Expert Systems with Applications*, pp. 59~64, Vol. 11, 1996.
 - [21] F. Javier Garcia, Virginia Izquierdo, Luis J. de Miguel, and Jose R. Peran, "Fault-diagnostic system using analytical fuzzy redundancy," *Engineering-Applications-of-Artificial-Intelligence*, pp. 441~450, Vol. 13, No. 4, 2000.
 - [22] Israel E. Alguindigue, Anna Loskiewicz-Buczak, and Robert E. Uhrig, "Monitoring

- and Diagnosis of Rolling Element Bearings Using Artificial Neural Networks,” IEEE Trans. on Industrial Electronics, Vol. 40, No. 2, pp. 209~217, 1993.
- [23] Mohamed El Hachemi Benbouzid, “A Review of Induction Motors Signature Analysis as a Medium for Faults Detection,” IEEE Trans. on Industrial Electronics, Vol. 47, No. 5, pp. 984~993, 2000.
- [24] Yunosuke Maki, Kenneth A. Loparo, “A Neural-Network Approach to Fault Detection and Diagnosis in Industrial Processes,” IEEE Trans. on Control Systems Technology, Vol. 5, No. 6, pp. 529~541, 1997.
- [25] Seong Soo Choi, Ki Sig Kang, Han Gon Kim, and Soon Heung Chang, “Development of an on-line fuzzy expert system for integrated alarm processing in nuclear power plants,” IEEE Transactions on Nuclear Science, Vol. 42, No. 4, Part: 1-2 , pp. 1406~1418, Aug. 1995.
- [26] H. Schneider, “Implementation of a Fuzzy Concept for Supervision and Fault Detection of Robots,” First European Congress on Fuzzy and Intelligent Technology, pp. 775~780, 1993.
- [27] R. Deibert, R. Isermann, “Examples for fault detection in closed loops,” IFAC artificial Intelligent in Real-Time Control, pp. 235~240, 1992.
- [28] Alan S. Willisky, “A Survey of Design Method for Failure Detection in Dynamic System Automation,” Automatica, pp. 601~611, 1976.
- [29] Rolf Isermann, “Process Fault Detection Based on Modeling and Estimation Methods-A Survey,” Automatica, pp. 387~404, 1984.
- [30] Daw-Shang Hwang, Shao-Kung Chang, and Pau-Lo Hsu, “A Practical Design for a

- Robust Fault Detection and Isolation System,” *International Journal of Systems Science*, Vol. 28, No. 3, pp. 265~275, 1997.
- [31] H. Schneider, P. M. Frank, “Observer-Based Supervision and Fault Detection in Robots Using Nonlinear and Fuzzy Logic Residual Evaluation,” *IEEE Trans. on Control Systems Technology*, Vol. 4, No. 3, pp. 274~282, 1996.
- [32] M. Borairi, H.Wang, “Actuator and Sensor Fault Diagnosis of Non-linear Dynamic Systems via Genetic Neural Networks and Adaptive Parameter Estimation Technique,” *Proceedings IEEE International Conference on Control Applications*, Vol. 1, pp. 278~282, 1998.
- [33] Arun T. Vemuri, Marios M. Polycarpou, “Neural Network Based Robust Fault Diagnosis in Robotic System,” *IEEE Trans. on Neural Network*, Vol. 8, No. 6, pp. 1410~1420, Nov. 1997
- [34] Chr. Angeli, A. Chatzinikolaou, “Fault prediction and compensation functions in a diagnostic knowledge-based system for hydraulic systems,” *Journal of Intelligent & Robotic Systems*, Vol. 25 No. 2, pp. 153~165, 1999.
- [35] Kelvin Hamilton, Dave Lane, Nick Taylor, and Keith Brown, “Fault Diagnosis on Autonomous Robotic Vehicles with Recovery: An Integrated Heterogeneous-Knowledge Approach,” *Proceedings of the 2002 IEEE International Conference on Robotics & Automation*, pp. 3232~3232, 2001.
- [36] W. R. Becraft and P. L. Lee, “An integrated neural network/expert system approach for fault diagnosis,” *Computers & Chemical Engineering*, Vol. 17, Issue 10, pp. 1001~1014, October 1993.

- [37] Z. Fathi, W. E. Ramirez, A. P. Tavaré, and G. Gilliland, "A knowledge-based system with embedded estimation components for fault detection and isolation in process plants," IFAC Symposium On-line fault detection and supervision in the chemical process industries, Vol. 1, pp. 43~48, 1993.
- [38] Kam S. Tso, Myron Hecht, and Neville I. Marzwell, "Fault-Tolerant Robotic System for Critical Applications," Proceedings of the 1993 IEEE International Conference on Robotics & Automation, pp. 691~696, 1993.
- [39] Paul M. Frank, "Fault Diagnosis in Dynamic Systems," Transaction of the IMACS/SICE International Symposium on Robotics, Mechatronics and Manufacturing Systems, pp. 821~ 828, 1992.
- [40] Steven E. Everett, "Human-Machine Cooperative Telerobotics Using Uncertain Sensor and Model Data," doctor of Philosophy in Mechanical Engineering University of Tennessee, August 1998.
- [41] A. Manocha, N. Pernaleté, and R. V. Dubey, "Variable Position Mapping Based Assistance in Teleoperation for Nuclear Cleanup," Proceedings of the 2001 IEEE International Conference on Robotics & Automation, pp. 374~379, 2001.
- [42] B. Freyermuth, "Knowledge based incipient fault diagnosis of industrial robots," IFAC/IMACS Symposium on Fault Detection, Supervision and Safety for Technical Processes -SAFEPROCESS'91, pp. 369~375, 1991.
- [43] Arun T. Vemuri, Marios M. Polycarpou, and Sotiris A. Diakourtis, "Neural Network Based Fault Detection in Robotic Manipulators," IEEE Trans. on Robotics and Automation, Vol. 14, No. 2, pp. 342~April, 1998.

- [44] Ernesto Lopez-Mellado, Rachid Alami, "A Failure Recovery Scheme for Assembly Workscells," Proceedings of the 1990 IEEE International Conference on Robotics & Automation, pp. 702~707, 1990.
- [45] Yung Ting, Sabri Tosunoglu, and Delbert Tesar, "A Control Structure for Fault-Tolerant Operation of Robotic Manipulators," Proceedings of the 1993 IEEE International Conference on Robotics & Automation, pp. 684~690, 1993.
- [46] Christiaan J. J. Paredis, Pradeep K. Khosla, "Mapping Tasks into Fault Tolerant Manipulators," Proceedings of the 1994 IEEE International Conference on Robotics & Automation, pp. 1~8, 1994.
- [47] Puneet Goel, Göksel Dedeoglu, Stergios I. Roumeliotis, and Gaurav S. Sukhatme, "Fault Detection and Identification in a Mobile Robot Using Multiple Model Estimation and Neural Network," Proceedings of the 2000 IEEE International Conference on Robotics & Automation, pp. 2302~2309, 2000.
- [48] J. Wunnenberg, P. M. Frank, "Dynamic Model Based Incipient Fault Detection Concept for Robots," Proceedings of the 11th Triennial World Congress of the International Federation of Automatic Control, pp. 61~66, Tallinn, Estonia, USSR, 13-17 Aug. 1990.
- [49] D. Sauter, G. Dubois, E. Levrat, and J. Bremont, "Fault Diagnosis in Systems Using Fuzzy Logic," EUFIT'93, First European Congress on Fuzzy and Intelligent Technologies, pp. 781~789, Aachen, German, Sept., 1993.
- [50] H. Schneider, P. M. Frank, "Observer-Based Supervision and Fault Detection for Robots," TOOLDIAG'93 International Conference on Fault Diagnosis, pp. 773~779,

