

Vital Sign Detection Using Millimeter Wave Radars

A Thesis Presented for the
Master of Science
Degree

The University of Tennessee, Knoxville

Kellen Oleksak

May 2020

© by Kellen Oleksak, 2020
All Rights Reserved.

For Kyle. Who always says the wrong thing at the right time...

Acknowledgments

There is no way I could possibly thank my family enough for their support, understanding and love throughout my life. I owe my mother and father some years of reciprocated venting. To my brother, I wouldn't have gone through with this endeavor had it not been for his confidence in me. If you are reading, you can stop now if you would like! I would also like to thank my advisor Dr. Aly Fathy for allowing me to join his research group and for his continuing life lessons which I will always hold dear. To the entire group, I offer my sincere gratitude for your assistance in experiments, coding, algorithms and ideas throughout my time at UTK. I would especially like to thank Farnaz for her patience with me when I was first learning about vital sign detection. Although we have never met, I am also grateful for the assistance from Dr. Gene Piou in support of state space order estimation. Also, the office environment would not have been so pleasant or enjoyable without Tsotne and Farshid. Thank you Toan, Farnaz, Tsotne and Chandler for helping with the experiments. Lastly, I would like to thank Abdel Moadi for being the best lab partner for over two years and a great friend for more.

Abstract

Using 60GHz and 77GHz frequency modulation continuous wave (FMCW) radars, multiple signal processing techniques have been applied on subject data to accurately extract vital signs remotely. In particular, phase based, parametric estimation and time varying window methods have been used with the addition of multiple input multiple output (MIMO) diversity channel combining to detect respiratory rates and heart rates of subjects with high confidence. The vital sign detection acquisition times and accuracy previously demonstrated in state of the art microwave radar systems at lower frequencies are compared in this work. Results from a single subject at varying distances will be presented and compared to other relevant contact measurement results. The ability and limitations of using the techniques on a real-time system is of paramount importance and will be demonstrated using a Texas Instruments mmwave vital sign detection chip.

Table of Contents

1	Introduction	1
1.1	State of the Art Vital Sign Detection	2
1.2	Current Vital Sign Detection with Mmwave Systems	4
1.3	Thesis Organization and Goals	5
2	Radar Theory	7
2.1	Operation	7
2.1.1	Types of Systems	9
2.2	A Focus on FMCW Radar	11
3	Mmwave Systems	14
3.1	System Hardware	15
3.1.1	RF Front End	16
3.1.2	Mmwave SoC	19
3.1.3	MSS	21
3.1.4	DSS	23
3.2	Configuration	24
4	Vital Sign Signal Processing	29
4.1	Phase Based Methods	30
4.2	State Space Method	32
4.3	Time Varying Windows	37
4.4	Real-Time Capabilities	39

4.4.1	Processing Chain	40
4.4.2	Extracting A Commercial Algorithm for Offline Testing	45
4.5	Programming the AWR1642 For MIMO Output	47
4.6	MIMO Processing	49
5	Vital Sign Estimation Results	54
5.1	System Comparison	55
5.2	FMCW Mmwave Systems For Vital Sign Detection	59
5.2.1	Single Subject at 0.6 Meter Distance	60
5.2.2	Single Subject at 1 Meter Distance	80
5.3	MIMO Results	95
5.3.1	Single Subject at 1 Meter Distance	96
5.4	Real-Time Results	105
6	Conclusion	109
6.1	Summary of Results	109
6.2	Contribution	111
6.3	Future Work	112
6.4	Concluding Remarks	112
	Bibliography	114
	Vita	118

List of Tables

1.1	Vital Sign State of the Art Results	3
1.2	Vital Signs Mmwave Results	5
3.1	Mmmwave SoC	14
3.2	TI Mmwave Comparison	25
4.1	AWR 1642 Memory Locations for Processing	48
5.1	TI Mmwave Comparison	59
5.2	Subject Respiratory Rate Estimates	62
5.3	Subject Heart Rate	64
5.4	HR % Error For One Subject Results @60GHz	73
5.5	HR % Error For One Subject Results @77GHz	79
5.6	HR % Error One Subject Result Comparison	80
5.7	Subject Heart Rate	80
5.8	HR % Error For One Subject Results @60GHz, 1 meter	88
5.9	HR % Error For One Subject Results @77GHz, 1 meter	94
5.10	HR % Error One Subject Result Comparison 60GHz and 77GHz, 1 meter	95
5.11	HR % Error MIMO Results @60GHz, 1 meter	100
5.12	HR % Error MIMO Results @77GHz, 1 meter	105
5.13	HR % Error MIMO Results 60GHz and 77GHz, 1 meter	105
5.14	Real-Time Estimation Averages	108

List of Figures

2.1	UWB Pulse	10
2.2	SFCW Transmission	11
2.3	FMCW Chirp	12
3.1	AWR1642 EVM	15
3.2	AWR1642 Front End	16
3.3	Fractional-N PLL	17
3.4	AWR1642 Antenna Array Structure	18
3.5	SoC	19
3.6	Mmwave System Flow	20
3.7	AWR1642 Subsystem	21
3.8	MSS Packets	22
3.9	DSS Timing	23
3.10	DSS Timing 1D FFT	24
3.11	Mmwave Chirp Settings	26
3.12	Object Detection CFAR Grouping	27
3.13	Object Detection Matrix Peak Grouping	27
4.1	Range Profile Example	30
4.2	Phase Variation	41
4.3	Vital Signs Emulator	47
4.4	Example of Vital Signs Code Additions	48
4.5	Vital Signs Stats Output Packet	49

5.1	Actuator Frequency w/ 60GHz System (1Hz) Using AD	56
5.2	Actuator Frequency w/ 60GHz System (1Hz) Using CSD	56
5.3	Actuator Displacement w/ 60GHz	57
5.4	Actuator Frequency w/ 77GHz System (0.5Hz) Using AD	57
5.5	Actuator Frequency w/ 77GHz System (0.5Hz) Using CSD	58
5.6	Actuator Displacement w/ 77GHz	58
5.7	FMCW Radar Systems	61
5.8	Spectrum of Breathing Rate @ 60GHz, 1 meter Using AD	63
5.9	Spectrum of Breathing Rate @ 77GHz, 1 meter Using AD	63
5.10	Spectrum of Vital Signs Using AD @60GHz	65
5.11	Spectrum of Vital Signs Using SSM-AD @60GHz	66
5.12	Spectrum of Vital Signs Using SSM-AD-BP @60GHz	67
5.13	Spectrum of Vital Signs Using CSD @60GHz	68
5.14	Spectrum of Vital Signs Using SSM-CSD @60GHz	69
5.15	TVW-AD Results @60GHz	70
5.16	TVW-CSD Results @60GHz	71
5.17	TVW-CSD Results @60GHz, 2.5s Window	71
5.18	Vital Signs TI Processed @60 GHz	72
5.19	Spectrum of Vital Signs Using AD @77GHz	74
5.20	Spectrum of Vital Signs Using SSM-AD @77GHz	75
5.21	Spectrum of Vital Signs Using SSM-AD-BP @77GHz	75
5.22	Spectrum of Vital Signs Using CSD @77GHz	76
5.23	Spectrum of Vital Signs Using SSM-CSD @77GHz	77
5.24	TVW-AD Results @77GHz	77
5.25	TVW-CSD Results @77GHz	78
5.26	Vital Signs TI Processed @77 GHz	78
5.27	Spectrum of Vital Signs Using AD @60GHz, 1 meter	81
5.28	Spectrum of Vital Signs Using SSM-AD @60GHz, 1 meter	82
5.29	Spectrum of Vital Signs Using SSM-AD-BP @60GHz, 1 meter	83
5.30	Spectrum of Vital Signs Using CSD @60GHz, 1 meter	84

5.31	Spectrum of Vital Signs Using SSM-CSD @60GHz, 1 meter	85
5.32	TVW-AD Results @60GHz, 1 meter	86
5.33	TVW-CSD Results @60GHz, 1 meter	86
5.34	Vital Signs TI Processed @60 GHz, 1 meter	87
5.35	Spectrum of Vital Signs Using AD @77GHz, 1 meter	88
5.36	Spectrum of Vital Signs Using SSM-AD @77GHz, 1 meter	89
5.37	Spectrum of Vital Signs Using SSM-AD-BP @77GHz, 1 meter	90
5.38	Spectrum of Vital Signs Using CSD @77GHz, 1 meter	90
5.39	Spectrum of Vital Signs Using SSM-CSD @77GHz, 1 meter	91
5.40	TVW-AD Results @77GHz, 1 meter, 4s Window	92
5.41	TVW-AD Results @77GHz, 1 meter, 2.75s Window	92
5.42	TVW-CSD Results @77GHz, 1 meter, 4s Window	93
5.43	TVW-CSD Results @77GHz, 1 meter, 2.25s Window	93
5.44	Vital Signs TI Processed @77 GHz, 1 meter	94
5.45	MIMO AD @60GHz, 1 meter	96
5.46	MIMO CSD @60GHz, 1 meter	97
5.47	MIMO SSM-AD @60GHz, 1 meter	97
5.48	MIMO SSM-CSD @60GHz, 1 meter	98
5.49	MIMO SSM-AD-BP @60GHz, 1 meter	98
5.50	MIMO TVW-AD @60GHz, 1 meter	99
5.51	MIMO TVW-CSD @60GHz, 1 meter	99
5.52	MIMO AD @77GHz, 1 meter	100
5.53	MIMO CSD @77GHz, 1 meter	101
5.54	MIMO SSM-AD @77GHz, 1 meter	101
5.55	MIMO SSM-CSD @77GHz, 1 meter	102
5.56	MIMO SSM-AD BP @77GHz, 1 meter	102
5.57	MIMO TVW-AD @77GHz, 1 meter	103
5.58	MIMO TVW-CSD @77GHz, 1 meter	103
5.59	AWR1642 Real-time Comparison	107

Chapter 1

Introduction

The need for millimeter wave (mmwave) sensor development is driven by frequency allocation demands, high-throughput wireless user services, reliable mobile connectivity, sensors and the internet of things (IoT). At higher frequencies, wireless transmissions can take advantage of wider bandwidths and an increased number of channels, resulting in faster services and more users in a given frequency band. Mmwave sensors are also significantly reduced in size and cost due to their smaller antenna structures and the developments of system-on-a-chip (SoC) technologies, allowing the deployment of many mmwave systems in the same area to serve mobile needs and IoT data demands. Despite the notable advantages, mmwave technology faces serious challenges in regards to electromagnetic wave propagation at higher frequencies, which can result in lower signal-to-noise ratios (SNR) for a signal of interest due to path loss and signal obstructions by small objects such as a mobile user's hand. This issue can be addressed with increased infrastructure and back haul network support or with advanced signal processing methods. In terms of the latter, each application has its own needs and complexities, which can be environment, system, frequency and time dependent.

Electromagnetic sensors operate in a variety of ways by stimulating the environment and processing the returned information. Examples include radar systems tracking a moving object, a flow meter responding to charged particles in a liquid to measure velocity, the reception of wireless communication signals, monitoring human gaits, and respiratory or heart rate detection. The focus of this work is to show how current mmwave radar systems can be used to detect human vital signs and to demonstrate how their performance can be

improved in time and accuracy using a combination of processing techniques and hardware configurations to address the issues that come with the use of mmwave sensors.

1.1 State of the Art Vital Sign Detection

Table 1.1 is a breakdown of the state of the art vital sign estimations for heart rate with an acquisition time of less than 20 seconds. The three radar types in the table are Ultra Wide Band (UWB), Stepped Frequency Continuous Wave (SFCW) and Continuous Wave (CW). Estimation error of the respiratory rate was not the main focus in the works from Table 1.1, so comparisons for respiratory estimation will not be directly made, however, it will be shown that the mmwave sensors used in this work can accurately predict the respiratory rate with minimal processing. A quick tour of the current methods used with systems below 24GHz will now be given.

References [1] and [2] utilize the state space method (SSM) to greatly improve the SNR of the measured heart rate. SSM was applied after processing with arctangent demodulation (AD) and complex signal demodulation (CSD). SSM is the only method in the table which greatly improves SNR, however current MIMO results have also shown SNR improvements [3]. SSM has been applied to UWB and SFCW systems in [1] and [2] at similar frequencies showing great performance and will again be shown in this work applied on the FMCW systems at 60GHz and 77GHz.

In [4], the estimation error in a 30s period is 1%, reaching the same metric as [1], however, it uses a significantly less computationally taxing method, which is the time varying window (TVW). TVW performs multiple Fast Fourier Transforms (FFTs) with varied sample numbers. The range in [4] was stated as "arbitrary", so "Not Reported" (NR) was also put for the distance. From a picture of the test setup in the literature, it is fair to assume the test took place between 0.8-1.5m. Phase based methods such as AD and CSD both using SSM, as well as TVW will be further described in Chapter 4 and the results using these methods with FMCW mmwave systems will be shown in Chapter 5.

Lastly, in [5], a feature-based topological similarity technique was used to correlate extracted features and minimize the inter-beat interval (IBI) difference compared to an

ECG, however, the work was done with non-breathing patients, so the comparison to the other works listed in Table 1.1 is not direct. The *, is used to identify the experiment where the subject held their breath. Throughout this work, BR will be used for breath rate and HR will be used for heart rate.

Table 1.1: Vital Sign State of the Art Results

Work	Type	Frequency	Distance	BR % Error	HR % Error	Method	Duration
[1] 2016	UWB	1.5–4.5GHz	0.8m	NR	1.7%	SSM-AD/CSD	18s
[2] 2015	SFCW	2-4GHz	1m	NR	1.6%	SSM	18s
[4] 2016	CW	5.8GHz	NR	NR	3.4%	TVW-CSD	2-5s
[6] 2013	CW	14GHz	5m	NR	2.2%	AD	20-30s
[5] 2016	UWB	24GHz	NR	NR	*1%	FBTS	20-55s

As was mentioned, the concern is mostly with heart rate measurements, as a simple FFT can very accurately predict the breathing rate, so most of the above literature does not mention breathing estimate error percentages. There have been other studies with similar estimation performance, but not in the same amount of time. Assuming the state of the art implies faster acquisitions, as is the case for a moving subject or surveying multiple subjects with one system, it seems appropriate to report shorter acquisition times.

For long range applications [6] shows promising results at 5m and also shows measurements at and beyond 25m with what appears to be great accuracy, however, no metric is mentioned at those distances. References [5] and [6] make estimates based on beat to beat time differences of the heart and compare them directly to an electrocardiogram (ECG). The error determination is based on the time difference of the peak from the radar system to that of the ECG, which is slightly different than the pulse references used in [1] and [4].

A background of the current state of the art systems was needed to set a metric for all vital sign detection systems extending into mmwave. The work done in signal processing to improve heart rate estimation should be further extended to mmwave systems, especially SSM, which greatly improves estimates in low SNR settings. It will be shown that few advanced signal processing methods have been applied to mmwave systems for vital signs

detection, as their development has been complex enough and generally focused on high throughput communications for applications such as 5G and the IoT.

1.2 Current Vital Sign Detection with Mmwave Systems

Table 1.2 shows the current mmwave state of the art results for vital signs detection. It is interesting that most recent work in mmwave vital sign estimation has taken place over time durations of greater than 100 seconds. In this work the estimation time is concerned with quick and accurate measurement as opposed to long term monitoring. Three of the tests in the table were performed at a distance of 1 meter or greater. In this work, results will be reported at 0.6m to first establish that the methods work well with the system at a close distance, then they will be compared with current state of the art results at 1m.

The most closely related system to this work is from [7] where a 77GHz Texas Instruments (TI) AWR1642 development kit is used. Their results showed that AD with FFT was used in addition to a DC compensation method using a linear least square estimator (LLSE). The work presented in [7] does not compare numerous processing techniques with the mmwave system, so the work done here is still a contribution. Additionally, in this work, the MIMO capabilities of the TI systems are utilized to improve estimation results.

Considering the CW systems in [8] and [9], their long term use may not be practical since FCC Part 15.255, Operation within the 57-65GHz bands must not exceed an average power of 40dBm Equivalent Isotropically Radiated Power (EIRP, which is the product of transmission power and gain in a direction relative to an isotropic antenna) for a transmission and must not exceed 43 dBm EIRP peak power (as of 2013 in FCC 78 FR 59844 (09/30/2013)). Similarly, 77GHz range systems need to operate under an average power limit of 50 dBm EIRP and a peak power of 55 dBm EIRP but these regulations are cited specifically for vehicular radars under Part 95 of the 76-81GHz frequency rules. The scope of operation is still lightly defined in terms of use case, however, FMCW systems seem to be promising since they operate in a pulsed manner, i.e., they can have lower average powers and higher

peak powers since the chirp takes place over a short period of time. For instance, a chirp repetition rate may be 50ms, however the pulse transmit time is $50\mu\text{s}$, resulting in a lower duty cycle. A CW system would not be able to continuously operate at the average transmit power of an FMCW system. This will be explained in more detail in Section 3.2.

The results in [5], show a 1% error and [3] states an 18% improvement from the estimations in [5] by using MIMO and Maximal Ratio Combining (MRC). These works show promise in feature extraction methods but [3] seems to lack proper performance reporting. Regardless, the MRC method will be shown in this work with both the 60GHz and 77GHz systems measuring over both 4 second and 20 second periods with good results. In [9], early experiments using mmwave CW systems were performed to demonstrate proof of concept with a subject holding their breath. No estimation accuracy was reported. References [7] and [8] are capable of reporting estimates on short time scales, however the error percentage reported in the work used the time duration shown in the table. It is unclear whether this helped or degraded the estimation accuracy. Also, in [8], the accuracy reported is based on seven subjects averages so it is labeled with an *.