- Toulouse, France, 1993.
- [51] M. Gini, R. Smith, "Monitoring Robot Actions for Error Detection and Recovery," Workshop on Space Telerobotics, pp. 67~78, Pasadena, California, 1987.
 - [52] Bernd Freyermuth, Rolf Isermann, "Model Based Incipient Fault Diagnosis of Industrial Robots via Parameter Estimation and Feature Classification," ECC 91, European Control Conference, pp. 1917~1923, Grenoble, France, 1991.
 - [53] Kajiro Watanabe, Ichiro Matsuura, Masahiro Abe, and Makoto Kubota, "Incipient Fault Diagnosis at Chemical Process via Artificial Neural Networks," Aich Journal pp. 1803~1812, Nov., 1989.
 - [54] V. Venkatasubramanian, R. Vaidyanathan, and Y. Yamamoto, "Process Fault Detection and Diagnosis Using Neural Networks-1 Steady State Process," Computer chemical Eng., pp. 699~712, 1990.
 - [55] Kurosh Madani, "A survey of artificial neural networks based fault detection and fault diagnosis techniques," IJCNN '99 International Joint Conference on Neural Networks, Vol. 5, pp. 3442~3446, 1999.
 - [56] Luis A. Aguirre, Marcus F. S. Pereira, "A modified observer scheme for fault detection and isolation applied to a poorly observed process with integration," Journal of Process Control, Vol. 8, Issue 1, pp. 47~56, 1998.
 - [57] Thomas Pfeufer, Mihir Ayoubi, "Application of a hybrid neuro-fuzzy system to the fault diagnosis of an automotive electromechanical actuator," Fuzzy Sets and Systems, Vol. 89, Issue 3, pp. 351~360, August 1997.
 - [58] Robert F. Stengel, "Intelligent failure-tolerant control," IEEE Control Systems

- Magazine, pp. 14~23, June,1991.
- [59] K. S. Narendra, "Neural networks for control theory and practice," Proceedings of the IEEE, Vol. 84, No. 10, pp. 1385-1406, Oct. 1996.
- [60] Lefteri H. Tsoukalas, Robert E. Uhrig, "Fuzzy and Neural Approaches in Engineering," John Wiley & Sons, Inc. 1997.
- [61] Yih-Guan Leu; Wei-Yen Wang; Tsu-Tian Lee, "Robust adaptive fuzzy-neural controllers for uncertain nonlinear systems," IEEE Trans. on Robotics and Automation, Vol. 15, No. 5, pp. 805~817, Oct. 1999.
- [62] K. Hunt, "Neural Networks for Control Systems A Survey," Automatica, Vol. 28, No. 6, pp. 1083~1112, 1992.
- [63] Soteris A. Kalogirou, "Applications of artificial neural-networks for energy systems," Applied Energy, Vol. 67, No. 1-2, pp. 17~35, Sep. 2000.
- [64] B. K. Bose, "Expert system, fuzzy logic, and neural network applications in power electronics and motion control," Proceedings of the IEEE, Vol.82, No. 8, pp. 1303~1323, Aug. 1994.
- [65] M. L. Mavrovouniotis, S. Chang, "Hierarchical neural networks," Computers & Chemical Engineering, Vol. 16, Issue 4, pp. 347~369, April 1992.
- [66] Mo-yuen Chow, Robert N. Sharpe, and James C. Hung, " On the Application and Design of Artificial Neural Networks for Motor Fault Detection-Part1," IEEE Trans. on Industrial Electronics, Vol. 40, No. 2, pp. 181~188, April 1993.
- [67] Y. S. Tarng, Y. W. Hseih, and S. T. Hwang, "Sensing tool breakage in face milling with a neural network," International Journal of Machinery Tools Manufacture, Vol. 34,

- No.3, pp. 341~350,1994.
- [68] R. J. Patton, F. J. Uppal, and C. J. Lopez-Toribio, "Soft computing approaches to fault diagnosis for dynamic systems: A Survey," 4th IFAC Symposium on Fault Detection Supervision and Safety for Technical Processes, Vol. 1, pp. 298~311, June 2000.
- [69] R. J. Machado, A. F. da Rocha, A.F, "Inference, inquiry and explanation in expert systems by means of fuzzy neural networks," IEEE International Conference on Fuzzy Systems, Vol. 1, pp. 351~356, 1993.
- [70] N. D. Rao, J. C. Chen, and W. C. Chan, "A new connectionist expert system scheme for distribution system fault diagnosis," 1994. Proceedings of 1994 Canadian Conference on Electrical and Computer Engineering, Vol. 1, pp. 50~54, 1994.
- [71] X. Z. Gao, S. J. Ovaska, "Soft computing methods in motor fault diagnosis," Applied Soft Computing, Vol. 1, Issue 1, pp. 73~81, June 2001.
- [72], Gary G. Yen, Phayung Meesad, "Constructing a fuzzy expert system using the ILFN network and the genetic algorithm," 2000 IEEE International Conference on Systems, Man, and Cybernetics, Vol. 3, pp. 1917~1922, 2000.
- [73] Feng-Yi Hsu; Li-Chen Fu, "Intelligent robot deburring using adaptive fuzzy hybrid position/force control," IEEE Transactions on Robotics and Automation, Vol. 16, Issue 4, pp. 325~335, Aug. 2000.
- [74] Bodapati Nageswararao B. Jeyasurya, "Fuzzy-expert system for voltage stability monitoring and control," Electric Power Systems Research, Vol. 47, Issue 3, pp. 215~222, Nov. 1998.
- [75] Shendy M. El-Shal, Alan S. Morris, "A fuzzy expert system for fault detection in

- statistical process control of industrial processes,” IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, Vol. 30, Issue: 2, pp. 281~289, May 2000.
- [76] Alexandre Evsukoff, Sylviane Gentil and Jacky Montmain, “Fuzzy reasoning in co-operative supervision systems,” Control Engineering Practice, Vol. 8, Issue 4, pp. 389~407, April 2000.
- [77] C. M. Lim, T. Hiyama, “Application of fuzzy logic control to a manipulator,” IEEE Transactions on Robotics and Automation, Vol. 7, Issue: 5, pp. 688~691, Oct. 1991.
- [78] Chun Siu; Qiang Shen; Robert Milne, “A fuzzy expert system for vibration cause identification in rotating machines,” Proceedings of the Sixth IEEE International Conference on Fuzzy Systems, Vol. 1, pp. 555~560, 1997.
- [79] M. Stephens, D. W. Shimmin, “Robust hierarchical expert system based fuzzy logic controller with application to subsea vehicles,” International Conference on Control '94, Vol. 1, pp. 276~281, 1994.
- [80] Burak Özyurt and Abraham Kandel, “A hybrid hierarchical neural network-fuzzy expert system approach to chemical process fault diagnosis,” Fuzzy Sets and Systems, Vol. 83, Issue 1, pp. 11~25, Oct. 1996.
- [81] B. K. Bose, “Modern power electronics and AC drives,” Prentice-Hall, Inc. 2002.
- [82] “Fuzzy logic toolbox user’s guide,” The mathworks, Inc., 2000.
- [83] Fiorenzo Filippetti, Giovanni Franceschini, and Carla Tassoni, “Recent Developments of Induction motor Drives Fault Diagnosis Using AI Techniques,” IEEE Trans. on Industrial Electronics, Vol. 47, No. 5, pp. 994~1004, Oct. 2000.

- [84] Olaf Moseler, Rolf Isermann, "Model-based fault detection for a brushless DC motor using parameter estimation," Proceedings of the 24th Annual Conference on Industrial Electronics, Control and Instrumentation, IECON '98, Vol. pp. 1956~1960, 1998.
- [85] A. Consoli, F. Gennaro, A. Raciti, and A. Testa, "Fuzzy logic application to pre-fault diagnoses of induction motors," Proceedings of the 1998 Second IEEE International Conference on Devices, Circuits and Systems, pp. 249~254, 1998.
- [86] Bo. Li, Mo-Yuen Chow, Y. Tipsuwan, J. C. Hung, "Neural-network-based motor rolling bearing fault diagnosis," IEEE Transactions on Industrial Electronics, Vol. 47, Issue 5, pp. 1060~1069, Oct. 2000.
- [87] S. Perovic, P. J. Unsworth, and E. H. Higham, "Fuzzy logic system to detect pump faults from motor current spectra," Thirty-Sixth IAS Annual Meeting Conference Record of the 2001 IEEE Industry Applications Conference, Vol. 1, pp. 274~280, 2001.
- [88] G. S. Stavrakakis, C. Lefas, C. and A. Pouliezos, "Parallel processing computer implementation of a real time DC motor drive fault detection algorithm," IEE Proceedings B, Electric Power Applications, pp. 309~313, Sept. 1990.
- [89] Jose C. Principe, Taehwan Yoon, "A new algorithm for the detection of tool breakage in milling," Int. J. Mach. Tools Manufact., Vol. 31, No. 4, pp. 443~454, 1991.
- [90] Joseph C. Chen, "Effective fuzzy-nets training scheme for monitoring tool breakage," Journal of Intelligent Manufacturing, Vol.11 No. 1, pp. 85~101, 2000.
- [91] P. T. Huang, J. C. Chen, "Fuzzy logic-base tool breakage detecting system in end milling operations," Computers Industrial Engineering, Vol. 35, Issues 1-2, pp. 37-40,

Oct. 1998.

- [92] E. Agüero, R. Haber, J. R. Alique, and C. Rodríguez, "Fuzzy modelling of machine-tool cutting process," Proceeding of IEEE '93 IFIS Third International Conference on Industrial Fuzzy Control and Intelligent Systems, pp. 191-196, 1993.
- [93] D. Neumann, "Fault diagnosis of machine-tools by estimation of signal spectra," IFAC/IMACS Symposium on Fault Detection, Supervision and Safety for Technical Processes – SAFEPROCESS '91, pp. 147-152, 1991.
- [94] K. Matsushima, P. Bertok, and T. Sata, "In process detection of tool breakage by monitoring spindle motor current of a machine tool," The winter annual meeting of ASME, Measurement and control for batch manufacturing, pp. 145~153, 1982.
- [95] D. Yan, T. I. El-Wardany, and M. A. Elbestawi, "A multi-sensor strategy for tool failure detection in milling," Int. J. Mach. Tools Manufact., Vol. 35, No. 3, pp. 383~396, 1995.
- [96] I. N. Tansel, C. McLaughlin, "Detection of tool breakage in milling operation-I. The time series analysis approach," International Journal of Machinery Tools Manufacture, Vol. 33, No. 4, pp. 531~544, 1993.
- [97] I. N. Tansel, C. McLaughlin, "Detection of tool breakage in milling operation-II. The neural network approach," International Journal of Machinery Tools Manufacture, Vol. 33, No. 4, pp. 545~558, 1993.
- [98] J. C. Chen, "A Fuzzy-nets tool-breakage detection system for end-milling operations," Int. J. Advanced Manufacturing Technology, Vol. 12, pp. 153~164, 1996.
- [99] S. Li, M. A. Elbestawi, "Fuzzy clustering for automated tool condition monitoring in

- machining,” *Mechanical systems and Signal Processing*, Vol. 10, No. 5, pp. 533~550, 1996.
- [100] Yusuf Altintas, “In process detection of tool breakage using time series monitoring of cutting forces,” *International Journal of Machinery Tool and Manufacture*, Vol. 28, No. 2, pp. 157~172, 1988.
- [101] R. X. Du, M. A.Elbestawi, and S. Li, “Tool condition monitoring in turning using fuzzy set theory,” *Int. J. Mach. Tools Manufact.*, Vol. 32, No. 6, pp. 781-796, 1992.
- [102] S. Lin, R. Yang, “Tool Wear Monitor in Face milling,” *Proceedings of the 1993 ASME Winter Annual Meeting Symposium on mechatronics*, pp. 127~133, 1993.
- [103] Y. Y. Chung, C. K. Sung, “Dynamic Behavior of the Band/Wheel Mechanical System of Industrial Band Saws,” *Trans of ASME-Journal of Vibration and Acoustics*, pp. 842~847, 1998.
- [104] E. Wu, M. Diftler, J. Hwang, and J. Chladek, “A fault tolerant joint drive system for the Space Shuttle remote manipulator system,” *Proceedings., 1991 IEEE International Conference on Robotics and Automation*, Vol. 3, pp. 2504~2509, 1991.
- [105] Christopher Cocca, Daniel Cox, and Delbert Tesar, “Failure recovery in redundant serial manipulators using nonlinear programming,” *Proceedings of the IEEE International Conference on Robotics and Automation*, Vol. 2, pp. 855~860, 1999.
- [106] M. C. Pan, H. Van Brussel, and P. Sas, “Intelligent joint fault diagnosis of industrial robots,” *Mechanical Systems and Signal Processing*, Vol. 12, No. 4, pp. 571~588, 1998.
- [107] M. Goel, A. A. Maciejewski, and V. Balakrishnan, “The design of control strategies

- tolerant to unidentified failures in kinematically redundant manipulators,” Proceedings of 1999 IEEE International Conference on Robotics and Automation, Vol. 2, pp. 867~873, 1999.
- [108] M. L. Visinsky, J. R. Cavallaro, and I. D. Walker, “Dynamic Sensor-Based Fault Detection for Robots,” SPIE Conference on Telemanipulator Technology and Space Telerobotics, pp. 385~396, 1993.
- [109] M. L. Visinsky, J. R. Cavallaro, and I. D. Walker, “Adaptive Fault Detection and Tolerance for Robots,” Proceedings of the First World Automation Congress (WAC'94) Intelligent Automation and Soft Computing: Trends in research, Development, and Application, pp. 205~210, 1994.
- [110] Jin-Ho Shin; Choon-Young Lee and Ju-Jang Lee, “Robust fault-tolerant control framework for robot manipulators with free-swinging joint failures: fault detection, identification and accommodation,” Proceedings of 1999 IEEE/RSJ International Conference on Intelligent Robots and Systems IROS '99, Vol. 1, pp. 185~190, 1999.
- [111] S. Kimura, M. Takahashi, T. Okuyama, S. Tsuchiya, and Y. Suzuki, “A fault-tolerant control algorithm having a decentralized autonomous architecture for space hyper-redundant manipulators,” IEEE Trans. on Systems, Man and Cybernetics, Part A: Systems and Humans, Vol. 28, Issue 4, pp. 521~527, July 1998.
- [112] M. Geol, A. A. Maciejewski, and V. Balakrishnan, “Undetected locked-joint failures in kinematically redundant manipulators: a workspace analysis,” Proceedings of 1998 IEEE/RSJ International Conference on Intelligent Robots and Systems, Vol. 1, pp. 317~322, 1998.