Table 1.2: Vital Signs Mmwave Results

Work	Type	Frequency	Distance	BR % Error	HR % Error	Method	Duration
[10] 2015	FMCW	75-85GHz	1m	6.89%	8.09%	FFT	100s
[7] 2019	FMCW	77-81GHz	1.7m	6%	20%	AD-FFT	40min
[8] 2016	CW	60GHz	1m	*2%	*3.3%	FFT	10min
[3] 2019	UWB	60.5GHz	NR	NR	NR	MRC	150s
[9] 2012	CW	60GHz	NR	NR	NR	FFT	20s

1.3 Thesis Organization and Goals

The following work will first explore radar system types and operations with a focus on the FMCW systems used in experimentation in Chapter 2. Next, an overview of mmwave system architecture and operation for a commercial radar system will be given during Chapter 3. Then the processing methods which are currently used for lower frequency vital sign

detection radar systems will be described in Chapter 4 and the results from their application will be shown in Chapter 5. Finally a summary of the work presented, contribution to the community and future work will be discussed in Chapter 6.

The goals of this work are;

- To verify that 60GHz and 77GHz mmwave systems can be used for vital sign detection with comparable accuracy to state of the art low frequency systems. Multiple algorithms have been used on experimental data to show which methods work best and why.
- To push vital sign detection to real-time systems. A commercial tool for real-time development by Texas Instruments is already available but this work aims to improve the existing program to allow for MIMO processing and show the potential for coding additional algorithms presented in this work onto a commercially available chip.
- To demonstrate the real-time abilities of each algorithm described and what its time constraints might be for reporting accurate results.

Chapter 2

Radar Theory

This chapter will provide the basic fundamental background for radar system theory and operation. Then a few common radar systems will be mentioned. Lastly, the FMCW radar in this work will be further explained. The focus here will be the generation of the transmitted electromagnetic wave, the wave propagation in space and the returned signal (echo). Processing the signal and the digital system involved in the radar design are further explained in Chapters 3 and 4

2.1 Operation

A radar system is a type of sensor which stimulates and listens to the environment. When the source of stimulation is known, information about the surveyed surroundings can be extracted. The mechanism for this process is a radiating antenna, which radiates a certain power, P_t , with an additional antenna gain, G . If there are objects in the vicinity, the objects will experience an incident power density, S_t , which is a function of the squared distance from the radiator [11] expressed in Watts/Meter² (W/m²) as,

$$S_t = \frac{P_t G}{4\pi r^2} \quad (2.1)$$

The incident wave on a target will be scattered which is governed by the material properties of the target. A metric for the scattered isotropic (isotropic is an equally radiated gain of 1dB in all directions) power is defined as the radar cross section, σ , which is used to determine the received power density, S_r , of a scattered wave by [11],

$$S_r = \frac{\sigma S_t}{4\pi r^2} \quad (2.2)$$

and the received power density can be expressed as,

$$S_r = \frac{P_t G \sigma}{(4\pi r^2)^2} \quad (2.3)$$

The above equations are for monostatic radar, which means the transmitting antenna is also the receiving antenna. For the radar applications in this work, the transmit and receive antennas are spaced close enough that the same relation can be applied. The power in Watts of the received scattered signal is,

$$P_r = A_e S_t \quad (2.4)$$

where A_e is the effective aperture area. This factor defines the effective capture area of the antenna. A_e is a function of the antenna Directivity (ideal gain), D , and wavelength, λ . It is expressed as,

$$A_e = \frac{D\lambda^2}{4\pi} \quad (2.5)$$

which shows that as the frequency of the antenna transmission increases, the effective aperture area decreases for a given directivity. Using A_e , P_t and S_r , the received antenna power can be expressed as a function of the radar cross section, gain and the transmission wavelength [11],

$$P_r = \frac{G^2 \lambda^2 \sigma}{(4\pi)^3 r^4} P_t \quad (2.6)$$

With this relationship and considering the application of millimeter waves, the challenge is readily apparent. At higher frequencies the received power decreases proportionally to the square of the wavelength of transmission for a given power and distance. Additionally, it is seen that distance significantly affects the received power. This relation can also be viewed using the Friis equation for system links, which defines the link budget in decibels (dB) as [12],

$$P(\text{dB}) = G_r(\text{dB}) + G_t(\text{dB}) + P_t(\text{dB}) - 10 \log \left(\frac{(4\pi)^{1.5} r^2}{\lambda \sqrt{\sigma}} \right)^2 \quad (2.7)$$

from which it is obvious that higher frequencies will experience a higher link loss.

Mmwave systems do still stand a chance albeit the above scenarios look unfortunate. The directivity of an antenna is a function of the transmission frequency such that [12],

$$D = \frac{4\pi A_e}{\lambda^2} \quad (2.8)$$

which explains that the antenna directivity will significantly increase with increasing frequency for a given physical area. This is also related to the antenna gain by $G = \eta_{eff} D$ where η_{eff} is the antenna efficiency, which reduces the gain. Therefore, amidst the difficulties of higher frequency transmission there is naturally increased gain. This will be restricted by application and FCC regulations on device output power ratings at high frequencies.

2.1.1 Types of Systems

Generation of the transmitted wave is a unique property for different types of radar systems. The CW, UWB, SFCW, and FMCW are all capable of extracting frequency information about the environment, but only UWB, SFCW and FMCW systems can also gather range

information of targets. This is because CW radars operate at a fixed frequency but transmit continuously. The SFCW system also transmits continuously, however the frequency of the transmission is "stepped" between a lower bound and upper bound for which the antenna and system components can produce a consistent gain across a frequency band. The waveforms of the UWB, SFCW and FMCW systems are of interest as they provide insight into how the received signal can be processed to extract target information such as range and vital signs when the received signal is down converted.

UWB signals generate a fast pulse on the scale of nanoseconds to picoseconds from which the delay time from a scatterer can be calculated. From a signals theory point of view, the UWB radar has a wide frequency band; where extremely narrow pulse widths correspond to a wide frequency range. In [1], a 700ps pulse corresponds to a system frequency bandwidth from 1.5GHz to 4.5GHz when upconverted by a local oscillator. The benefits of UWB is that it has high range resolution and low power. Vital sign information is determined by the received pulse's frequency modulation [1]. An example of a UWB pulse and a modulated pulse is shown in Figure 2.1.

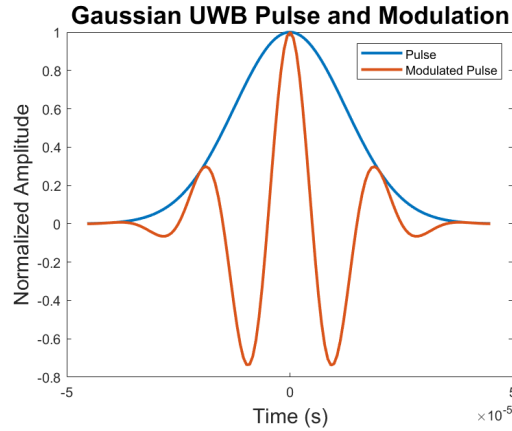


Figure 2.1: UWB Pulse

An example of a SFCW transmission is shown in Figure 2.2. In the SFCW system, the transmitting signal is also used to down convert the received signal to base band, so

the received signal is down converted with a stair step type waveform. From this, a beat frequency which is directly related to the delay time of the returned signal can be found. The beat signal identifies the range information of the target and the number of range bins, i.e., the different ranges that can be observed is dependent upon the number of frequency steps.

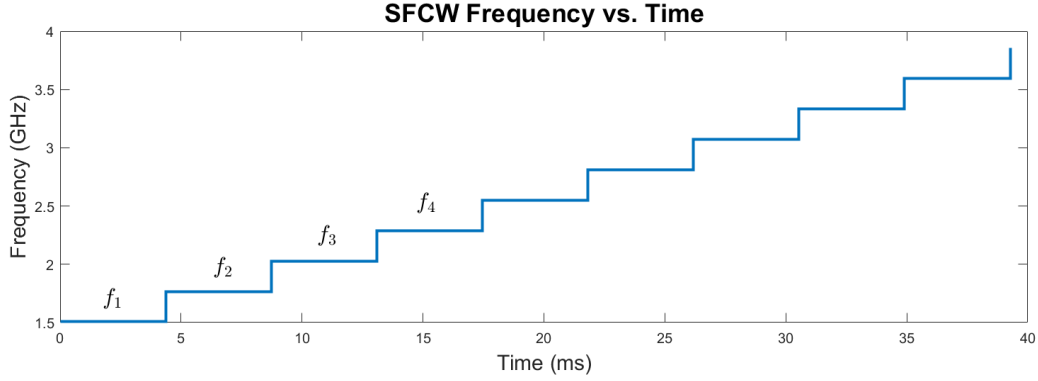


Figure 2.2: SFCW Transmission

A Section will be devoted to the FMCW radar since it is the focus of this work. It is very similar to the SFCW system, however the FMCW signals are "chirps" which have a shorter transmit duration in time and they cover a larger frequency range in a shorter amount of time.

2.2 A Focus on FMCW Radar

Figure 2.3 shows the linear frequency modulation (FM) Chirp. The chirp duration for this work is $50\mu\text{s}$ which covers a bandwidth of 4GHz. The number of frequencies that can be observed corresponding to the range information is chosen by the number of sample points taken after the chirp down conversion process. Similar to the SFCW radar, the down conversion is performed with the same signal that was transmitted, resulting in beating frequencies which are directly related to time delays of scattered signals. An example of

time delay and beat frequency for the FMCW radar is shown in Figure 2.3. The beat frequency is described as [11],

$$f_b = \frac{B_W \tau}{T} \quad (2.9)$$

where B_w is the sweep bandwidth, τ is the round trip time delay $2d/c$ (c is the speed of light) and T is the sweep time. Since B_W and T are known, viewing the spectrum of the received signal reveals τ which in turn reveals the range of the target.

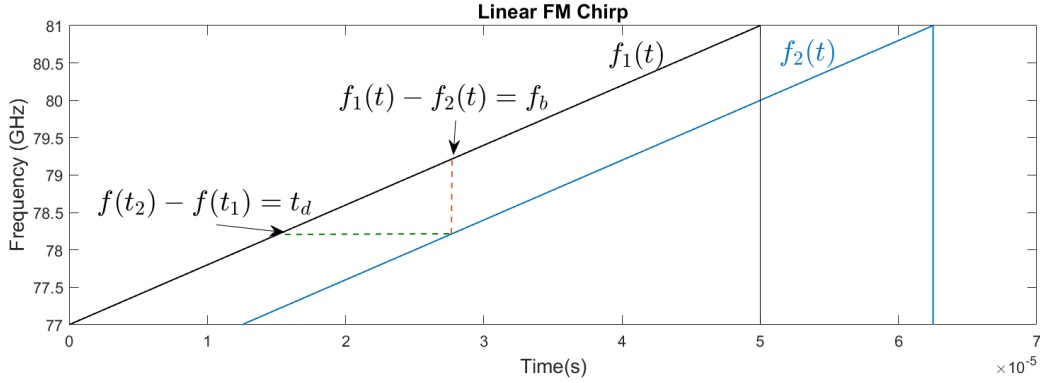


Figure 2.3: FMCW Chirp

A mathematical model of the transmitted linear FMCW chirp can be described as [11],

$$T(t) = A \cos(2\pi f_0 t + \frac{\pi B_W}{2T} t^2 + \Phi_T) \quad (2.10)$$

with f_0 being the center frequency, T the transmit time, and Φ_T the phase of the transmitted signal. Based on the time delay of the received signal it follows that,

$$R(t) = A\Gamma \cos(2\pi f_0(t - \tau) + \frac{\pi B_W}{2T}(t - \tau)^2 + \Phi_R) \quad (2.11)$$

where Φ_R is the phase of the received signal and Γ is the reflection coefficient magnitude. After down conversion, the radar output signal is,

$$B(t) = A_b \cos(2\pi f_b t + 2\pi f_o \tau - \pi f_b \tau + \Phi) \quad (2.12)$$

with $B(t)$ being the received signal at base band, A_b the amplitude of the beat signal and Φ the phase.

Radar theory is applied in general to a broad class of system types, frequencies and applications. The advantages of mmwave is that the system size can be greatly reduced since the antenna structure size is now in the millimeters range. This allows for integrated front end/digital systems. With the addition of SoC technology, a powerful yet miniature radar system can be developed for a multitude of applications.

Chapter 3

Mmwave Systems

Table 3.1 shows the current mmwave state of the art SoCs. The table shows the operation frequency of the chip, the type of radar system, whether or not MIMO is available, if the chip has a development kit, and if the system has an application programming interface (API). It is clear that the amount of SoC mmwave products are few, but many companies have chips in development. This list contains those that are currently available for commercial use. Some vendors offer SoC solutions but the systems are not available for self-evaluation. This list contains only SoCs which can be self-evaluated.

Table 3.1: Mmmwave SoC

Manufacturer	Type	Frequency	MIMO	Dev. Kit	API
Texas Instruments (TI)	FMCW	60-64GHz	✓	✓	✓
Peraso	CW	60GHz	×	×	×
Acconeer	Pulsed	60-64GHz	×	✓	✓
Sivers IMA	CW	57-71GHz	✓	×	×
Omniradar	FMCW	57-64GHz	×	✓	✓
STMicroelectronics	FMCW	77-81GHz	✓	×	×
TI	FMCW	77-81GHz	✓	✓	✓
NXP	FMCW	77-81GHz	✓	✓	✓

The Acconeer and Omniradar models have on-chip antennas whereas the rest of the SoCs have external antennas. Although the Omniradar has two receive elements, it is not clear if these channels are both accessible, so at the very least the system would be single input multiple output (SIMO). Systems with development kits or an evaluation module (EVM) require printed circuit board (PCB) designs. Often times, design recommendations, layout patterns, device footprints and possibly CAD files are available from the manufacturer. Purchasing an EVM kit at the beginning allows designers to develop applications for the chip quickly and see if their requirements can be met fundamentally, then adjustments can be made depending on the use case. The following sections describe the hardware for mmwave systems.

3.1 System Hardware

Since TI chips were used in this work they will be the focus, however, some of the general concepts could surely be applied to the other SoCs. The EVM for the AWR1642 is shown in Figure 3.1.

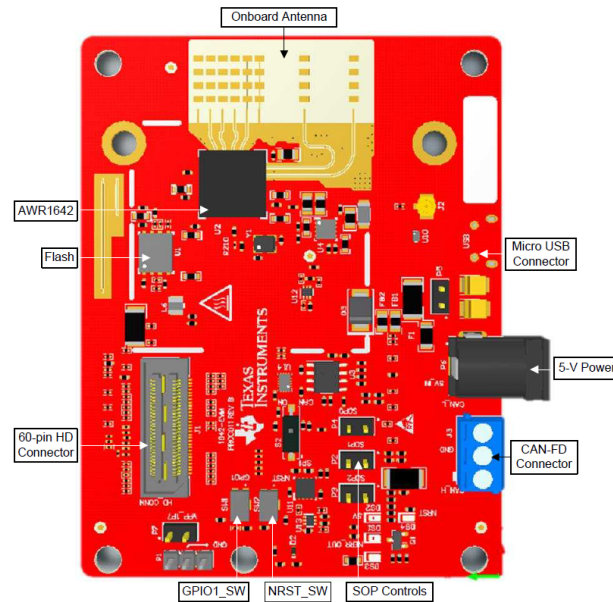


Figure 3.1: AWR1642 EVM

3.1.1 RF Front End

Figure 3.2 shows the radio frequency (RF) front end for the system. First, generating the chirp requires a phase-locked loop (PLL) and an oscillator. The reference oscillator for the PLL is 40MHz and the RF oscillator is 20GHz. The output is based on the fractional-N PLL. A basic fractional-N PLL is shown in Figure 3.3 adapted from [12] to better represent the AWR1642 hardware. Exact details of the chirp synthesis are not in the TI datasheets. The frequency multiplier is a non-linear device which uses the 4th harmonic of the fundamental and filters the undesired harmonics.

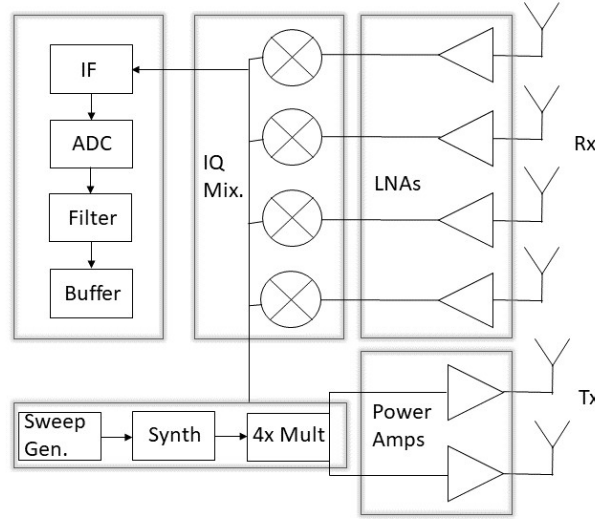


Figure 3.2: AWR1642 Front End

Following the chirp generation is a power amplifier (PA) and the transmit antennas. On the receive side is the receiver antennas and a low noise amplifier (LNA). The PA and LNA differ in terms of design goals. For the LNA, the goal is to minimize the noise figure by choosing appropriate input and output matching to the LNA. Often this means sacrificing

maximum gain. For PA design, the goal is to maximize the radiated power level, which means design must be done with large signal non-linear parameters.