- [113] John V. Draper, Stephen Handel, and Christopher C. Hood, "The Impact of Partial Joint Failure on Teleoperator Task Performance," Proceedings of the Fourth ANS Topical Meeting on Robotics and Remote System, pp. 433~439, 1991.
- [114] Krzysztof Kozlowski, "Modelling and Identification in Robotics," Springer, 1998.
- [115] Jean-Jacques E. Slotine, Weiping Li, "Adaptive Manipulator Control: A Case Study," Proceedings of the International Conference on Robotics and Automation, pp. 1392~1400, 1987.
- [116] Christopher G. Atkeson, Chae H. An, and John M. Hollerbach, "Estimation of Inertial Parameters of Manipulator Loads and Links," The International Journal of Robotics Research, Vol. 5, No. 3, pp. 101~119, 1986.
- [117] Lorenzo Sciavicco, Bruno Siciliano, "Modeling and Control of Robot Manipulators," McGraw-Hill, 1996.
- [118] H. Z. Yang, K. Yamafuji; K. Arita, and N. Ohara, "Development of a robotic system which assists unmanned production based on cooperation between off-line robots and on-line robots: Concept, analysis and related technology," International Journal of Advanced Manufacturing-Technology, Vol. 15, No. 6, pp. 432~437, 1999.
- [119] Sewoong Kim, William R. Hamel, "Force assistance function for human machine cooperative telerobotics using fuzzy logic," Proceedings of the International Conference on Robotics and Automation, pp. 2165~2170, 2002.
- [120] Stefano Chiaverini, Lorenzo Sciavicco, "The Parallel Approach to Force/Position Control of Robotic Manipulators," IEEE Trans. on Robotics and Automation, Vol. 9, No. 4, pp. 361~373, Aug. 1993.

- [121] Daniel E. Whitney, "Historical Perspective and State of the Art in Robot Force Control," *International Journal of Robotics Research*, Vol. 6, No. 1, pp. 3~14, 1987.
- [122] Tseneo Yoshikawa, Akio Sudou, "Dynamic Hybrid Position/Force Control of Robot Manipulators On-Line Estimation of Unknown Constraint," *IEEE Trans. on Robotics and Automation*, Vol. 9, No. 2, pp. 220~226, April 1993.
- [123] Bruno Siciliano, Luigi Villani, "Robot Force Control," Kluwer Academic Publishers, 1999.
- [124] Rajiv V. Dubey, Tan F. Chan, and Steve E. Everett, "Variable Damping Impedance Control of a Bilateral Telerobotic system," *IEEE Control Systems Magazine*, Vol. 17, No. 1, pp. 37~45, Feb. 1997.
- [125] Debaprasad Kastha, Asim Kumar Majumdar, "An improved starting strategy for voltage-source inverter fed three phase induction motor drives under inverter fault conditions," *IEEE Trans. on Power Electronics*, Vol. 15, No. 4, pp. 726~732, July 2000.
- [126] R. Rengaswamy, V. Venkatasubramanian, "An integrated framework for process monitoring, diagnosis, and control using knowledge-based systems and neural networks," *IFAC Symposium On-Line fault detection and supervision in the chemical process industries*, Vol. 1, pp. 49~54, 1993.
- [127] M. L. Visinsky, J. R. Cavallaro, and I. D. Walker, "A Dynamic Fault Tolerance Framework for Remote Robots," *IEEE Trans. on Robotics and Automation*, Vol. 11, No. 4, pp. 477~490, Aug. 1995.
- [128] Rolf Isermann, Mihai Ayoubi, Heiko Konrad, and Thomas Reib, "Model Based

- Detection of Tool wear and Breakage for Machine tools,” IEEE conference on Systems Man and Cybernetics, pp. 72~77, 1993.
- [129] F. Jiang, Z. Q. Bo, and Q X Yang, “The wavelet transform applied to distinguish between transient and permanent faults,” Proceedings of International Conference on Power System Technology 1998 POWERCON '98, Vol. 2, pp. 1116 -1120, 1998.
- [130] A. Lazkano, J. Ruiz, E., Aramendi, and L.A. Leturiondo, “Evaluation of a new proposal for arcing fault detection method based on wavelet packet analysis,” Power Engineering Society Summer Meeting 2001, Vol. 3, pp. 1328~1333, 2001.
- [131] Gary G. Yen, Kuo-Chung Lin, “Wavelet packet feature extraction for vibration monitoring,” IEEE Transactions on Industrial Electronics, Vol. 47, Issue: 3, pp. 650~667, June 2000.
- [132] A. M. Gaouda, M, M, A, Salama, M.R. Sultan, and A.Y. Chikhani, “Power quality detection and classification using wavelet-multiresolution signal decomposition,” IEEE Transactions on Power Delivery, Vol. 14, Issue 4, pp. 1469~1476, Oct. 1999.
- [133] K. Mori, N. Kasashima, J. C. Fu and K. Muto, “Prediction of small drill bit breakage by wavelet transforms and linear discriminant functions,” International Journal of Machine Tools and Manufacture, Vol. 39, Issue 9, pp. 1471~1484, Sept. 1999.
- [134] R. Isermann, “On fuzzy logic applications for automatic control, supervision, and fault diagnosis,” IEEE Trans. on Systems, Man and Cybernetics, Part A, Vol. 28, Issue, 2, pp. 221~235, March 1998.
- [135] John J. Craig, “Introduction to Robotics Mechanics & Control,” Addison-Wesley Publishing Co., 1986.

- [136] Se-Han Lee, Jae-Bok Song, Woo Chun Choi, and Daehie Hong, “Workspace and Force-Moment Transmission of a Variable Arm Type Parallel Manipulator,” Proceedings of the 2002 IEEE International Conference on Robotics & Automation, pp. 3666~3671, 2002.
- [137] “DSP Blockset user’s guide,” The mathworks, Inc., 2000.
- [138] “Signal Processing Toolbox user’s guide,” The mathworks, Inc., 2000.

Appendix

Appendix A:

Simulink Model of Two Link Manipulator

The two-link planar manipulator used in this study is shown in Figure A.1 with coordinate definitions. The general joint space dynamic model of a manipulator based on the Lagrange formulation can be written in the compact matrix form:

$$B(q)\ddot{q} + C(q, \dot{q})\dot{q} + F_v\dot{q} + F_s\text{sgn}(\dot{q}) + g(q) = \tau - J^T(q)h \quad (\text{A-1})$$

Where C is a suitable ($n \times n$) matrix such that its elements C_{ij} satisfy the equation

$$\sum_{j=1}^n C_{ij}\dot{q}_j = \sum_{j=1}^n \sum_{k=1}^n h_{ijk}\dot{q}_k\dot{q}_j \quad (\text{A-2})$$

In the first term of (1), the coefficient b_{ii} represents the moment of inertia at joint i -axis, in the current manipulator configuration, when the other joints are blocked. The coefficient b_{ij} accounts for the effect of the acceleration of joint j on joint i . The second term has two components, centrifugal and Coriolis effects, whose magnitudes depend upon joint velocities. The last term g_i represents the moment generated at the joint i axis of the manipulator, in the current configuration, by gravity.

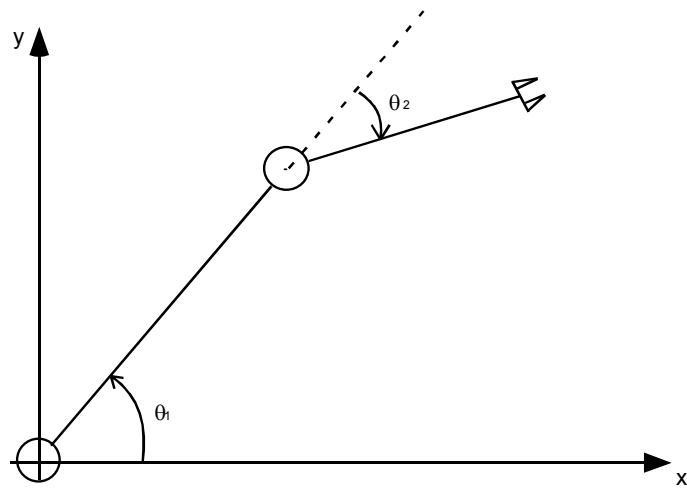


Figure A.1 Two-link planar manipulator.

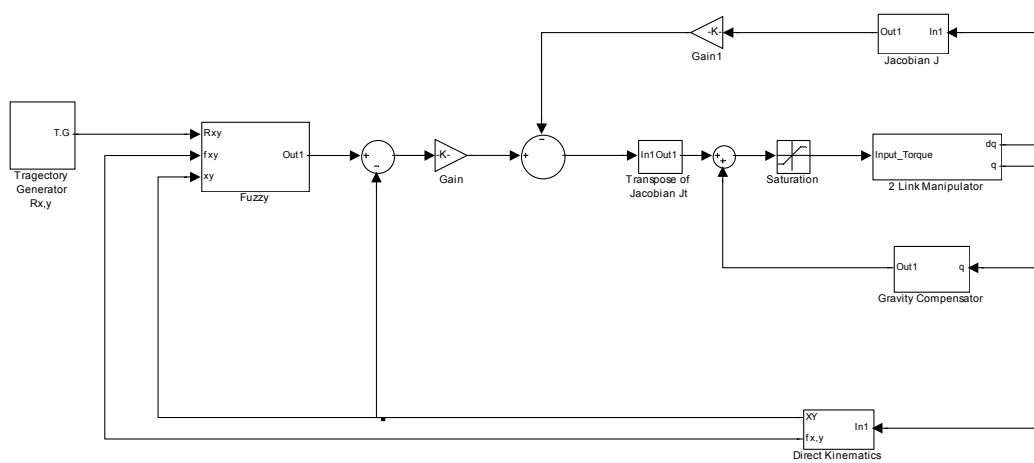


Figure A.2 Top level of the Simulink program.

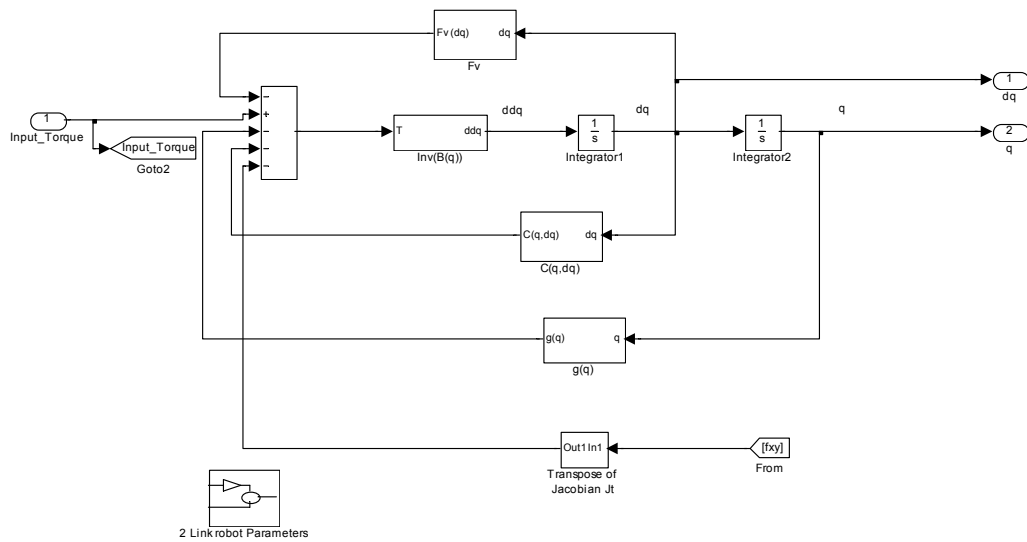


Figure A.3 Two link manipulator Simulink block.

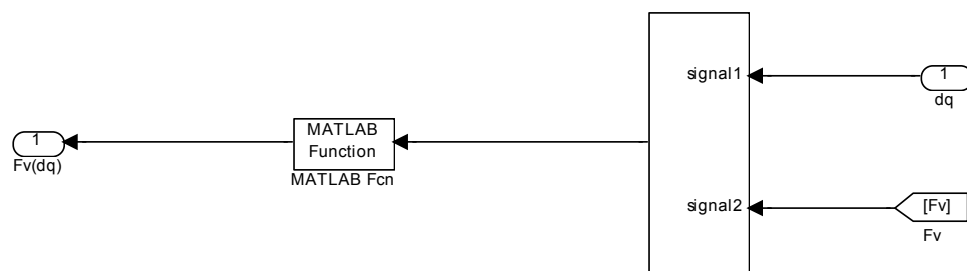


Figure A.4 Simulink block for Fv.

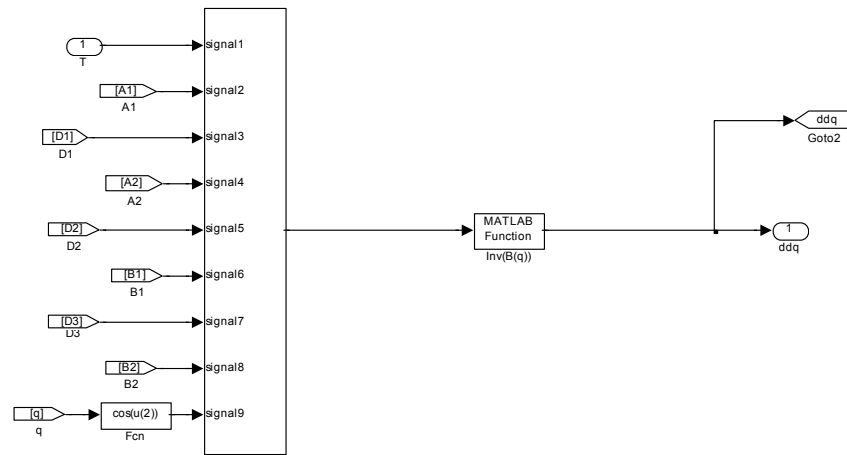


Figure A.5 Simulink block for Inverse B(q).