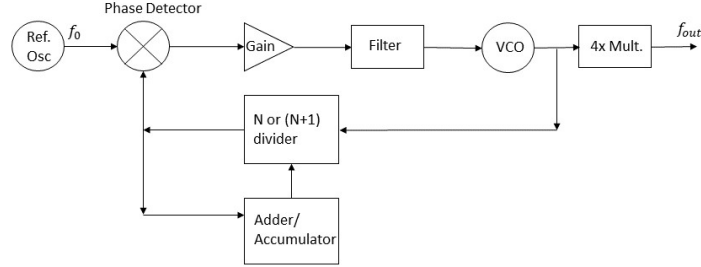


Figure 3.3: Fractional-N PLL

Matching for a non-linear PA means the gain circles used to design an amplifier on the smith chart are no longer circular. These are referred to as load pull contours [12]. Once the signal is amplified it is radiated with the transmit antenna and the delayed signal is captured by the receive antenna.

The antennas structure is shown for the AWR1642 which includes two transmitters and four receivers. The antennas are series patches. This simplifies the complexity of the feed network for the 16 element receiver array and 8 element transmit array. However, there is a cost of gain with series feed patches due to non-uniform current distribution which decreases away from the feed point. Ideally, a single patch has a gain of 3 decibels (dB), which is doubled when an additional patch is added, then doubled again when two more patches (a total of four) are added. This would result in a total gain of 9dBi (dB relative to isotropic antenna) for a single series patch. The data sheets for the AWR1642 show an antenna peak gain of slightly greater than 9dBi, however this is from simulation. In reality the gain is lower when it is not compared to an isotropic antenna and even more so as a series patch. The actual transmitter gain for the AWR1642 is 12.5dBm and the gain for the IWR6843 is 10dBm. The peak output power is less than 55dBm EIRP due to regulations and the peak average power must be less than 48dBm EIRP. For a 50 μ s chirp, this means that up

to 256 chirps can occur in 50ms to meet the regulations. This requires a 33% duty cycle for the EVM. For vital signs detection, a high pulse repetition rate (PRF) is not necessary. Typically 20 frames per second (fps) can be used. This is because the heart rate and breath rate frequencies are generally below 2Hz. It will be shown in Chapter 4 that higher PRF can decrease the frequency resolution of the processed signal.

Receive antenna spacing follows the $\lambda/2$ rule to avoid grating lobes and maximize gain. Grating lobes increase the directivity of the main beam but also introduce side/grating lobes which radiate in unwanted directions. The transmit antennas are spaced such that the coupling is reduced. Figure 3.4 shows the transmitter (Tx) and receiver (Rx) antenna array structure for the system.

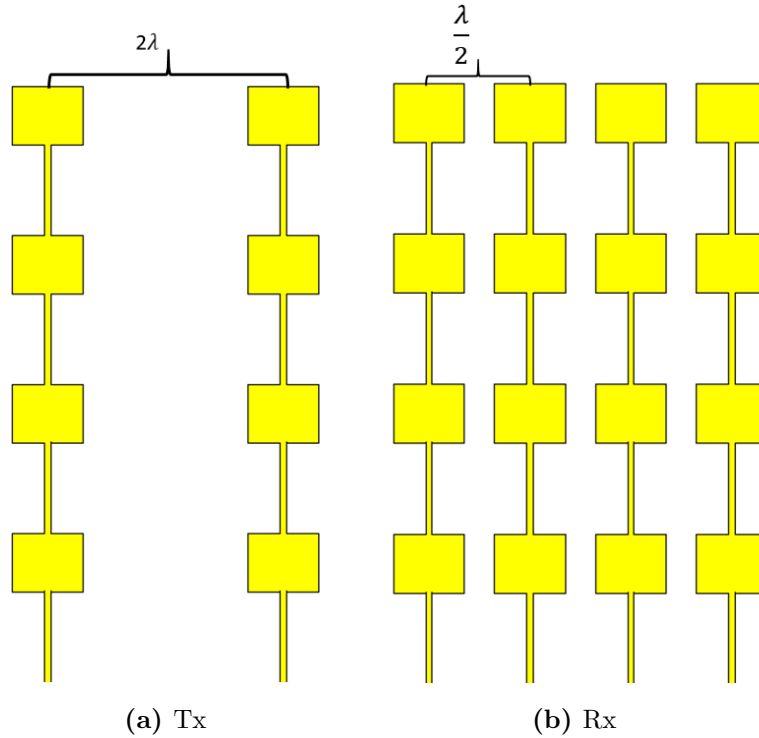


Figure 3.4: AWR1642 Antenna Array Structure

After the LNAs, an in-phase and quadrature (IQ) mixer is used. This decomposes the incoming signal into its in-phase and quadrature components. The advantage of this is an improved noise figure, improved interference tolerance and a reduction in intermodulation distortion [13]. Once the received signal is down converted to baseband, it is filtered to prevent aliasing prior to sampling. The received signal is down mixed with the transmit signal frequency so the FMCW system does not require fast ADCs. After decimation, the sampled data is stored in the ADC buffer.

3.1.2 Mmwave SoC

The flip chip ball grid array (FCBGA) chip structure and fabrication is shown in Figure 3.5 [14]. TI uses a 45-nm RFCMOS process to develop the chip. The average power consumption at the power terminals is between 1.38W-2.14W for 25-50% duty cycles.

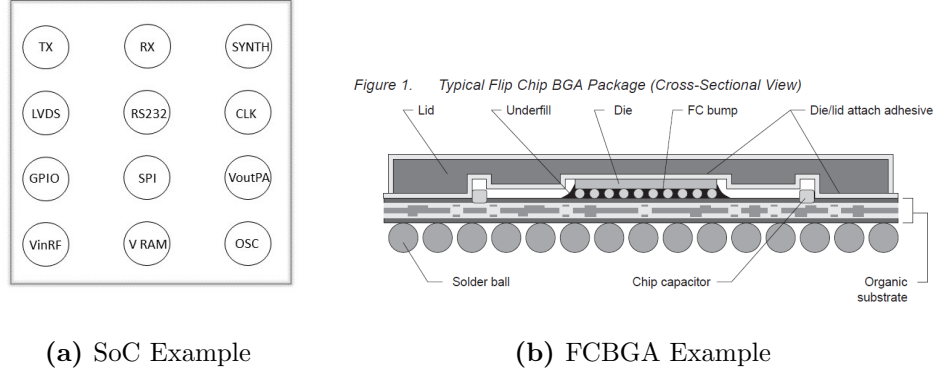


Figure 3.5: SoC

System operation is controlled by the Master Subsystem (MSS) in Figure 3.6, which then communicates to the Digital Signal Processing Subsystem (DSS) in order to pass Radar Subsystem (BSS) data and request processing tasks to be done. The BSS communicates to both the DSS for chirp processing and frame processing of the sampled data. The MSS gives tasks to the DSS for starting and stopping chirps and frames. These are referred to

as events. When the DSS posts a task, it waits for the BSS to respond that the task/event was completed. Then processing can occur and the results can be sent back to the MSS for further control or peripheral streaming. The MSS is responsible for handling command line interface tasks to control or configure the hardware system and start/stop the sensor.

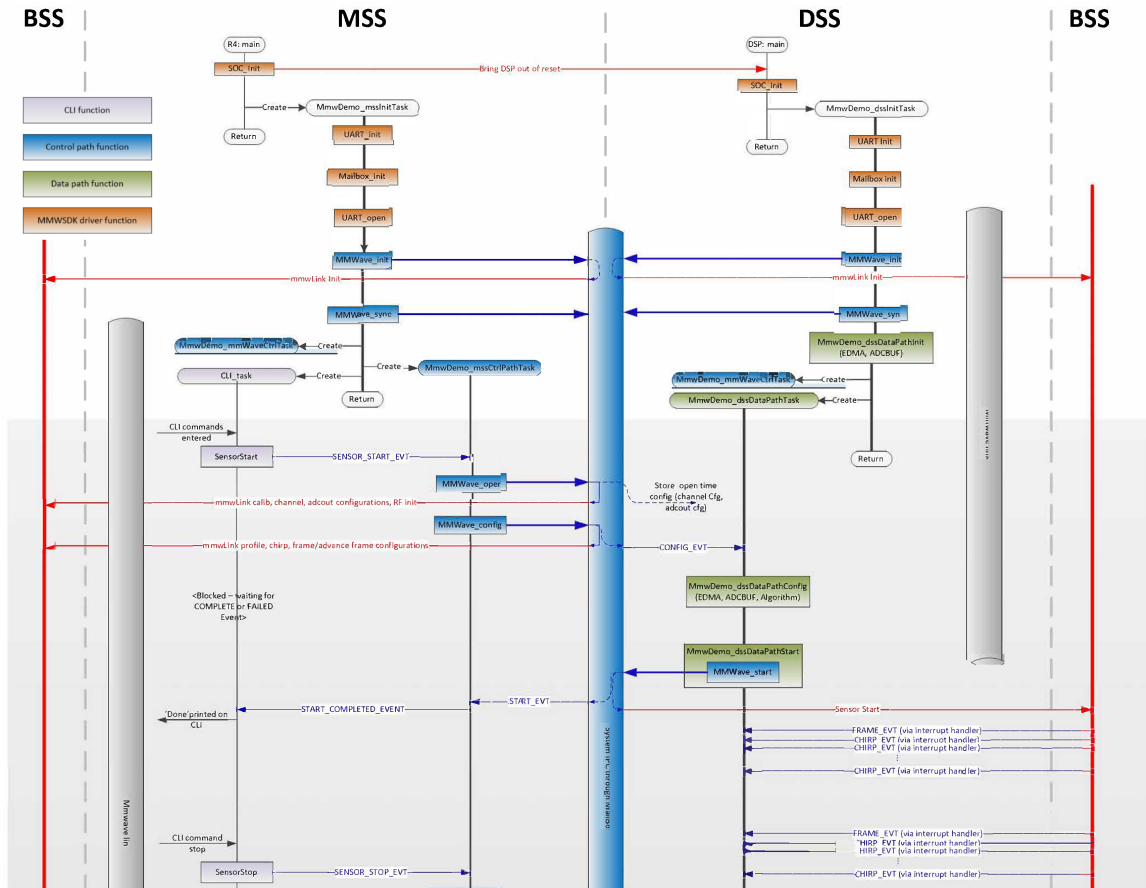


Figure 3.6: Mmwave System Flow

Figure 3.7 shows the subsystem layout. L1, L2 and L3 are for memory. Direct Memory Access (DMA) allows access to memory bypassing the central processing unit (CPU) (Cortex RF4), and Enhanced Direct Memory Access (EDMA) is an upgraded version of the DMA with more transfer channels, priority scheduling abilities and data transfer to and from addressable memory space. It can be seen from the figure that the DSS is responsible for

ADC data and memory access, while the MSS handles messages, peripheral communication and CPU tasks. The low voltage differential signaling (LVDS) is for high speed data transfer, which enables transfer of raw analog to digital conversion (adc) data from the DSS without impacting the MSS or CPU processing tasks. The Joint Test Action Group (JTAG) port handles universal serial bus (USB) connectivity to a host computer for debug purposes. Hardware in the loop (HIL) can be used for high speed data input to run the EVM as an emulator. Read only memory (ROM) is used to boot the system. A notable peripheral is the (Universal Asynchronous Receiver/Transmitter (UART) which can transfer limited data from the EVM to a host computer and send controls from a computer through the command line interface (CLI) to the MSS.

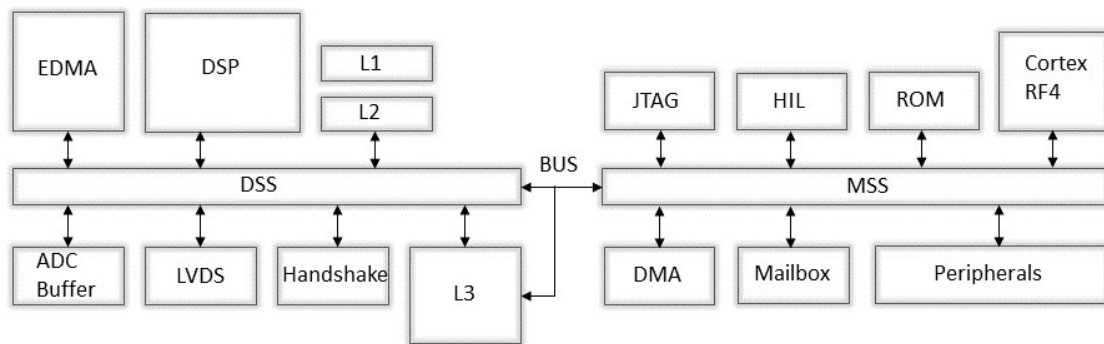


Figure 3.7: AWR1642 Subsystem

3.1.3 MSS

The MSS is responsible for message passing from the CLI to the DSS and BSS as well as handling the DSS processed data appropriately. Figure 3.8 shows example packets for the MSS. The DSS to MSS packet in Figure 3.8a contains a header which holds the message type. The message tags contain further data information, the length of the data's byte size

and the pointer to the data's memory address location. The payload is the data stored in L3 memory that the MSS is responsible for retrieving. The message type tells the MSS what it should do with the data once it is retrieved. Another packet example is from the MSS to a host computer. This transfers data over UART for viewing or further processing. This packet structure will be further analyzed in Section 4.5. The principal is the same, except the payload is no longer stored in memory, it is a part of the serial communication byte stream. When the data is received, the host can parse through the byte stream according to the tag information and payload length to extract the corresponding data.

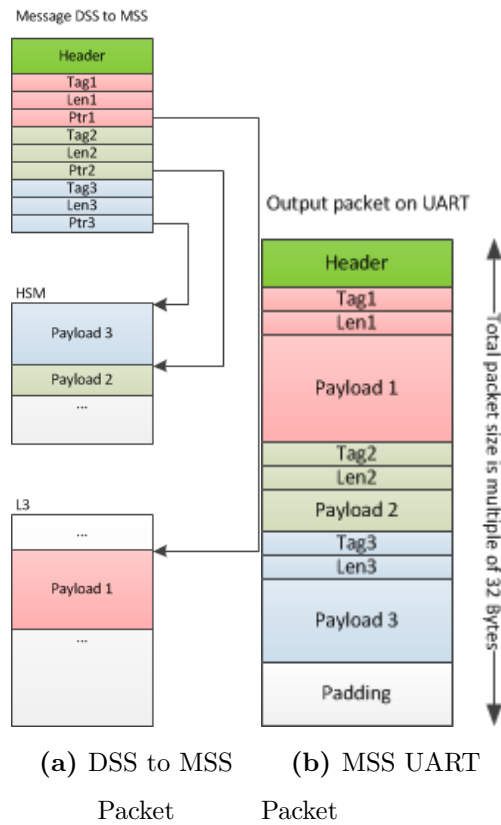


Figure 3.8: MSS Packets

Prior to UART transmission, some processed data must be available. This operation takes place in the DSS.

3.1.4 DSS

Figure 3.9a shows an example of a DSS process and sending the data to the MSS. The timing diagram is shown in 3.9b. For each frame the DSS process must complete before the BSS is required to start another event. Missed data can occur if the BSS sends an interrupt to the DSS because processing has not finished but the hardware wants to transmit. The operating system handles these issues with start and stop event flags to inform other subsystems of when a dependent process is completed.

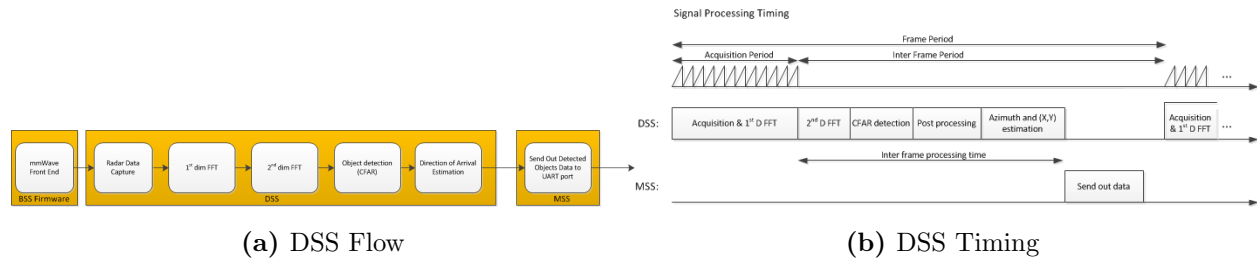


Figure 3.9: DSS Timing

Figure 3.10 shows data path processing between multiple transmitters. It shows how the DSS receives data from the BSS, the order it is processed in and how the data is aligned in memory. The transmitters operate in time-division-multiplexing (TDM) mode. Sampled data is sent to L2 memory using EDMA for all receive antennas and aligned such that the data from one transmitter is sequential. The ping-pong nomenclature refers to TDM. After performing the FFT on each chirp's data samples, a radar cube is constructed. This aligns the data such that all of the chirps from Tx1 are sequential followed by the set of sequential Tx2 chirps. The data stored is data from each receiver element.