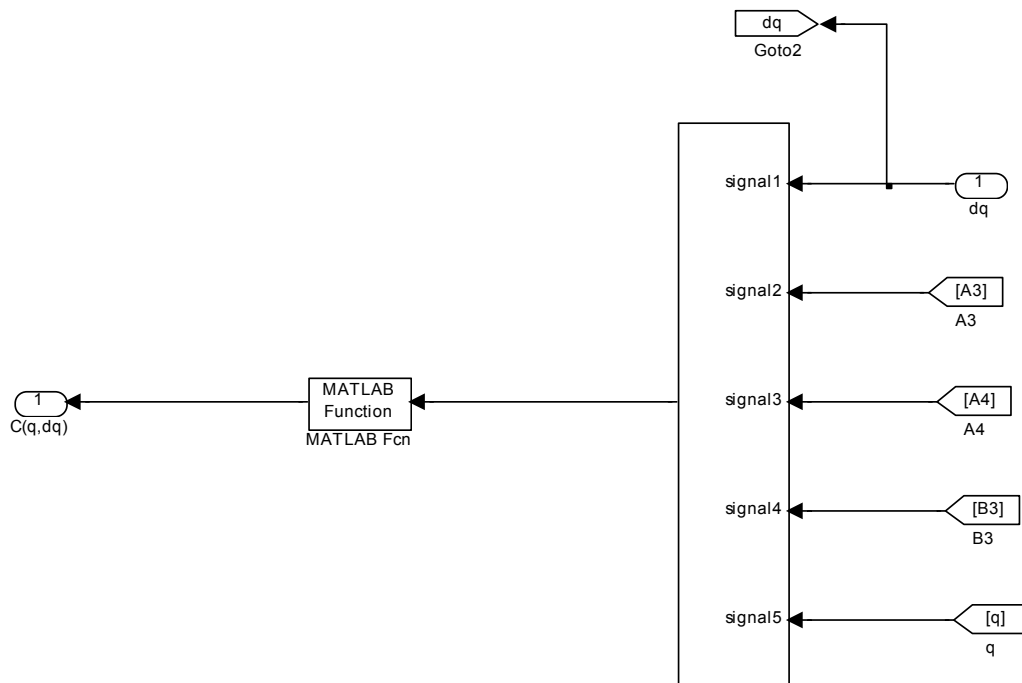


Figure A.6 Simulink block for C (d,dq).

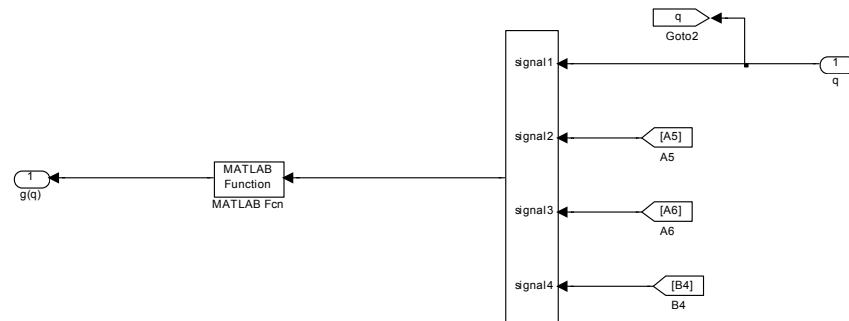


Figure A.7 Simulink block for $g(q)$.

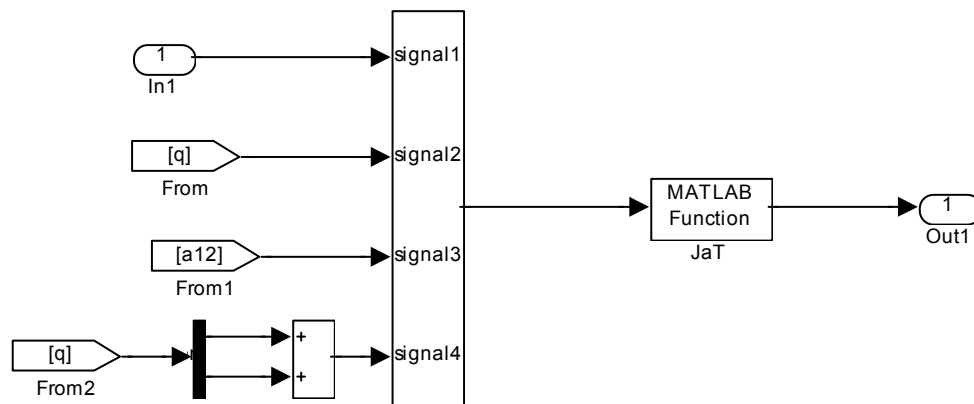


Figure A.8 Simulink block for Transpose of Jacobian.

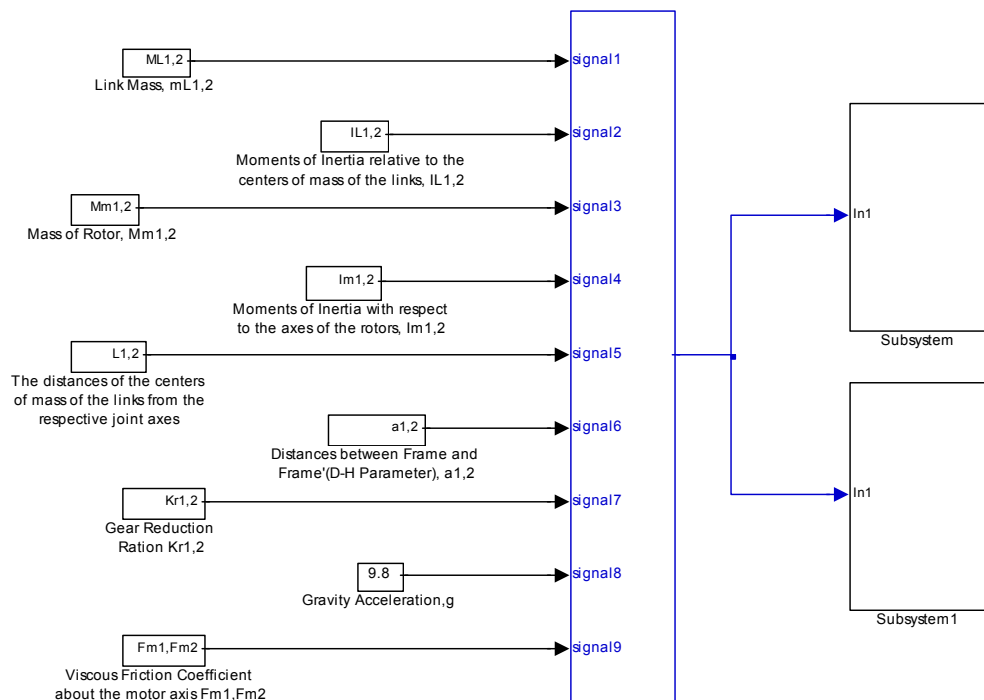


Figure A.9 Simulink block for parameters of two link manipulator.