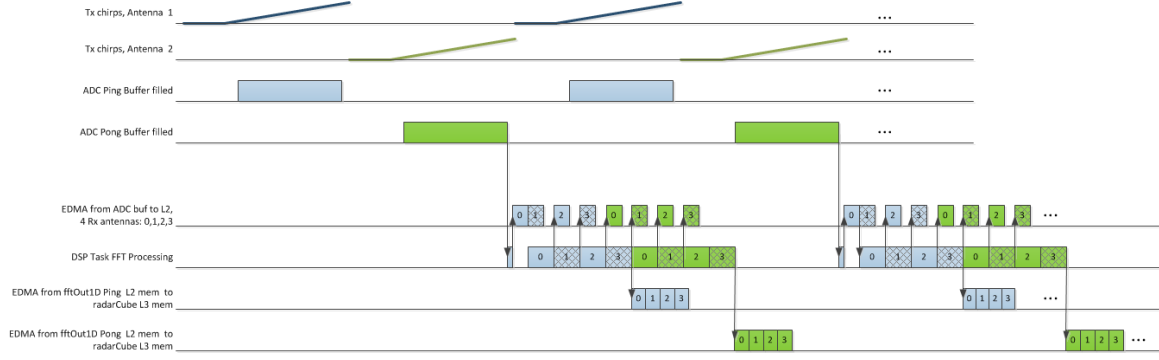


Figure 3.10: DSS Timing 1D FFT

Further processing in the DSS is application dependent. The DSS accesses each Tx-Rx pairs data by memory access in the L3 buffer. Additionally, as processing takes place, memory allocations in L3 are used to store and write data during each processing step.

3.2 Configuration

The configuration of the FMCW system directly affects the interpretation of the measured results and the capabilities considering target distance, frequency resolution of the slow time axis, and resolution between range bins. This section explains some of the system settings and their meanings in regards to extracting information from the received signal. Table 3.2 is an AWR and IWR chip comparison.

Table 3.2: TI Mmwave Comparison

Spec.	IWR 6843	AWR1642
Frequency Range	60-64GHz	77-81GHz
Tx Gain	10dBm	12.5dBm
Max Sampling Rate	10MHz	10MHz
Chirp Samples	512/1024 ¹	512/1024
Phase Shift	6bit	×
Range Res.	3.75cm	3.75cm
Angle Res.	9.5°	14.3°
Tx	3	2
Rx	4	4
Memory	1.5MB	1.5MB

Figure 3.11 shows the chirp configurations. These settings have a direct impact on the information that can be extracted from each received chirp. The range information is determined from the sampling frequency, f_s , and the chirp sweep slope using,

$$R_{max} = \frac{0.9 \cdot f_s \cdot c}{2 \cdot \text{sweepslope}} \quad (3.1)$$

Range resolution for the system is found from the sweep bandwidth B_W ,

$$R_{res} = \frac{c}{2B_W} \quad (3.2)$$

¹512 samples per chirp in complex (IQ) mode, 1024 samples in real mode.

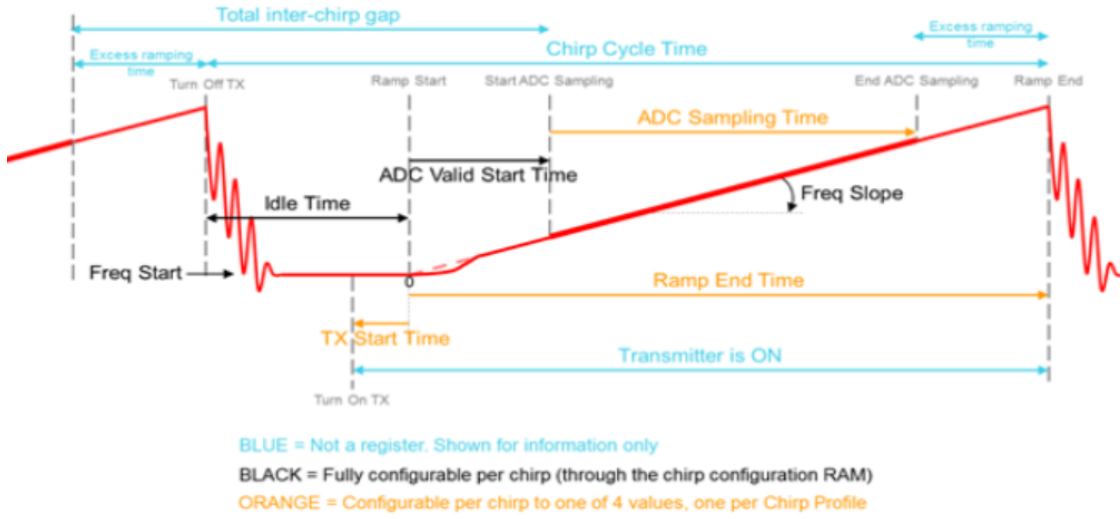


Figure 3.11: Mmwave Chirp Settings

Further chirp configurations can change the number of chirps per second and how many points are sampled. The number of chirps per second increases the duty cycle but can provide detailed object information for range and azimuth angle. The sampling points coincide with the frequency bins that are sampled. Higher sampling rates provide more sample points per chirp and result in more processed range bins. This can be beneficial for resolving closely spaced objects.

A last important note of the subsystem is object detection. This is used to determine targets and store target information and is useful for multiple subject scenarios. The detection matrix operates in two ways. The object detection constant false alarm rate (CFAR) groups the peaks surrounding a CFAR detection point and adds them to the object list. Alternatively, the peak grouping method checks if the peaks surrounding a CFAR detection point are less than the detection point. If the CFAR detection point is not the peak of the surrounding kernel, the object is not detected. Figure 3.12 shows the grouping of peaks next to a CFAR detection point.

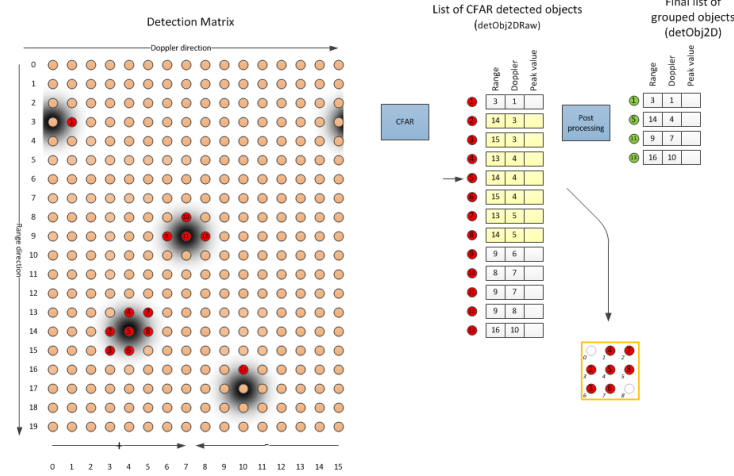


Figure 3.12: Object Detection CFAR Grouping

The detection matrix is useful for minimizing DSS processing tasks on unnecessary objects. Figure 3.13 shows the object detection matrix using peak grouping.

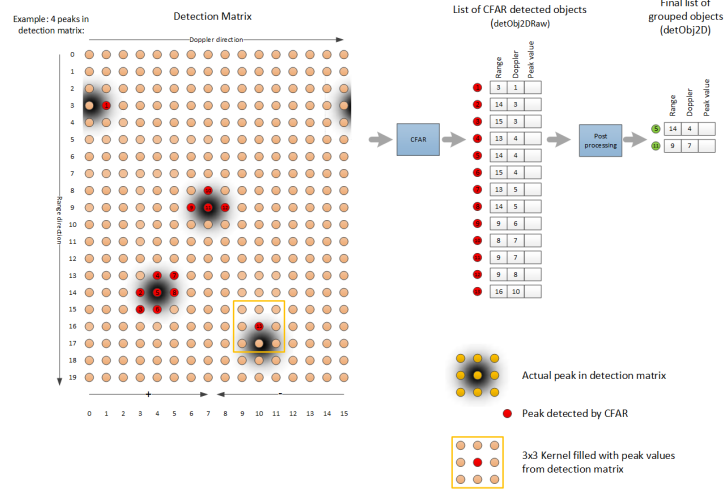


Figure 3.13: Object Detection Matrix Peak Grouping

The detection matrix informs the DSS of any processing steps to take if range and azimuth information is available. This would include 2D FFT and direction of arrival (DOA)

estimation if operating the system strictly for radar purposes. In order to properly provide azimuth information, the system must have a high PRF to make DOA calculations on short time scales to keep up with a moving target. With an understanding of the system capabilities and operation, signal processing techniques for data acquired with the AWR and IWR systems can now be discussed.

Chapter 4

Vital Sign Signal Processing

Extracting subject vital information is a multi-stage process which varies slightly for each radar system type. The explanation here applies specifically to SFCW and FMCW systems. A signal is transmitted towards the subject and the receiver collects a delayed version of the original transmission with a corresponding beat frequency. This corresponds to the range of the subject. When this process occurs multiple times a *range profile* is built. The range profile is shown in Figure 4.1. It is constructed by taking the FFT of one chirp for the FMCW system, or one cycle of the SFCW received signal. This is one column in the range profile and each row is a beat frequency corresponding to target distance called a *range bin*. The radar configuration determines the distance between successive range bins. For every chirp or transmission cycle, a new column is added which is called the *slow-time axis*. In Figure 4.1 it is clear that the target is in the 21st-26th range bin and is stationary, however, the magnitude of the beat frequency is strongest at bin 23. Methods for choosing the range bin include choosing the maximum magnitude at a range bin or finding the maximum signal energy of the ranges where the target is found. Once the range bin is chosen, the vital sign signal processing algorithms can begin.

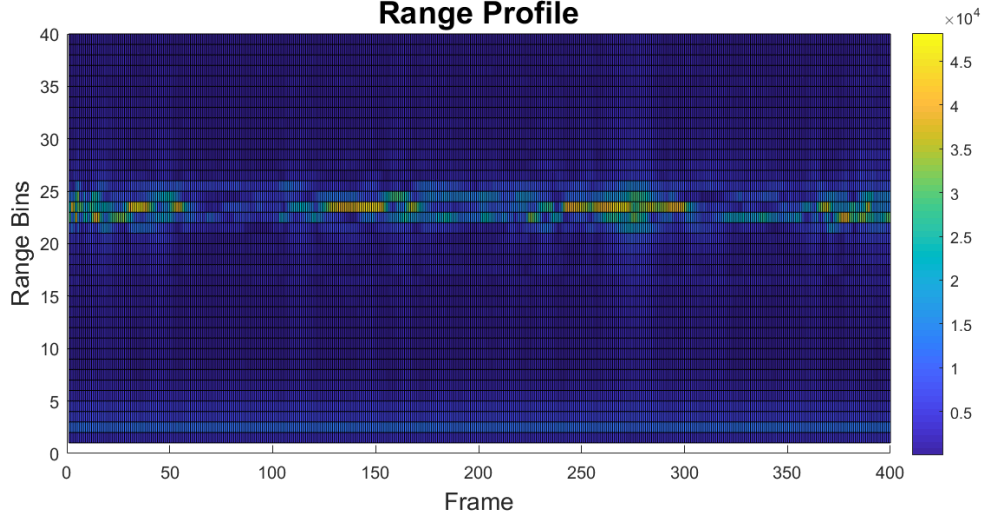


Figure 4.1: Range Profile Example

4.1 Phase Based Methods

The phase based methods here are presented for complex data from IQ down mixing. The methods are CSD and AD. CSD extracts the range profile of the target over the slow-time axis, then the FFT can be performed over a chosen range bin to extract HR and BR signals. AD takes the phase of the IQ signal over the range profile, then FFT is performed at a specified bin. Additional processing steps can be added to these methods like SSM and TVW which are described in this chapter. The CSD mathematical model for a demodulated signal is [15],

$$B_I(t) \approx \cos \left[\frac{4\pi x(t)}{\lambda} + \theta_0 + \Delta\phi(t) \right] \quad (4.1)$$

$$B_Q(t) \approx \sin \left[\frac{4\pi x(t)}{\lambda} + \theta_0 + \Delta\phi(t) \right] \quad (4.2)$$

where $\Delta\phi(t)$ is residual phase from the demodulation process. The complex signal is constructed by,

$$S(t) = B_I(t) + j \cdot B_Q(t) = \exp \left\{ j \left[\frac{4\pi x_h(t)}{\lambda} + \frac{4\pi x_r(t)}{\lambda} + \phi \right] \right\} \quad (4.3)$$

$$(4.4)$$

where $x_h(t)$ and $x_r(t)$ are due to the heart beat and respiration signals and ϕ is the total residual phase. The expansion of Eq. 4.2 yields sine and cosine components with amplitudes described by nth-order Bessel functions of the first kind. One of the inherent disadvantages of CSD is harmonics generated from the down conversion process. This effect will be seen in Chapter 5, however the above representation was done for a CW system. From Eq. 2.11, it can be seen that the FMCW CSD signal will be expressed slightly differently. The next method for signal processing vital signs also relies on complex data.

Arctangent demodulation follows the range profile and bin selection as was previously mentioned. Now, instead of summing the IQ channels, AD finds the angle of the complex signal and performs phase unwrapping to remove discontinuities when the phase exceeds π . This is described as [1],

$$S(t) = \arctan \left(\frac{B_I(t)}{B_Q(t)} \right) + F \quad (4.5)$$

$$(4.6)$$

where F is added to deal with phase discontinuities. The constructed signal represents the physical displacement of the target from which the breath displacement and heart displacement can be measured. FFT is then performed on the slow-time axis to extract frequency information of the HR and BR. AD does not suffer from the same harmonic issues as CSD however DC offsets must be accounted for. This offset creates imbalance in the I and Q signal amplitudes and phase. The result is a non-uniform circle in the complex plane which does not center itself at $I=0$ and $Q=0$ [7]. The TI systems used in this work were verified to be calibrated after checking the IQ data constellation.

The above methods become weaker in the presence of noise or when neighboring spectral peaks have similar amplitudes. They must also fill a sample buffer for the slow-time range profile axis so that the frequency resolution of the FFT is adequate. The next method also needs a high number of slow-time samples (between 150-200 slow-time frames) for adequate frequency resolution, but can significantly increase the SNR using parametric estimation.

4.2 State Space Method

The development of the Robust State Space Method (SSM) is now described and will be used to present the background for its application to vital sign detection. The previously described phase based methods are used for signal input to SSM processing. SSM origins are found in the imaging of targets with complex shapes which yield scattering fields that contain weak signal information [16]. The application of SSM in the literature is towards system identification, however the nature of its theory can be generally applied to a class of linear signal combinations. In this way, SSM takes advantage of linear systems to apply control methods which allow a system to be transferred to an arbitrary state according to a defined performance measure [17], with the goal of extracting the signal information from a scattering source. The theory that follows regarding SSM is developed in [16] and [1].

The SSM signal model first defines the scattered field collected data as,

$$y[k] = \sum_{i=1}^M a_i e^{-(\alpha_i + j2\pi\tau_i)f_k} + w[k], k = 1, \dots, N \quad (4.7)$$

From this model, it is seen that the amplitude is a_i , the attenuation of the complex exponential is α_i and τ_i represents the round-trip delay time of a scattered signal. In the applications to vital signs, the scattered field is comprised of all the motions of the human body and noise, $w[k]$. This poses a challenge for determining the corresponding signal origin from a scattered signal. In applications to respiratory and heart rate estimation, significant reductions to the scattered signal can be made through selective filtering and a priori knowledge of the scenario (if available). For instance, the expectations of such measurements would vary significantly from a calm, sitting subject as opposed to one engaging in physical

activity. Knowledge of these scenarios can help identify outliers which may imply a health complication.

In Eq. 4.7, range information is contained in τ_i since the round-trip delay time is $\tau_i = \frac{2R_i}{c}$. SSM aims to extract, a_i , α_i and R_i from the signal model using the observability and controllability matrices from linear system theory. In this effort, the controllability matrix is focused on because it yields the system poles which describe the scattered signal. The definition of controllability is explained in [17]. It states in Definition 1.8 that for a system $\dot{x}(t) = a(x(t), w(t), t)$ with initial state $x(t_0) = x_0$, if there is a finite time for $t_f \geq t_0$ and a control $w(t), t \in [t_0, t_f]$, which transfers the state x_0 to the origin at time t_f , then the state x_0 is controllable [17]. This definition of controllability relies on uniqueness to the solution of a linear, time-invariant $n \times mn$ matrix consisting of the A and B matrices and is shown in [18]. First, using state space representation, a set of difference equations are formed,

$$x[k+1] = Ax[k] + Bw[k] \quad (4.8)$$

$$y[k] = Cx[k] + w[k] \quad (4.9)$$

where $x[k]$ is the state matrix, $w[k]$ is the control matrix, $y[k]$ is the output, A is the open-loop matrix and B and C are constant matrices. The goal of SSM is to determine the A , B and C matrices which then allows the eigenvalues of A to be determined using a modal decomposition method [19]. From there, the signal model poles are found from the z -transform of Eq. 4.9,

$$H(z) = C(zI - A)^{-1}B + 1 \quad (4.10)$$

where I is the identity matrix and the system poles are the eigenvalues of A . Calculation of the constant matrices A, B , and C first requires the formation of the Hankel Matrix. Hankel matrices are shown to aid in eigenvalue decomposition of various time-series data in [20], which investigates signal processing for linear, time-invariant signals using state space

methods. The general definition of the Hankel matrix is defined as,

$$H[N, L] = \begin{pmatrix} y[1] & y[2] & y[3] & \cdots & y[N] \\ y[2] & y[3] & y[4] & \cdots & y[N+1] \\ y[3] & y[4] & y[5] & \cdots & y[N+2] \\ \vdots & \vdots & \ddots & \vdots & \\ y[N] & y[N+1] & y[N+2] & \cdots & y[2N] \end{pmatrix} \quad (4.11)$$

The Hankel matrix format used for the processing in this work is,

$$H[N, L] = \begin{pmatrix} y[1] & y[2] & y[3] & \cdots & y[L] \\ y[2] & y[3] & y[4] & \cdots & y[L+1] \\ y[3] & y[4] & y[5] & \cdots & y[L+2] \\ \vdots & \vdots & \ddots & \vdots & \\ y[N-L+1] & y[N-L+2] & y[N-L+3] & \cdots & y[N] \end{pmatrix} \quad (4.12)$$

where N is the number of time-series samples and L is a window length of the series often chosen as $\frac{N}{2}$. Hankel matrices are referred to as persymmetric, meaning the diagonals are skew. They are used to form a square matrix so that eigendecomposition can occur.

Next, singular value decomposition (SVD) is performed on the Hankel matrix H . The purpose of SVD is to decompose the matrix H into the sub matrices U, Σ and V^* such that $H = U\Sigma V^*$, where U is a unitary matrix such that $U^*U = I$, Σ is a diagonal matrix containing the square roots of the real, non-negative eigenvalues of H , and V^* is a unitary matrix. The asterisk, $*$, is the conjugate transpose. Additionally, U and V are orthogonal. The dimensions of U, Σ and V^* are $N \times K$, $K \times K$ and $K \times L$ respectively. The constant matrices A, B and C can be determined from the observability matrix Ω and the controllability matrix Γ . Their definitions and relation to the Hankel matrix H are,

$$\Gamma = \Sigma^{\frac{1}{2}} V^* \quad (4.13)$$

$$\Omega = U \Sigma^{\frac{1}{2}} \quad (4.14)$$

$$H = \Omega \Gamma \quad (4.15)$$

The method for finding A, B and C as described in [16] and [19] will now follow. It is of prime importance for the SSM results for vital signs estimation in Chapter 5.

Stating a subset of Γ to be Γ_{c1} and Γ_{cl} , which means the first and last columns of the matrix Γ have been removed respectively, the relationship between the poles of $H(z)$, i.e., A is,

$$A \Gamma_{cl} = \Gamma_{c1} \quad (4.16)$$

which is solved using a pseudo inverse least square method to give,

$$A = \Gamma_{c1} \Gamma_{cl}^* (\Gamma_{c1} \Gamma_{cl}^*)^{-1} \quad (4.17)$$

Next, by forming an augmented matrix of the observability matrix Ω now defined as Ω_N containing the first $N - 1$ rows of Ω , the constant matrix B can be computed by first taking the inverse z transform of $H(z)$ to form the infinite impulse response approximation sequence, $\hat{y}[k] = CA^k - B$ for $K = 1, 2, \dots, N$. The relationship of the matrix $\hat{Y}$ to Ω_N is then,

$$\Omega_N B = \hat{Y}^T \quad (4.18)$$

$$B = (\Omega_N^* \Omega_N)^{-1} \Omega_N^* \hat{Y} \quad (4.19)$$

The constant matrix B is computed using the augmented controllability matrix from the first $N-1$ columns of Γ , Γ_N , and the least squares fit of $\hat{Y}$ such that,

$$\Gamma_N = \hat{Y} \quad (4.20)$$

$$C = \hat{Y} \Gamma_N^* (\Gamma_N \Gamma_N^*)^{-1} \quad (4.21)$$

Lastly, extracting the eigenvalues from A , the signal model parameters can be estimated, specifically a_i , α_i and R_i . The eigenvalues and eigenvectors of A are λ_i , and $\psi_i, i = 1, 2, \dots, M$ and M is the rank of A . Let the phase of $\lambda_i = \phi_i$, let f_1 be the carrier frequency and let the frequency resolution $\Delta f = \frac{f_s}{N}$, where f_s is the sampling frequency and N is the number of sampled points. The signal model parameters are now expressed as,

$$a_i = \frac{(C\psi_i)(\psi_i^{-1}B)}{(\lambda_i)^{\frac{f_1}{\Delta f}}} \quad (4.22)$$

$$\alpha_i = -\frac{\log|\lambda_i|}{\Delta f} \quad (4.23)$$

$$R_i = -\frac{c\phi_i}{4\pi\Delta f} \quad (4.24)$$

Estimation using SSM in low SNR environments relies strongly on the rank of the singular value matrix Σ and can be used to suppress noise [16]. Additionally, the estimation requires determining an appropriate rank for the singular value matrix Σ to suppress noise components. In Chapter 5, the effects of fixed order and order estimation SSM methods for 60GHz and 70GHz radar systems of different frequencies will be shown.

It is clear that the calculation for SVD and the constant coefficients of the state space model can become computationally taxing as N increases. Another method which is drastically simpler is the time varying window. Compared to SSM, the time varying window lacks significant SNR improvement, but is able to operate on less samples, allowing quicker initial estimations.

4.3 Time Varying Windows

Considering the need to acquire heart rate estimations over shorter durations of time, a novel method which functions on the variation of frequency resolution was developed [4]. The metric for fast acquisition of the heart rate takes place within 2-5 seconds. This poses a problem regarding spectrum resolution, since the resolution depends on the slow-time axis, f_s , and the number of points in the FFT, N . This relationship was previously shown as $\Delta f = \frac{f_s}{N}$. Its implications are that for the aforementioned radar system, N must be increased, which corresponds to taking more cycles (1 cycle contains the number of points sampled in 1 second) and therefore a longer acquisition time. Alternatively, if the sampling rate f_s is decreased, the spectrum resolution intervals can decrease, but this does not apply for the slow-time axis sampling with FMCW and SFCW radar systems, since N is dependent on the number of range bins calculated from such systems, and for 1 cycle N can never be greater than f_s . Therefore, only increasing the duration of acquisition with standard FFT methods can increase the frequency resolution. For example, with a common slow-axis sampling rate of $f_s=20\text{Hz}$, in 4 seconds of acquisition time the best resolution that can be obtained is 0.25Hz . FFT number padding can of course be used to interpolate the frequency response, however, this does not provide more frequency information from the obtained signal.

To combat this issue, the time varying window technique takes multiple FFT's with different values of N , effectively spreading the frequency resolution by values of $\frac{f_s}{N+\delta N}$. A sequence of FFT's are performed on the input signal, and can be described as,

$$\Delta f_{N+\delta N} = \frac{f_s}{N + \delta N}$$

where δN is an integer value such that $N + \delta N \geq 0$ and $N + \delta N \leq \Delta t \cdot f_s$ and $\Delta f_{N+\delta N}$ are the resulting frequency resolution variations.

For vital signs estimation, the time varying window aims to find the true peak magnitude at an estimation frequency which otherwise may be slightly degraded depending on the spectrum resolution. After a sweep is performed with varying δN , the maximum value is chosen for heart rate estimation. Interestingly, since the time varying window method takes place from 2-5 seconds, depending on the heart rate, the breathing rate can be estimated

based on the time window. This has multiple advantages. One being that the respiratory harmonic is reduced, which has already been presented as an issue when using CSD phase methods [1]. Secondly, the estimation for the breathing rate can be determined using zero crossing methods [4], which results in a breath estimate of $\frac{n}{T}$, where n is the number of respiratory cycles in the chosen window time T . A third advantage of the short time estimation is that the variation in heart rate is tracked more realistically. Traditional FFT methods relying on more sample points and therefore longer acquisition times eventually produce a spectrum which contains the variation of the heart rate frequency over time. This can degrade the estimation as there may be multiple peaks closely spaced together caused by the slight variation in HR during the measurement time.

Results of the proposed time varying window method show HR estimation errors of 3.4% over a 2-5 second measurement time, and errors of 1% over a 30 second measurement time. Comparing this to [1] using SSM methods which report a 1.5% error over a 20 second measurement, the benefits of the time varying window can readily be seen. However, in low SNR environments the advantages of SSM-AD and SSM-CSD methods in conjunction with time varying windows could provide further estimation improvement. The consideration for the method of choice relies on the computational needs and real-time constraints of the system application. The lower bound for the time varying window is $O(A \cdot N \cdot \log_2(N))$ where A is the number of varied windows used [4]. Real-time applications will be further discussed in Section 4.4.

A drawback of the time varying window method is a built-in system error which depends on whether or not the optimal time window for the heart measurement can be achieved. This requires that the time window be an integer multiple of $\frac{1}{HR_{est}}$. Since the sampling rate determines Δt by $\frac{1}{f_s}$, the time window must be integer multiples of Δt . In [4], it is stated that increasing the sampling rate can alleviate this issue, however, this approach may seem counterproductive, since we have already shown that Δf will not have a finer resolution with increasing f_s over an equivalent amount of cycles.

A comparison of the time varying window technique, SSM, and FFT methods on 60GHz and 77GHz FMCW systems is reported in Chapter 5. Additionally, combinations of the

techniques as well as MIMO channel diversity show promising studies towards further improving fast-acquisition vital sign estimation accuracy.

4.4 Real-Time Capabilities

SSM methods are hindered by the need to compute the SVD factorization, which has a lower bound complexity of $O(M \cdot N)$, where M is the number of singular values and N is the diagonal matrix dimension [21]. SVD time complexity depends largely on the algorithm chosen and for vital signs estimation, it must be used in addition to the FFT which is well known to have a complexity of $O(N \cdot \log_2(N))$ using the Cooley-Tukey Algorithm for general values of N . More efficient methods have been developed for computing the Fourier Transform over subsets of the frequency range $0 \leq \omega < 2\pi$ such as the Goertzel algorithm [22], however the efficiency boost depends on a reduced number of points as the methods are $O(N^2)$ regarding time complexity.

A commercial implementation of vital signs estimation developed by Texas Instruments, illustrates the need for a balance between complexity, available memory and desired accuracy. An explanation of the vital sign estimation process as is implemented on the TI C674x DSP core will follow. The hardware and software architecture were previously defined, but now the TI vital signs processing method will be discussed in full detail to expand on the breadth of the vital signs estimation techniques. First the theoretical processing steps will be covered. Then, the description of using the DSP code on a general system will be explained. Results from real-time measurements are presented in Chapter 5.

Presented here is the processing methods for the 60GHz and 77GHz TI radar systems which is programmed to function on the AWR1642 and IWR6843 chips for vital signs processing. The method follows the same initial steps as the previous algorithms described by first finding the range bin index, then extracting the phase variation as described in Eq. 4.6. Operating in real time, the TI chain relies mainly on filtering and FFT peak estimations to meet the memory constraints. Time constraints in this case are required to enable the chip to transfer the processed data (estimations) in time and begin the next chirp sequence.

4.4.1 Processing Chain

The processing chain begins with a circular buffer for the heart and breathing slow-time axis samples. The buffer size must be long enough that a full cycle of the breath or heart waveform is stored, but it only needs to be as long as the designer wishes to keep memory of the previous samples.

Next an Infinite Impulse Response(IIR) Bi-quad Cascaded filter is used, which is described as,

$$H(z) = \frac{b_0 + b_1z^{-1} + b_2z^{-2}}{a_0 + a_1z^{-1} + a_2z^{-2}} \quad (4.25)$$

The filter is dubbed bi-quadratic because of the quadratic terms in the numerator and denominator. It is IIR because the design utilized has no poles at zero and the impulse response $h[n]$ is not time limited. Since this can lead to an unstable system, the bi-quad filter is often cascaded as N separate IIR systems which have poles inside the unit circle to guarantee convergence. Using partial fractions expansion, an IIR system is more easily seen from the following equation [22],

$$H(z) = \sum_{r=0}^{M-N} B_r z^{-r} + \sum_{k=1}^N \frac{A_k}{1 - d_k z^{-r}} \quad (4.26)$$

where $M - N$ is the number of finite terms and $N - 1$ is the number of infinite terms. Removing the second term of the summation yields a Finite Impulse Response (FIR) system. The bi-quadratic filter in Eq. 4.25 system poles will be made of complex conjugate pairs, resulting in a bandpass filter. The bi-quad filter is used to filter the breathing rate between 0.1-6Hz and the heart rate between 0.6-4Hz. The TI method uses two cascaded systems for the breathing rate filter and four for the heart rate filter.

Next, auto-correlation is performed on the buffered samples and each additional slow-time axis sample. Auto-correlation is a metric comparing the similarity of a signal with a delayed copy of itself. This is done in the TI chain by creating a circular breathing and heart

buffer, which stores the past N filtered phase variation points and computes auto-correlation to determine the amount of delay between the signal and its delayed version which yields the greatest correlation. If there is correlation, a confidence metric is assigned to the estimate as the magnitude of the auto-correlation function at that delay index. Auto-correlation is described as,

$$R_{XX} = \sum_{k=1}^N X_k X_{k+n}^T \quad (4.27)$$

where X is the input signal, k is the discrete time starting sequence index and n is the delay of the sequence. The use of the confidence metric becomes apparent from the phase variation graph shown in Figure 4.2.

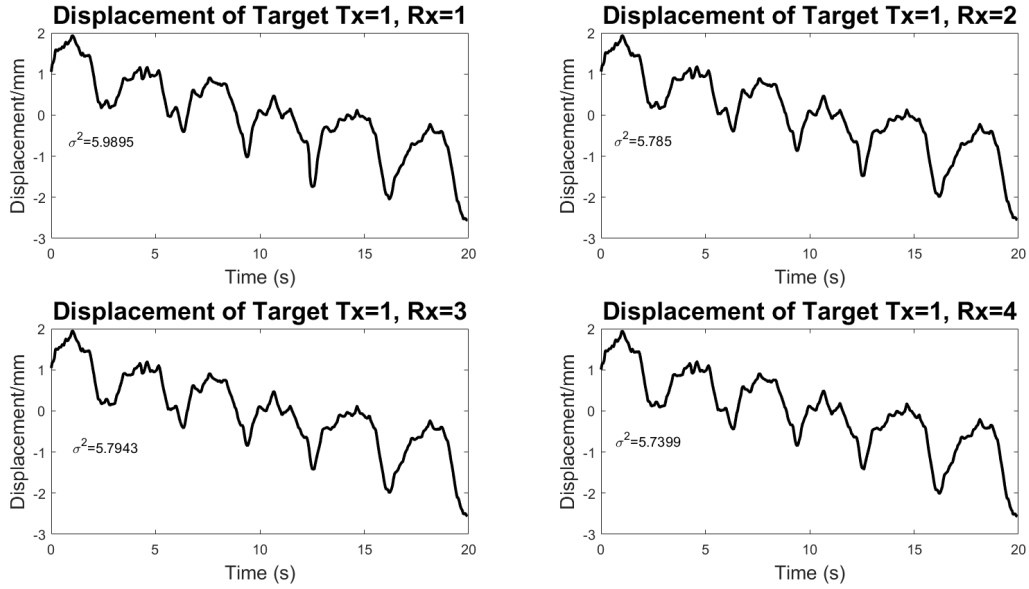


Figure 4.2: Phase Variation

If the subject remains in the same range bin, the phase variation should have a strong confidence from the auto-correlation function, however, if the successive phase values are

drastically different, there is an indication that the correct range bin has not been chosen, that the subject may be moving, or the subjects vitals are changing. This metric, along with signal energy can generally be used to tell the algorithm if it should re-estimate the range bin chosen before extracting the phase variation. An approximation to Power Spectral Density (PSD) in the frequency domain, is approximate to the average power in the time domain of the output signal over a given frequency band [22],

$$\phi_{YY}[0] = \frac{f_s}{N} \sum_{k=f_1}^N |X_k(\Omega)|^2 \quad (4.28)$$

where $\phi_{YY}[n]$ is the output auto-correlation, f_s , and N are the sampling rate and the number of samples used in the FFT of the input signal and k is the starting index of the bandwidth of the output signal. Since the FFT of the chirp signal has already been taken, a gauge on how much the signal is varying from the signal mean (variance) at a range bin can indicate if there is target motion, i.e., the range bin needs to be changed. The TI processing algorithm has an option for tracking the range bin according to this metric. If an assumption is made such that the noise is "white" noise, and the noise signal is approximated as the range bins for which the signal of interest is not located, an approximation to the system noise can be made using a similar equation, however, now the auto-correlation function is equal to the signal variance, as the white spectrum is constant,

$$\phi_{YY}[0] = \sigma^2 \quad (4.29)$$

Auto-correlation also provides an estimate for vital signs using the delay index. The periodicity of the vital sign of interest will correspond to the delay index if the signals are highly correlated. This estimate can be used if the confidence metric is also considered. From the set of auto-correlation functions R_{XX} , one must choose the delay index resulting in the highest auto-correlation. Then, choosing $\mathbf{argmax}\{R_{XX}(l)\}$, the estimate for HR or BR can be made by,

$$est_{vital} = 60 \cdot \frac{f_s}{l_{max}} \quad (4.30)$$

More estimates for the HR and BR are made using the FFT method and searching for the maximum peak in the range of interest. Prior to performing the FFT, a hamming window is applied to the raw adc data. From [22],

$$w[n] = \begin{cases} 0.54 - 0.46 \cos(\frac{2\pi}{N}), & 0 \leq n \leq M \\ 0, & otherwise \end{cases}$$

In the vital signs processing used by TI, a 32 point hamming window is used and the coefficients are stored in memory at startup. In real-time systems, it is important to pre-calculate anything that will not change often, or is computational intensive, and store the values in RAM or in a look up table (LUT) if the values will not be updated and they form a large set. This is precisely what needs to be done to make the FFT computation efficient and this logic was also seen regarding the bi-quad filter coefficients. After windowing, the FFT is performed on the extracted phase variation at the target distance using arctangent demodulation from Eq. 4.6.