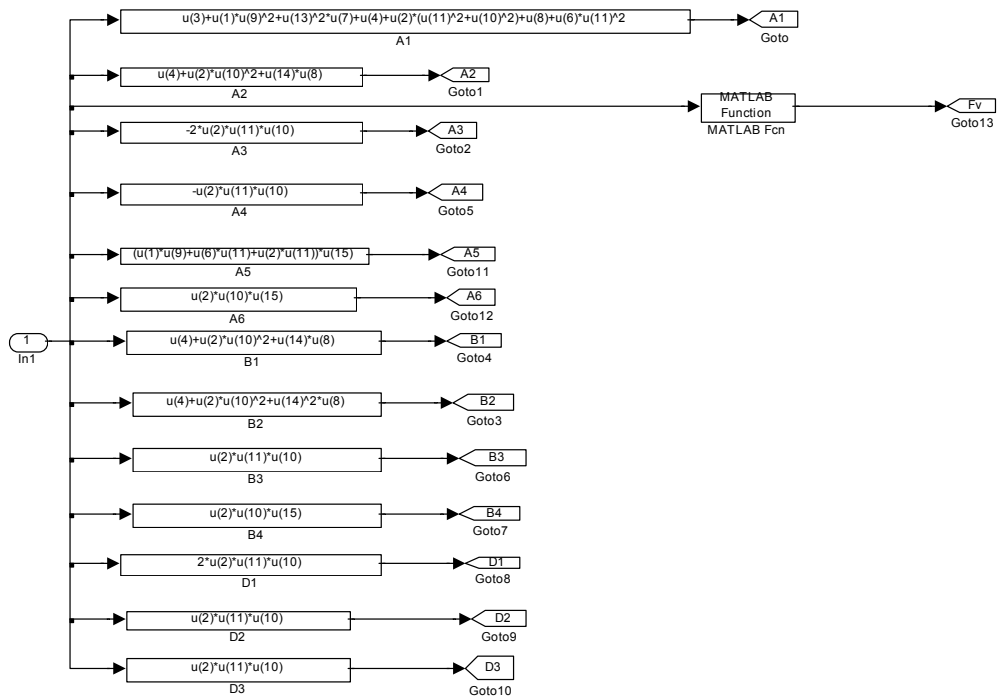


Figure A.10 Simulink block for the parameters (subsystem).

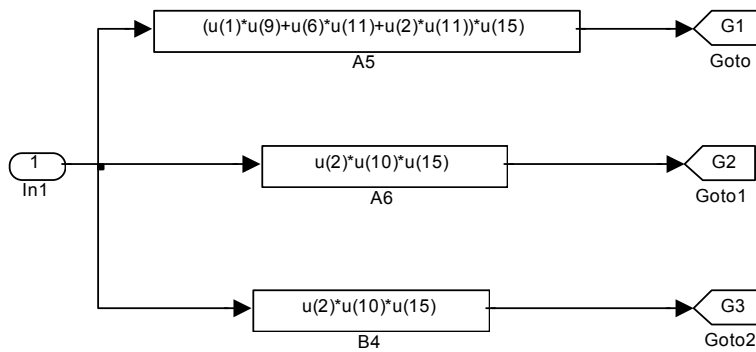


Figure A.11 Simulink block for the parameters (subsystem1).

Appendix B:

Simulink Program for Signal Analysis

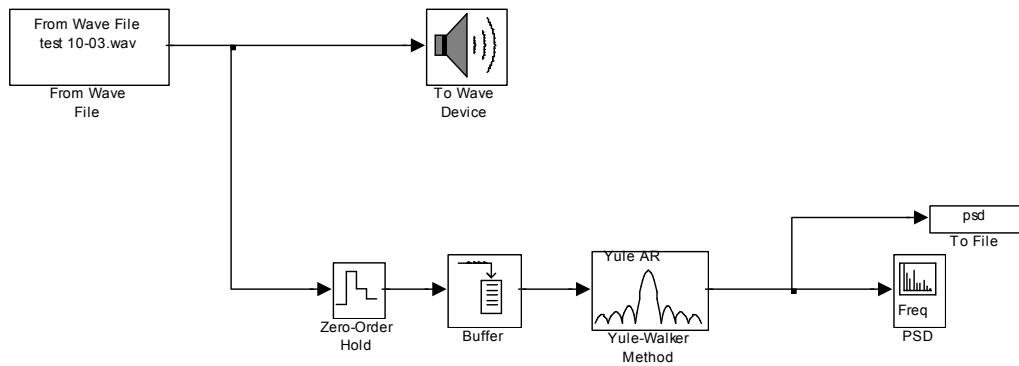


Figure B.12 Simulink block for PSD analysis of acoustic noise data.

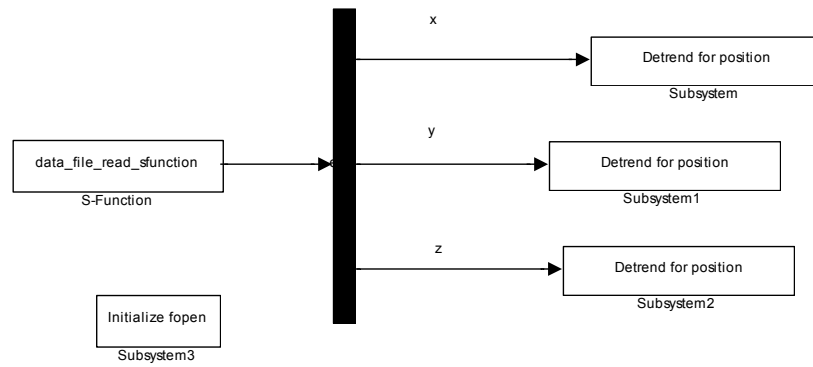


Figure B.13 Simulink block for detrend analysis of position data.

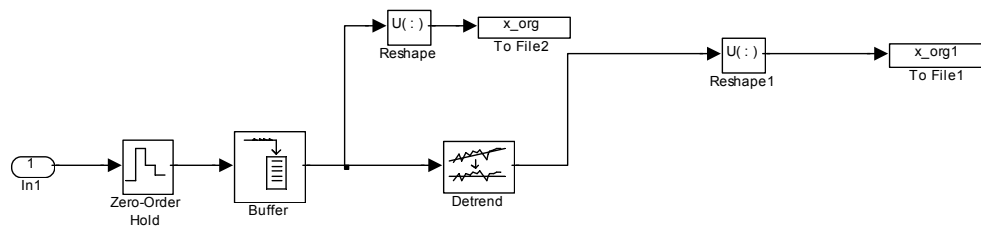


Figure B.14 Simulink block for detrend analysis (subsystem1: Detrend for position).