The peak values in predetermined frequency ranges, 0.1Hz-0.6Hz for breathing, and 0.8Hz-4Hz for cardiac, are searched and the corresponding peak index is stored. If a breathing peak is found that would result in a second harmonic in the cardiac spectrum, the second highest peak in the cardiac spectrum is chosen for the estimate. This is not a robust method and improvements can surely be made, such as with a nulling filter which can account for multiple harmonics. Care must be taken when applying such a filter if the HR is an integer multiple of the BR. For an additional vital estimate, the peak counting method can be used, however the frequency resolution for the estimates is slightly more coarse. Peak counting estimates are made by,

$$Est_{vital} = 60 \cdot \frac{numPeaks \cdot f_s}{BufferSize} \quad (4.31)$$

where the buffer size is the length of the phase variation samples kept in a circular buffer, i.e., when the buffer is full, it operates as first in first out. The method determines the peak distance by counting the number of peaks in the buffer than using Eq. 4.31 to determine the peak interval based on the slow-time sampling rate and buffer size.

This is the last of the HR and BR estimates made by the TI signal processing chain. A mixture of the methods can be utilized, or the confidence metrics can be used to choose one estimate over the other. Before transmitting processed data, a few final steps are performed on the breath and heart waveforms. The estimates are then transmitted to a serial receiver for display or further processing.

Prior to sending the processed data, exponential smoothing is used to update the phase values extracted from the chosen range bin during each chirp cycle. The processing scheme on the TI chip does this after performing the FFT, but prior to transmitting the estimated values over UART, however an FFT could also be performed on this signal as an improvement. For exponential smoothing, let the sequence of phase values be $\phi[k]$ and let α be a chosen smoothing coefficient (higher alpha means less contribution from previous values), then exponential smoothing of a signal is,

$$\phi[k] = \alpha(\phi[k])^2 + (1 - \alpha)\phi[k - 1] \quad (4.32)$$

The "exponential" term $\alpha(\phi[k])^2$ places a higher weight on the current phase sample, while α strictly determines how much of the previous value contributes. Considering the difference in periodicity of the heart and breath rates, it is clear that α_{br} for the breathing waveform will be much higher than α_{hr} , which is a relatively more transient signal. An additional processing step can be made using the confidence metric for the chosen range bin, C_{rb} , and the previous phase value for either signal. This method is called exponential averaging, and behaves as follows. Let $C[k]$ by the sequence of confidence metrics and let α be a confidence metric coefficient. A new confidence metric is now made based on the relation,

$$C[k] = \alpha(C[k] + (1 - \alpha)C[k - 1]) \quad (4.33)$$

This value is then used to choose either the FFT heart rate estimate or the peak based method which makes estimates based on inter-peak intervals in the time domain. If $C[k] > C_{threshold}$, the FFT based method is used. From experiments, it appears that the FFT method is most often reported. Also at this stage in the process, the FFT method is chosen if the difference between the peak method and FFT method estimates are below a difference threshold T_{diff} . The confidence metric is also used to display a "0" value estimate if $C[k] < 0.01$. Exponential averaging using the confidence metric is performed on the breath rate, heart rate and the chosen range bin.

Lastly, there are two additional thresholds which are used to void an estimate. One for low signal energy, corresponding to no subject presence, and another for the range bin, which also corresponds to no subject being present. These are based on Eq. 4.28 and the ratio of the signal energy at a specific bin versus the total calculated energy for all range bins.

4.4.2 Extracting A Commercial Algorithm for Offline Testing

The process for extracting an algorithm designed to run on the AWR1642 chip and the C674x DSP core began with the need to understand real-time processing methods, system architecture and communication. The TI AWR1642 chip was not designed solely for the purpose of vital sign detection, but has a multitude of applications and starting points for system design engineers or RF front end engineers. It was the goal to extract the real-time vital signs methods for offline processing and comparison to a general class of radar systems data for vital signs estimation, not just the TI 77GHz system for which the chip is designed for.

During this process, a vital signs development package in C was created as a test-bed for further vital signs processing development with the AWR1642 and IWR6843 chips. Seeing as the TI development kit was a ready-to-go radar system, it was appropriate to focus some time on improving future real-time applications with mmwave systems using the TI mmwave API.

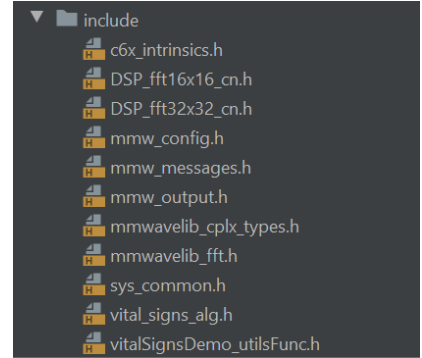
The potential benefits for the development of this offline processing package are restricted by the chips limited memory and the difficulty of grasping the immense mmwave API and the TI radar system architecture. Nonetheless, the code is a near replica of the code which is flashed to the AWR and IWR chips, including the fixed-point precision data types to try and mimic memory considerations as best as possible. The reverse process of implementing test bed code to the actual AWR and IWR chips is a challenging effort as it requires advanced knowledge of the TI embedded system hardware. Issues with using the original code with non-TI system hardware are not surprising, but can be accommodated for. The offline code served as the development grounds for the chip programming which was later done to process all MIMO channels data for vital signs estimation. A description of the package and its usage will now be presented.

The package is a condensed and reduced set of the necessary operations, dependencies, data types and utilities for full operation. It was a goal to keep the complexity to a minimum as the largeness of the code for the package is already overwhelming. Besides reorganizing the system flow, which meant cutting out the DSS and MSS communication tasks and the MSS kernel, it was necessary to create and add a driver file to emulate data input/output and data transfer over UART, which is then post-processed with MATLAB. Clearly, alternative data transfer methods could be used in conjunction with a microcontroller for data transfer and system controls. Having an offline vital signs package such as what has been described now allows teams developing mmwave systems to develop in parallel, without the need for the radar hardware until deployment. For instance, one team could develop processing algorithms, another the communication interface between the MSS software on the AWR1642 chip to a microcontroller for data transfer and controls while even another team develops visualization and data analysis tools.

The vital signs emulator directories are seen in Figure 4.3



(a) Vital Signs Source



(b) Vital Signs Includes

Figure 4.3: Vital Signs Emulator

4.5 Programming the AWR1642 For MIMO Output

The offline vital sign processor was designed to allow multiple developers to interact with the TI processing chain and get familiar with the AWR1642 DSS and MSS so that adjustments to the existing software can be made or new processing methods can be added. For this work, MIMO processing was coded on the AWR1642 chip to allow data transfer for all processed Tx-Rx pairs. This involved adjusting the memory allocations in L1, L2 and L3 Random Access Memory (RAM) on the AWR1642 as well as creating a new data structure to store the vital signs output results from the EVM for each Tx-Rx pair. The layout of L1, L2 and L3 RAM is shown in Table 4.1 with size in kilobytes (KB) and the new data structure type is shown in Figure 4.4a. The second column, "Type" refers to type of memory where Data means the memory is non-volatile whereas RAM is volatile. For MIMO processing to take place, the memory allocations on the AWR1642 chip had to be adjusted to store data for additional Tx-Rx pairs. Most of these changes were made for the circular buffers for HR and BR. In total, just over 12KB of additional storage was needed for the buffers if circular buffers of size 128 are chosen for the breath and heart rates. Considering slow-time, this means the buffer contains about 6 seconds of data. This shouldn't be an issue since most

of it was allocated in L3 memory. An example of the memory allocation is shown in 4.4b which was for the median HR and BR estimates using the past 20 estimates.

Table 4.1: AWR 1642 Memory Locations for Processing

Name	Type	Size
L1	Data	32KB
L2	RAM	256KB
L3	Shared RAM	786KB



Figure 4.4: Example of Vital Signs Code Additions

The new data structure stores the vital signs output stats which are transferred over UART for viewing results in the MATLAB or QtCreator Graphical User Interface(GUI). Essentially, the structure holds a number of **VitalSignsOutputStats** structures based on the processed Tx-Rx channels. **VitalSignsOutputStats** is an original data structure from the TI code. A new output packet has been created which must be parsed in MATLAB. Additional coding had to be done to allow for parsing multiple channels as opposed to one. The emulator was invaluable in assisting with this process, since binary packets could be built and tested with existing MATLAB parsers to ensure correct code operation. Figure 4.5 shows the original packet structure and the modified packet structure for transferring data over UART.

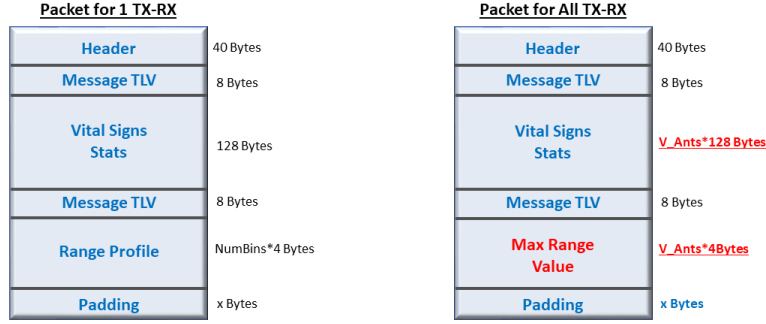


Figure 4.5: Vital Signs Stats Output Packet

The consideration for transmission time over UART may cause missed frames on the receive end. If this is the case, a reduced data structure for the **VitalSignsOutputStats** was created which requires only 32 Bytes of memory as opposed to the original 128 Bytes. On the receive side, original parsing indexing was maintained but an offset of 32 Bytes for each Tx-Rx pair needed to be added to each index to get through the full packet.

The last step for coding on the AW1642 was adjusting the MSS process output packet construction. This involved adjusting the MSS output packet pointer buffer to step through all the vital signs stats as opposed to one. Additionally, the original range profile bytes were altered to only add the value at the maximum range profile index for each frame. Now that the processing steps for offline estimation and real-time estimation have been reviewed, one last processing step for MIMO channels will be covered.

4.6 MIMO Processing

Mmwave systems make antenna structures smaller and allow for additional transmitters and receivers to be used for additional channels. The limitations here come mostly from the system components cost, but with a low number of Tx-Rx pairs and SoC technology,

additional RF front end chains can be used with minimal cost. This is the case for both the AWR1642 and IWR6843 systems by TI which have 8 and 12 channels respectively. The channels are described as virtual channels because each Tx channel stimulates each of the 4 receive antennas which will all have accessible data to process. Since there are 2 transmitters for the AWR1642 this gives 8 channels of received data. The IWR6842 has 3 transmitters so there are 12 channels of accessible data. In this case, the transmitters operate in TDM, where one chirp is after the other. Other MIMO methods allow for simultaneous transmission using orthogonal signals. An example of this would be orthogonal frequency division multiplexing (OFDM). The TI development kits do not offer this ability so the TDM mode must be used. There are numerous MIMO processing techniques for different use cases, but the most recent and powerful are diversity selection and channel combining.

Many methods of MIMO processing are subsets of the following two high level descriptions. Diversity selection refers to choosing channels to use or not use for improved results, or using multiple channels to transmit different information. The applications are very broad. Channel combining techniques can be used for improving SNR, or weighting the channels for beamforming techniques which can cancel interfering signals. Today, digital beamforming is a great research area for the communications industry and the IoT as it can beam scan for multiple users or block interfering signals by changing the radiation pattern of the transmit/receive antenna. This is crucial in 5G to allow for greater line of sight operation for users who may be mobile, but it involves tracking. Beamforming relies on vector weights that are calculated using advanced methods such as minimum variance distortionless response (MVDR) which is an optimization problem and robust minimum variance beamforming [23] which is a convex optimization problem. These topics are very advanced and much work must be done to utilize their abilities for vital sign detection. The simplest method seems to be physical beamforming of the radiation pattern based on the subject location, however, this requires knowledge of the subject location which must be determined by the same system. In this work, channel combining techniques are used but beamforming is not explored. The method discussed here will be Maximal Ratio Combining.

The goal of MRC is to meet the theoretical maximum of combining all the channels such that the channel power after combining is maximum, i.e., summing the channels is

constructive and preserves the signal content of each channel individually. In other words, the aim is to increase the SNR by combining the channels appropriately. MRC is defined in [24] from literature that reviews multiple linear combining channel techniques. The channel combining in [3] seems to be an adoption of MRC which accounts for a few rules that MRC demands to be followed for channel combining. From [24], optimal channel combining using MRC must at least adhere to the following,

- A - The noise in each channel is independent of the signal of interest and additive
- B - The signals of interest are locally coherent
- C - The noise components are locally incoherent (uncorrelated) and slowly time varying or constant

Determining the signal's agreement with the above methods is left for future work and can serve as a confidence metric for channel combining results. Specifically, channel coherence. In fact, many types of MRC combining techniques can be derived from these basic rules for linear combining. The MRC model for combining channels is given in [24] by,

$$f(t) = \sum_{j=1}^N a_j f_j(t) \quad (4.34)$$

where $f(t)$ is the combined signal and a_j is the channel ratio of root-mean-square (voltage) to noise. The value a_j is also described as $\frac{x_j}{n_j^2}$ where x_j is the channel rms voltage and n_j^2 is the mean square noise source at the channel. In effect, this summation reduces the channels which are noisy prior to combining so they do not contribute to the summation as much. In the work in Chapter 5, this method is used and titled MRCopt, meaning it is from the definition of MRC optimality. The conditions just stated are proved mathematically in [24]. For the purposes of vital signs, the signal meanings must be adapted for the application. MRCopt finds the rms signal based on the maximum range bin indices, and classifies the noise as the range bins which do not contain the target. This creates ratios dependent on the signal of interest and the channel noise for each channel and applies these ratios to each signal before combining. The operation takes place at the received data level resulting in

one row of data samples that is further processed with the other algorithms described in this chapter. The second method is a technique described in [3] which relies on signal correlation.

In [3], first a correlation matrix is formed from all of the virtual antennas time domain sampled data.

$$R_{XY} = \sum_{k=1}^N X_k Y_{k+n}^T \quad (4.35)$$

in this case, cross-correlation was used because technically the signal is not quite the same. They could have different channel noise. The literature uses auto-correlation instead. Now that a square matrix has been created, eigenvalue decomposition is performed resulting in [3],

$$R_{XY} = [v_1 v_2 \dots v_N] \text{diag}[\sigma_1 \sigma_2 \dots \sigma_N] [v_1^* v_2^* \dots v_N^*]^T \quad (4.36)$$

where σ_{1-N} are the eigenvalues and v_{1-N} are the eigenvectors for N channels. This MRC method uses the first eigenvector as weights for the received signal on all Tx-Rx pairs such that [3],

$$f_{MRC}(t) = v_1^H f(t) \quad (4.37)$$

where H represents a complex conjugate transpose. Furthermore, the eigenvector v_1 is normalized such that its norm is 1. Results for this method are labeled MRC in Chapter 5. Both of the MIMO techniques could continually calculate weighting coefficients, which may be expensive for the method which requires eigendecomposition. In that case, it may be suitable to calculate the coefficients every X cycles or for whatever interval the use demands. The MRCopt method can afford to continually calculate coefficients at little cost, since determining signal energy and noise can be done from the fast-time axis FFT which constructs the range profile for a subject. The major cost from MRCopt is applying the coefficients to each ADC data point with multiplication, then summing all of the data points across the Tx-Rx pairs.

A thorough description of all signal processing methods to be used in this work has been presented. Their uses have been discussed as well as their computational complexity in a minimal sense. The results which follow operate on measured data and are post processed to compare the methods all at once, however it is clear that some methods have already been designed for real-time operation (TI) and some may be computationally expensive (SSM). The results comparison uses the algorithms over the time frames which they are best suited. A short real-time comparison and the issues to be addressed will also be discussed in Section 5.4.

Chapter 5

Vital Sign Estimation Results

In this chapter, estimation results using the methods described in Chapter 4 will be presented and compared for the case of one subject at a distance of 0.6m, then at a distance of 1m. The same subject was used for both tests. First, results considering individual Tx-Rx channels will be shown. This method shows the consistency or lack thereof of each Tx-Rx pair estimation and is crucial in improving future MIMO work using channel selection. In each test, the best Tx-Rx pair and worst Tx-Rx pair for each processing method is shown in a table along with the average of all Tx-Rx pairs. Averages are shown such that comparison to the MIMO techniques shown later on can be put into perspective when the MIMO system is evaluated as well. Also, each test used a reference sensor for the heart rate. Since the breath rate can be easily verified within 1 bpm (beats per minute), it is not the focus of this section and the results will be briefly discussed. An example will be given showing the breath rate estimates of a subject for each system to conclude the BR can be properly estimated with 60GHz and 77GHz systems using FFT. Meanwhile, all HR tests involved the TI AWR1642 EVM and TI IWR6843 EVM operating at the same time and spaced closely together to have a similar incident angle on the subject and reflected angle from the subject. The comparison shows the performance for each measurement, however, it should be clear that both systems FCC allocations serve different purposes. The IWR system is tailored for industrial applications whereas the AWR system is for automotive. It seems unlikely that these systems would be operating in the same environment for the same task, however, the experiments have been conducted to directly compare the two systems nonetheless.

5.1 System Comparison

Prior to carrying out the experiments, both systems faced a ground truth test involving a linear actuator oscillating at 0.5Hz and 1Hz. This was done to verify that the systems could detect motion accurately in the presence of ambient noise only and not random body movements. A triangular wave was used for the actuator because the mechanical performance for the equipment used operated better in this mode. This results in a $\text{sinc}^2(f)$ function in the frequency domain, so integer multiples of the fundamental frequency should be zero, although there should be some frequency content in between the null points with very low energy. It is seen that this is not exactly the case, which is explained by the impurity of the linear actuator triangular motion (not purely triangular) used for the experiment. As a matter of fact, this gives some insight into what type of frequency response is expected from the HR and BR signals. In other words, they will not be pure sinusoids, so surely, they will have a varying spectrum, regardless of any mixing products introduced from the system.

The two systems with different chips successfully extracted the correct fundamental frequency accurately. For each case, AD and CSD were applied to evaluate the harmonics from each respective spectrum. Only the first transmitter and all receivers are shown for both tests. The linear actuator frequency was set at 1Hz for the 60GHz system and 0.5Hz for the 77GHz system. These different experiments demonstrated the accuracy of extracting the fundamental frequency from the actuator motion.

For the CSD technique, the harmonics are very strong for both systems, and in fact, are stronger than the fundamental. This was not expected, nor mentioned to be so strong in previous literature using CSD, so it is anticipated that the CSD results will have strong harmonics making heart rate estimates challenging. Additionally, although the FMCW sweep is linear, it does exhibit non-linear behavior in regards to chirp generation which can cause issues when demodulating the received signal. This non-linearity would result in frequency shifting of the target signals beat frequency. *Further investigation into this hardware limitation should be done in future work along with the mathematical representation of a FMCW received signal using the CSD method.* Figure 5.1 shows the actuator experiment for the 60GHz system using the AD method.

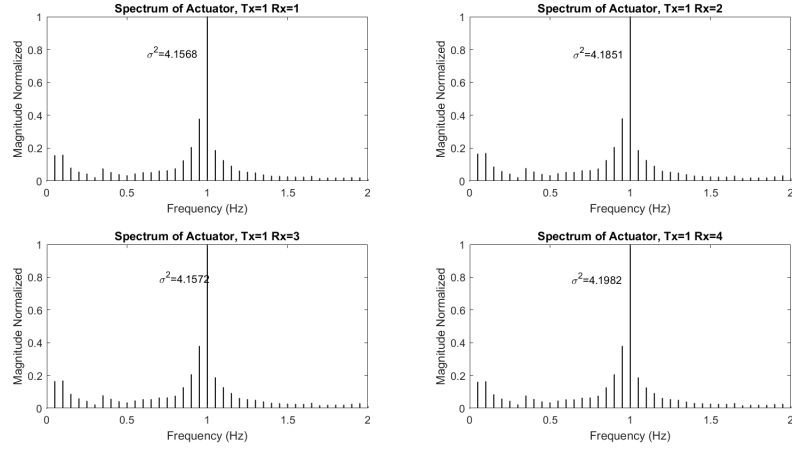


Figure 5.1: Actuator Frequency w/ 60GHz System (1Hz) Using AD

Figure 5.2 shows the actuator experiment for the 60GHz system using the CSD method.

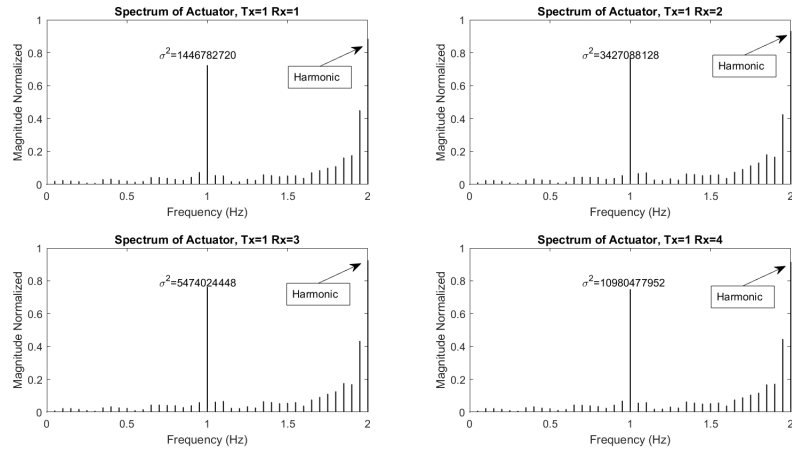


Figure 5.2: Actuator Frequency w/ 60GHz System (1Hz) Using CSD

Figure 5.3 shows the actuator displacement for the 60GHz system.

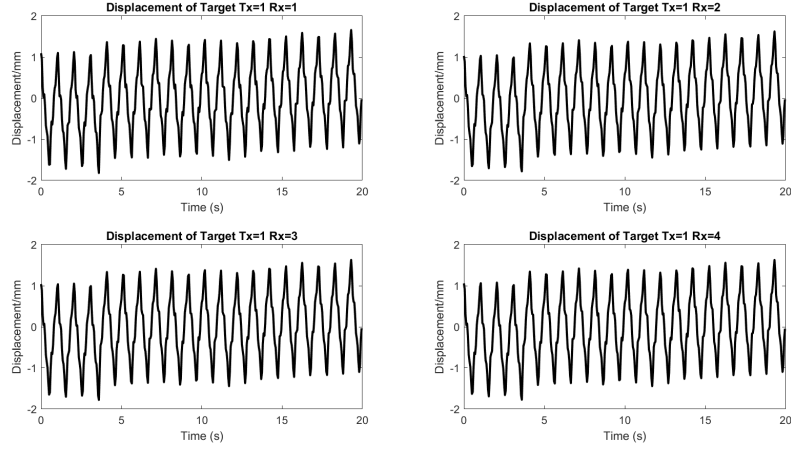


Figure 5.3: Actuator Displacement w/ 60GHz

Figure 5.4 shows the actuator experiment for the 77GHz system using the AD method.

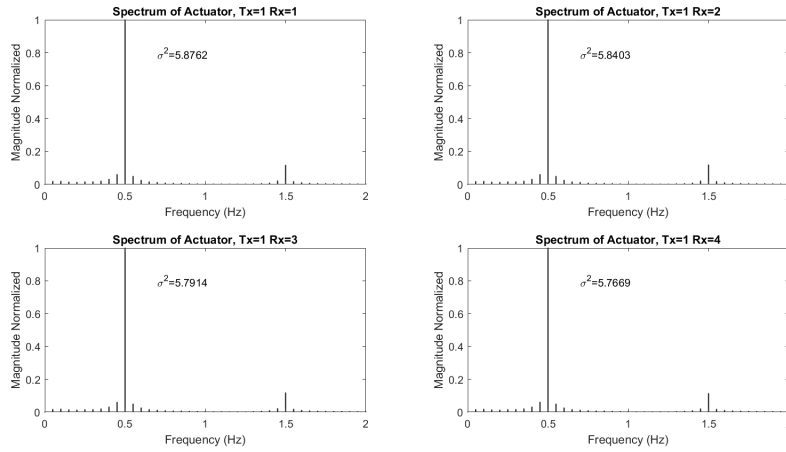


Figure 5.4: Actuator Frequency w/ 77GHz System (0.5Hz) Using AD

Figure 5.5 shows the actuator experiment for the 77GHz system using the CSD method.

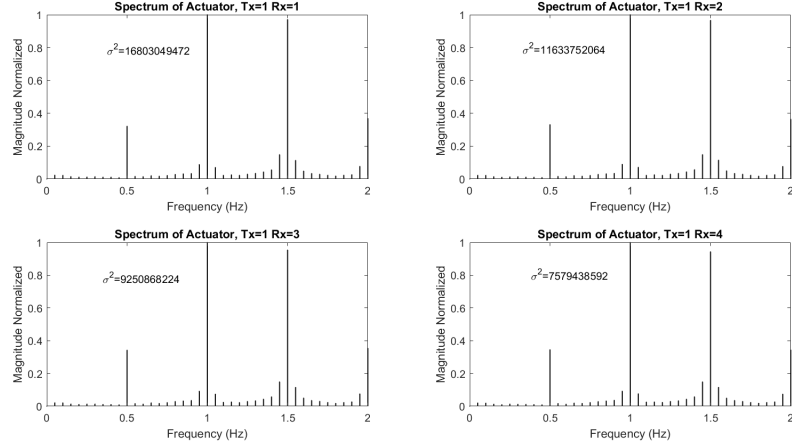


Figure 5.5: Actuator Frequency w/ 77GHz System (0.5Hz) Using CSD

Figure 5.6 shows the actuator displacement for the 77GHz system.

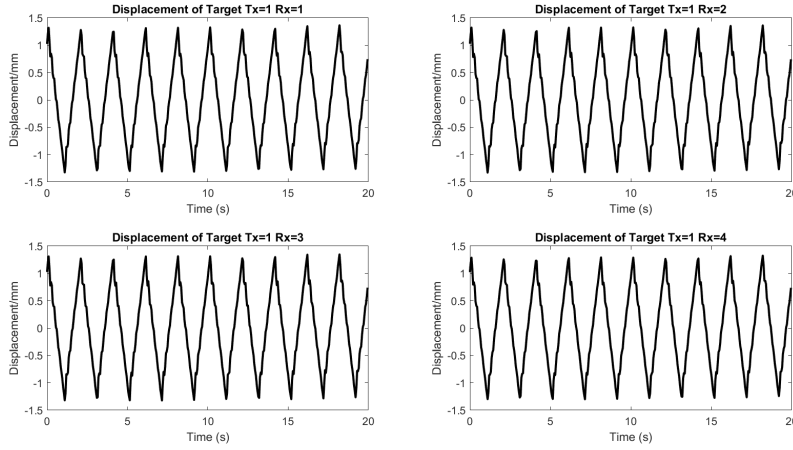


Figure 5.6: Actuator Displacement w/ 77GHz

It has been established that both the 60GHz and 77GHz systems operating in AD mode and CSD mode can produce accurate fundamental frequency estimates. However, CSD seems to be problematic due to the strong harmonics content from the demodulation process. In

the next section, the results on a human subject will be discussed and shown to demonstrate the ability of the mmwave FMCW systems to be used for vital sign detection with high accuracy.

5.2 FMCW Mmwave Systems For Vital Sign Detection

The IWR6843 and AWR1642 are chips developed by TI that are aimed at development for industrial and automotive applications, respectively. The IWR6843 ranges from 60-64GHz and the AWR1642 ranges from 77-81GHz for its operating frequency. Both chips have development kits available for testing the chip capabilities and programming new functionality onto the chips. In addition, Millimeter Wave Studio (Mmwave Studio) created by TI can be used to configure the systems operation and hardware. For the experimental results that follow, each radar system was configured in Mmwave Studio according to Table 5.1.

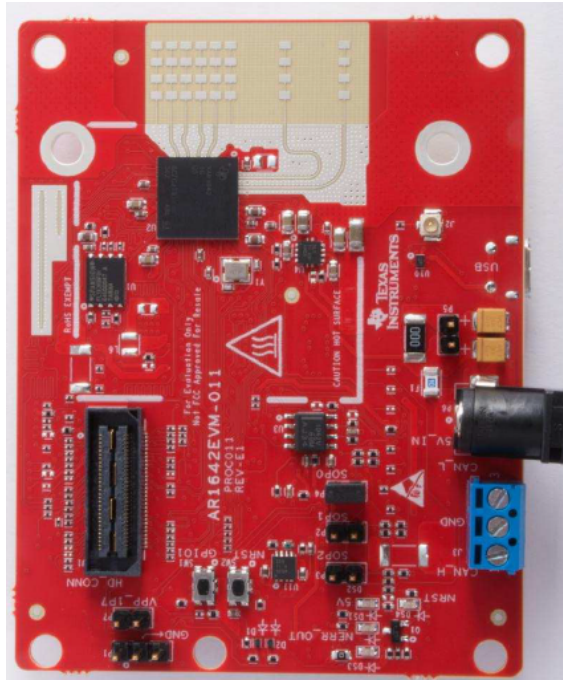
Table 5.1: TI Mmwave Comparison

Spec.	IWR 6843	AWR 1642
Frequency Range	60-64GHz	77-81GHz
f_s	5MHz	5MHz
Chirp Samples	256	256
Frames Per Second (fps)	50ms	50ms
Chirp Duration	50 μ s	50 μ s
Sweep Slope	60MHz/ μ s	60MHz/ μ s
Sweep Bandwidth (BW)	3.57GHz	3.57GHz
Chirps Per Frame (cpf)	255	256
Total Tx	3	2
Total Rx	4	4
Mode	TDM	TDM

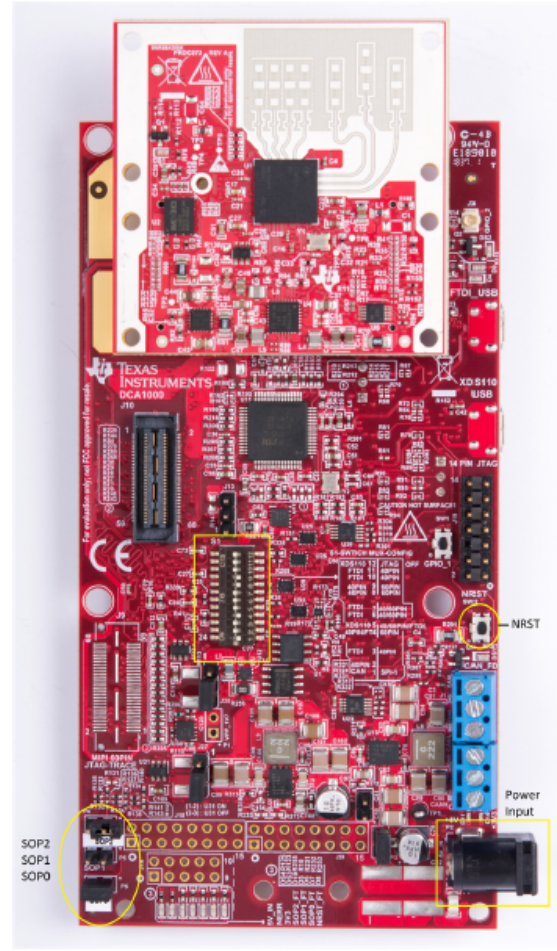
As seen in the table, the settings are nearly identical for both systems. Since the IWR6843 has 3 transmitters and the max cpf is 256 (from average power limitations) when the fps is 20, it has one less cpf than the AWR1642 so that each transmitter for the IWR6843 sends an equivalent number of transmissions. The other parameter to note is the BW of the sweep is not 4GHz. This is due to the sweep duration slope and sampling frequency. For the experiment conducted, the range resolution is adequate at 42mm since the target is stationary anyway.

5.2.1 Single Subject at 0.6 Meter Distance

The first experiment was conducted at a 0.6 meter distance. This was chosen so that the subject could be placed in between both systems, while reducing the reflection angle since the subjects chest would not be directly facing either system. Measuring with both systems simultaneously makes this issue unavoidable. However, both radar systems should experience a similar reflected angle for the return signal. The 60GHz system was slightly higher than the 77GHz system due to mechanical mounting. A picture of the two systems is shown in Figure 5.7.



(a) AWR1642



(b) IWR683

Figure 5.7: FMCW Radar Systems

Breathing Rate Experiment

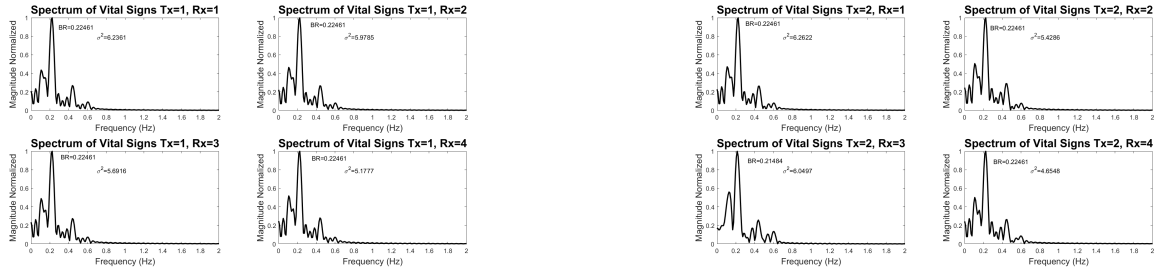
Breathing rate can be determined with simple bandpass filtering, AD and a FFT. Results for the 60GHz and 77GHz system with a respiratory rate reference sensor will be shown to deviate by less than 1bpm. % error calculations at low bpm make less sense than bpm deviation at rates below 20bpm; so it is preferred to use the bpm deviation as an indicator in these cases. Table 5.2 shows the 60GHz and 77GHz respiratory rate estimates. The 60GHz experiment had a reference sensor rate of 13.47bpm or 0.225Hz and the 77GHz experiment

had a reference sensor rate of 10.5bpm or 0.1758Hz. The reference sensor is a 2.4GHz system which has been verified with a belt sensor to consistently report at a 99% accuracy. The results for the breathing estimations are shown in Figure 5.8 and Figure 5.9 for each Tx-Rx pair to show the filtered spectrum and estimation. Since the breathing results can be estimated within 1 bpm of the true value easily, comparisons for breathing rate will not be made in the majority of the work presented. The rest of the focus will be on cardiac estimation.

Table 5.2: Subject Respiratory Rate Estimates

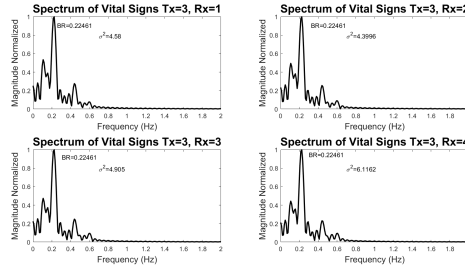
System	Distance	Max. Deviation	Min % Error	Max % Error	Ref.
60GHz	1m	0.6bpm	0%	4.5%	13.47bpm(0.225Hz)
77GHz	1m	0.48bpm	4.5%	10.1%	10.5bpm (0.175Hz)

Figure 5.8 shows respiratory estimates using bandpass filtering, arctangent demodulation and a FFT for processing for the 60GHz system.