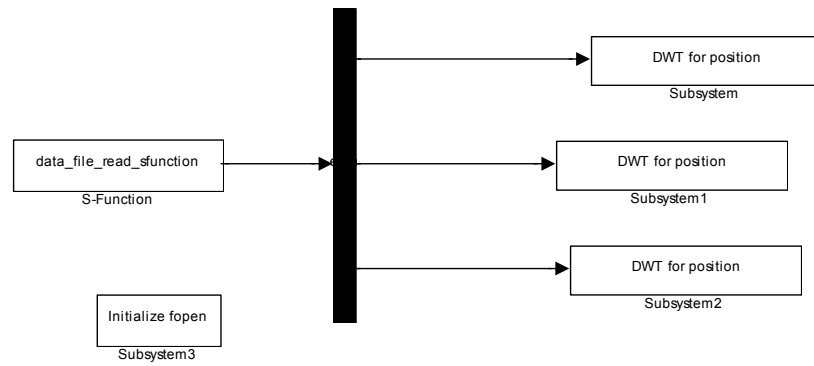


Figure B.15 Simulink block for DWT analysis of position data.

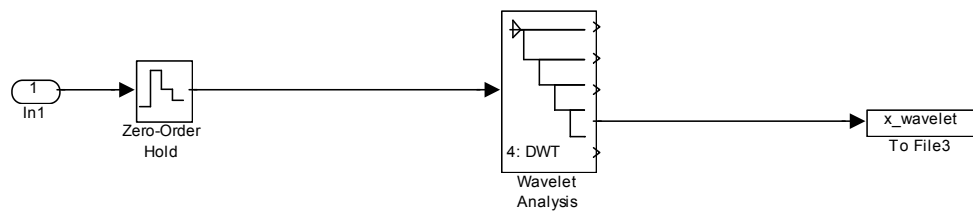


Figure B.16 Simulink block for DWT analysis (subsystem1: DWT for position).

Appendix C:

Simulink Program for Load Estimator using Neural Network

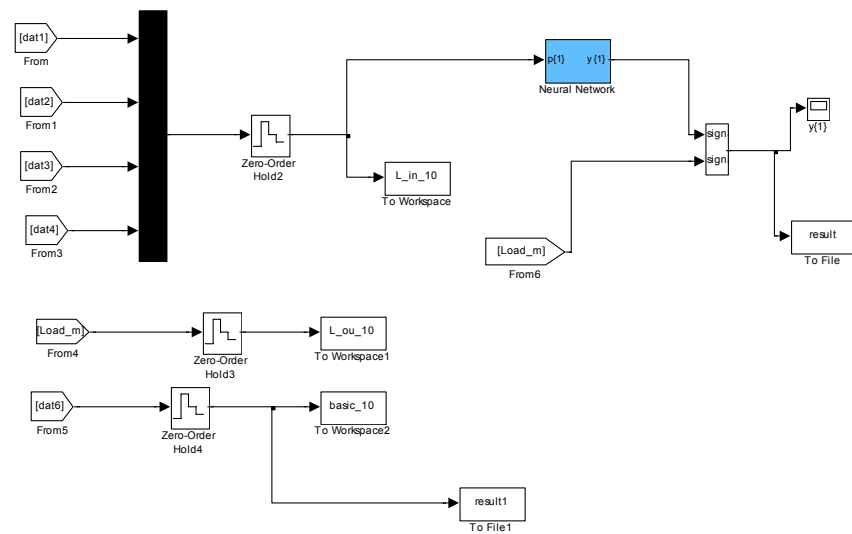


Figure C.17 Simulink block for neural network load estimator.

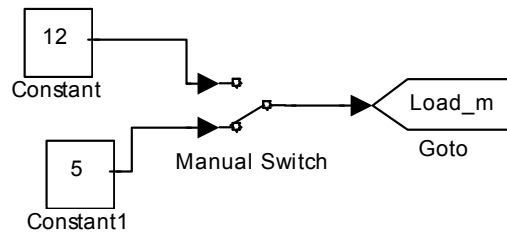


Figure C.18 Simulink block for load change.

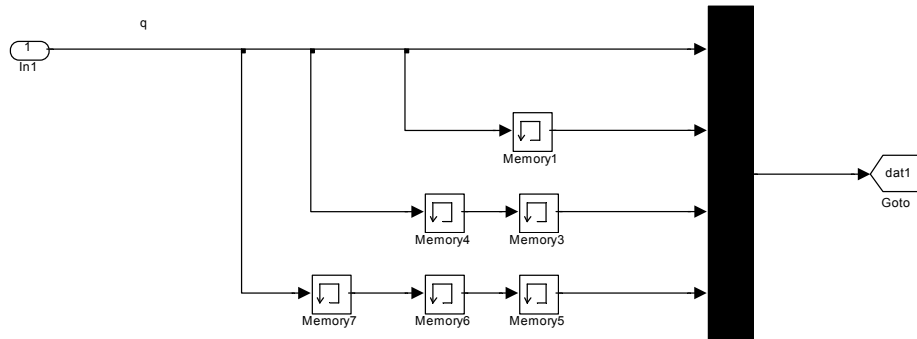


Figure C.19 Simulink block for time delay data.

Appendix D:

Simulink Program for Fault Recovery using Fuzzy Logic

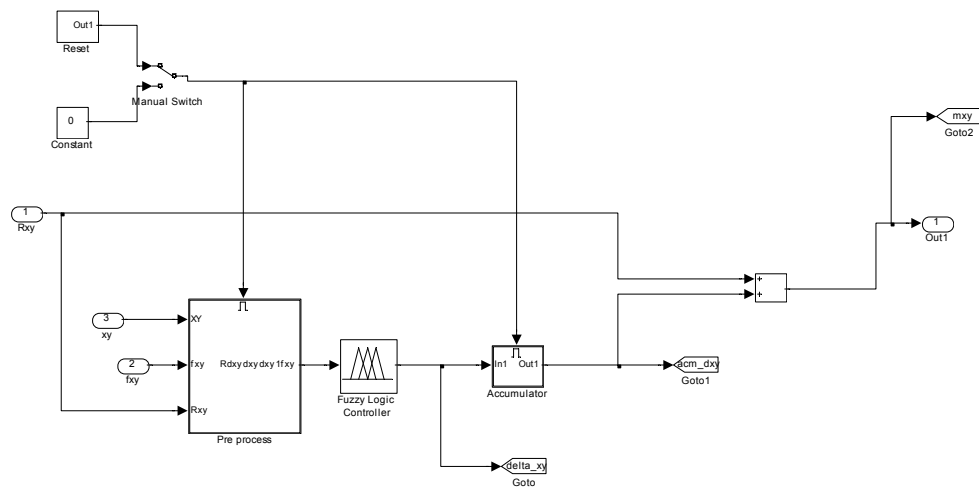


Figure D.20 Simulink block for the fuzzy force limiter.

Vita

Sewoong Kim was born in Seoul, Korea, on September 28, 1965, and he had lived in Seoul until he left when he was 26. In 1984 he graduated from Kyung-Shin High School and entered the Han-Yang University, Seoul, Korea. He received a Bachelor of Science degree and a Master of Science degree in Electrical Engineering from Han-Yang University in 1988 and 1990, respectively. Following graduation, he joined Agency for Defense Development for 7 years. He began his Ph.D. program in Electrical Engineering at University of Tennessee, Knoxville in 1997, and switched his major to Robotics and Automation in the Mechanical and Aerospace Engineering and Engineering Science Department at UT in 1999. He completed his working toward Ph.D. degree in 2002.