(a) Tx 1

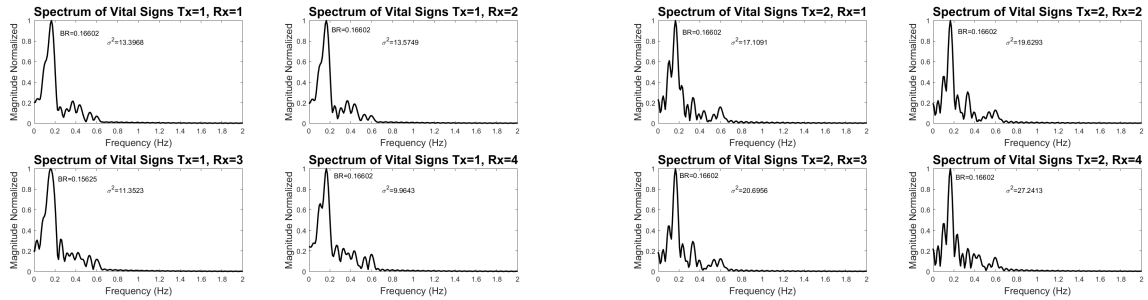
(b) Tx 1



(c) Tx 1

Figure 5.8: Spectrum of Breathing Rate @ 60GHz, 1 meter Using AD

Figure 5.9 shows respiratory estimates using bandpass filtering, arctangent demodulation and a FFT for processing for the 77GHz system.



(a) Tx 1

(b) Tx 2

Figure 5.9: Spectrum of Breathing Rate @ 77GHz, 1 meter Using AD

The spectrums shown above verify that each channel has successfully indicated a BR estimate with less than 0.5bpm deviation from the reference.

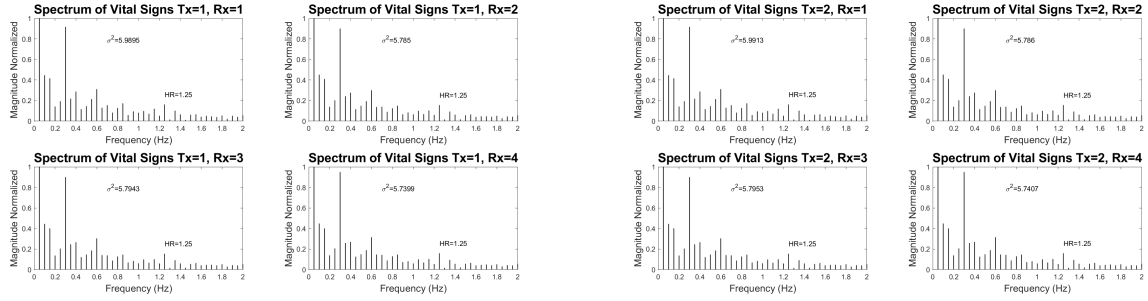
Heart Rate Estimate Experiments

Now the experimental results for all the processing methods for cardiac rate estimation will be presented. Table 5.3 shows the experiment reference sensor HR for the subject. The heart rate was verified with a contact pulse sensor made by NellcorTM.

Table 5.3: Subject Heart Rate

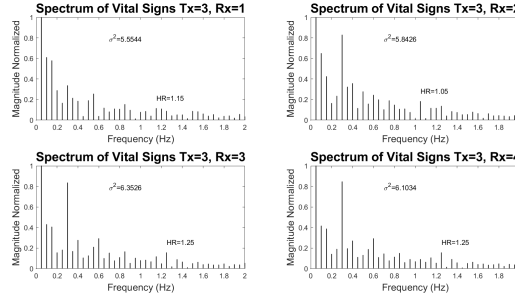
Distance	Heart Rate
0.6m	76 (bpm) $\approx$ 1.27 Hz

All results will first be presented for each processing step for each system independently. A table will be shown at the end of each section summarizing the estimation accuracy and finally both systems will be compared showing results of the best case and worst case channels as well as the results of averaging all of the channel estimates. Each estimate made for the cardiac rate was in the range of 0.8Hz to 2.0Hz and a contact pulse sensor for the heart rate was used for reference. 0.9Hz is chosen to be just above the third breathing harmonic which is between 0.85-9Hz. This way, estimates in favor of the third harmonic, will instead choose the next highest peak above 0.9Hz. For CSD, this method could not be applied due to multiple harmonics above 0.9Hz. Additionally, for the AD and CSD spectrum, the signal variance is shown on the graph so there is another metric for comparing the channels against one another. This will be useful for identifying large changes in a channel estimate from the group and signal variance will be used in MIMO combining results shown in Section 5.3. Figure 5.10 shows AD results for 60GHz. It is seen that all of the channels make good estimates except for Tx3-Rx2 which is a bit low.



(a) Tx 1

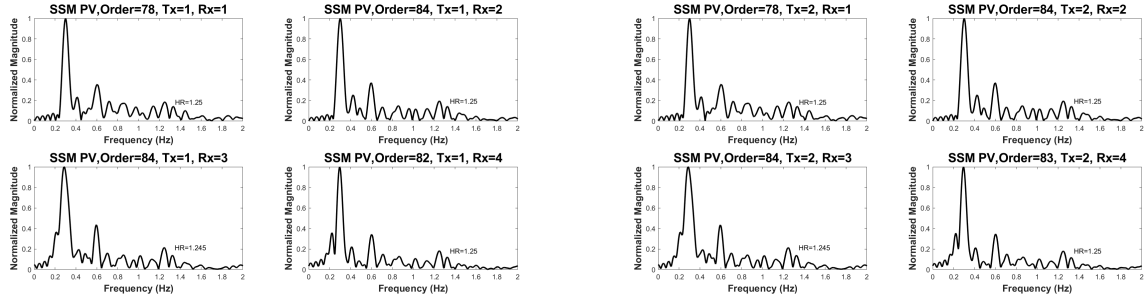
(b) Tx 2



(c) Tx 3

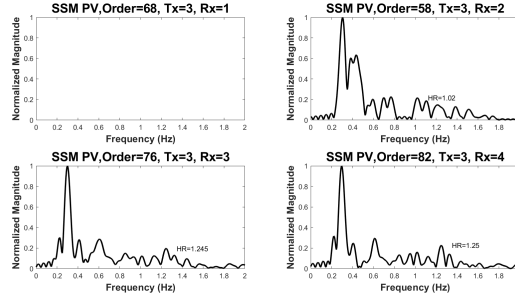
Figure 5.10: Spectrum of Vital Signs Using AD @60GHz

Using SSM can help improve SNR, but there is an issue of order estimation. Having a higher order, means more signals are used in the signal model to determine the poles of the system but more computation time is also required. Order estimation in these experiments used the akaike information criterion (AIC) and minimum description length (MDL) as mentioned in [16]. Figure 5.11 shows AD results with SSM using the phase variation (PV) of the signal. Most of the channels agree on an estimate and it appears breath and heart rate can be estimated with SSM-AD, however one channel returned a null answer. This is an issue with the possibility of the SSM controllability matrix being singular, which was the case with Tx3-Rx1. Null answers are removed from the averaging process.



(a) Tx 1

(b) Tx 2



(c) Tx 3

Figure 5.11: Spectrum of Vital Signs Using SSM-AD @60GHz

In order to alleviate the issue of order estimation, bandpass filtering for the cardiac waveform can be applied and then a lower SSM order number can be used. Prior to filtering, low SSM orders are dominated by the breathing rate and its harmonics if any are present. Note, that SSM using AD and order estimation appears to be capable of reporting both the breath and heart rate with reliable accuracy. After filtering, a low SSM order of two is chosen such that only one peak will be represented. Now all the channel estimations are accurate and have a significantly increased SNR. Figure 5.12 shows AD results with SSM and bandpass filtering.

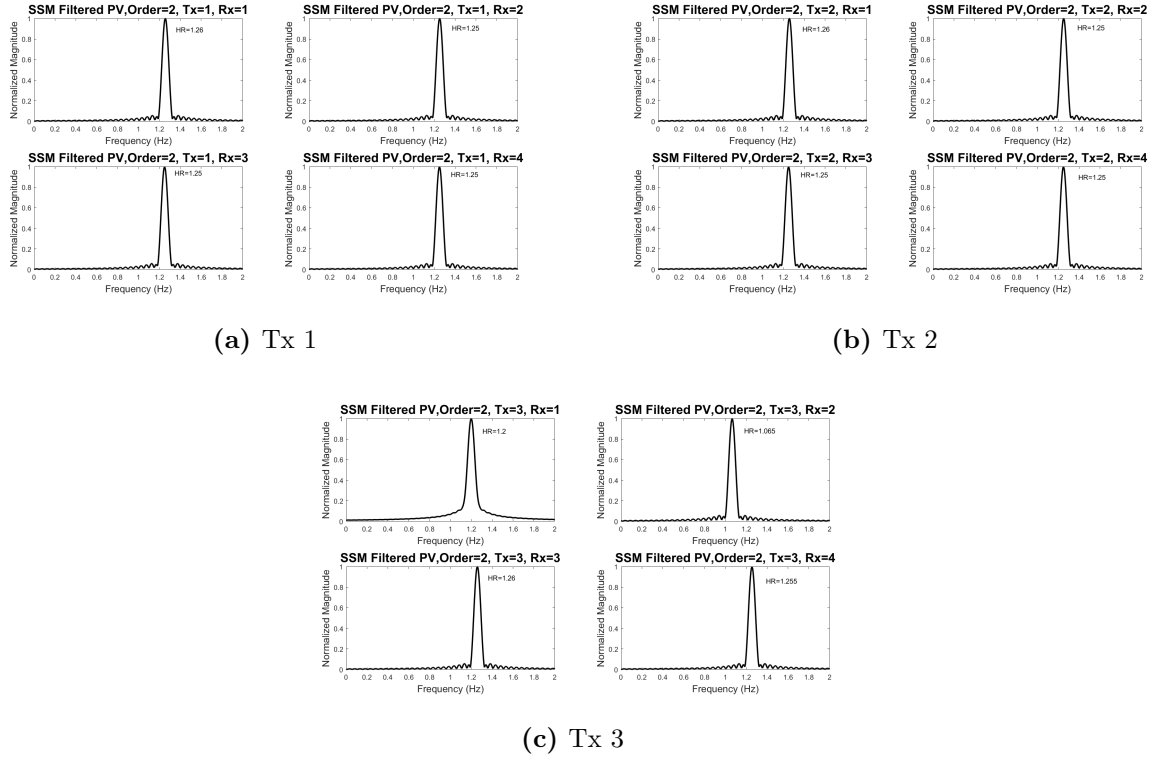


Figure 5.12: Spectrum of Vital Signs Using SSM-AD-BP @60GHz

Next the CSD method results will be shown as well as results from the SSM-CSD method. As was predicted in the linear actuator experiments, the harmonics using CSD for the FMCW system are more prevalent, but not as bad as the actuator experiment had shown. This is most likely due to the triangular motion of the actuator, which contains very strong harmonics of the fundamental in the frequency domain. Assuming the breathing rate is peaking around 0.29Hz, the 2nd and 3rd and even 4th harmonics are very strong and may in fact be masking the ability to accurately report the heart rate estimate. Knowing that the traditional filtering and FFT method for breath rate estimation is very accurate, a nulling filter could be designed to clean up the CSD experiment results. This could greatly improve the results unless the cardiac waveform was very close in frequency to one of the breathing harmonics, but would result in a very high order filter considering the low frequency range for the application. Figure 5.13 shows CSD results. In the CSD plots, RP stands for range

profile. It was chosen not to filter the CSD results and use low order SSM estimation like the AD method due to the harmonics introduced by CSD. The figure shows that the next peak outside of the 3rd breathing harmonic would be another harmonic at 1.2Hz.

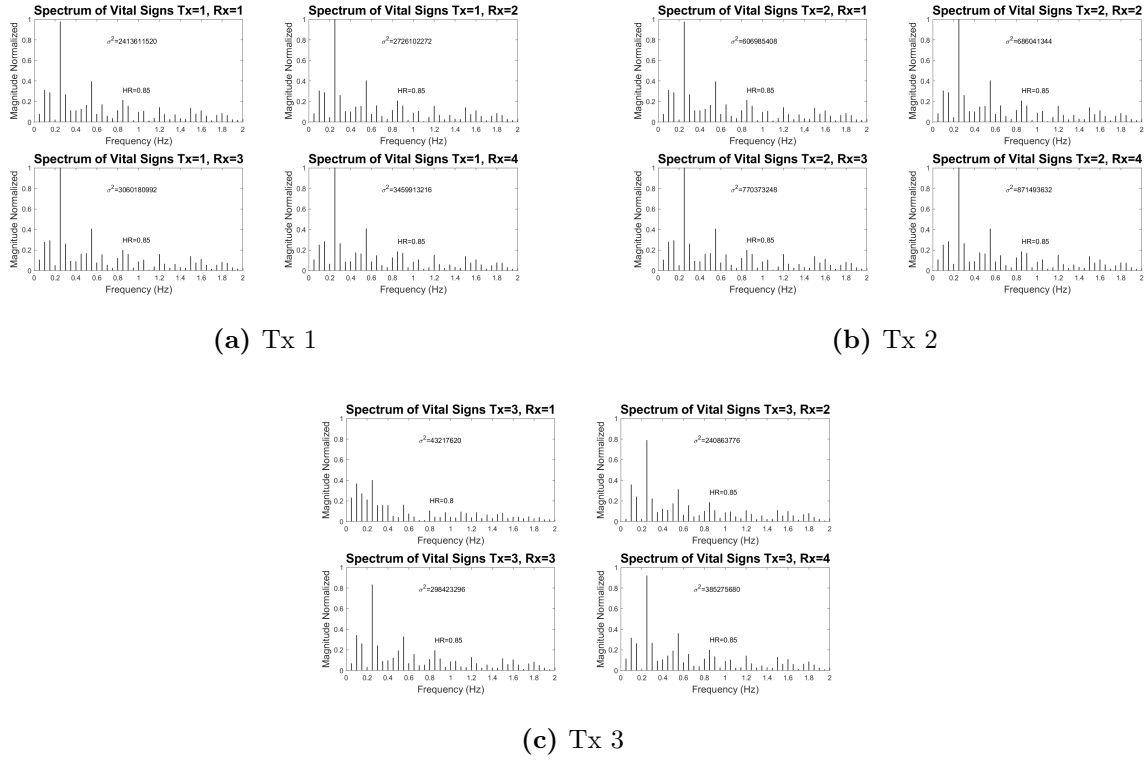
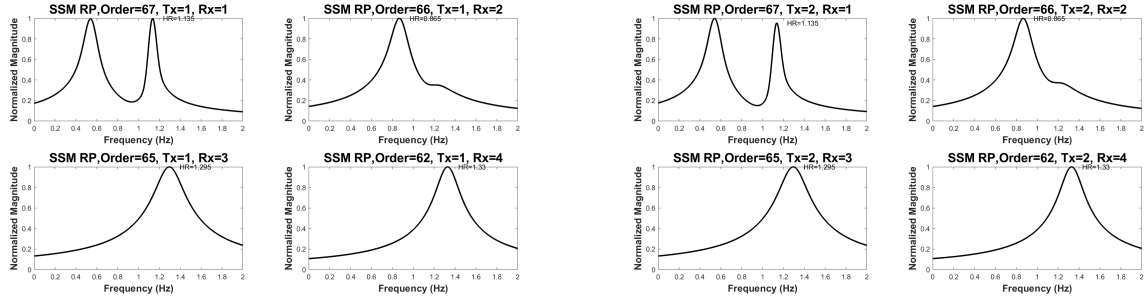


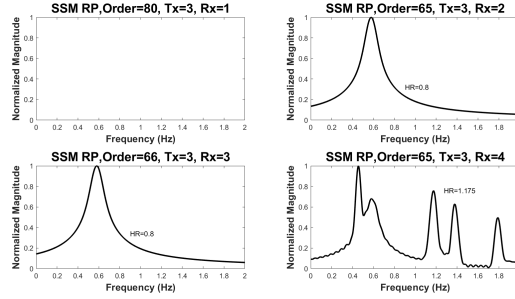
Figure 5.13: Spectrum of Vital Signs Using CSD @60GHz

Figure 5.14 shows CSD results with SSM. The results are significantly improved with parametric estimation. Although multiple channels choose the harmonic, they can be disregarded, greatly improving the average channel results.



(a) Tx 1

(b) Tx 2



(c) Tx 3.

Figure 5.14: Spectrum of Vital Signs Using SSM-CSD @60GHz

Next, the TVW method is used. The spectra shown in the following figures explore varying FFT numbers at 16 different levels. 100 sample points are kept, corresponding to 5 seconds of data. Then the sweep is done such that the FFT number is swept from 64 points to 96 points. In the figures, the value for $N/2$ is reported for frequency resolution reference. TVW is capable of filtering the breath rate if the window time is short enough to remove the full breathing cycle. Only one group of Tx-Rx pairs was shown. Tx1-Rx pairs show good heart rate predictions for AD and Tx1-Rx pairs had similar results. Figure 5.15 shows TVW-AD results for one set of Tx-Rx channels.

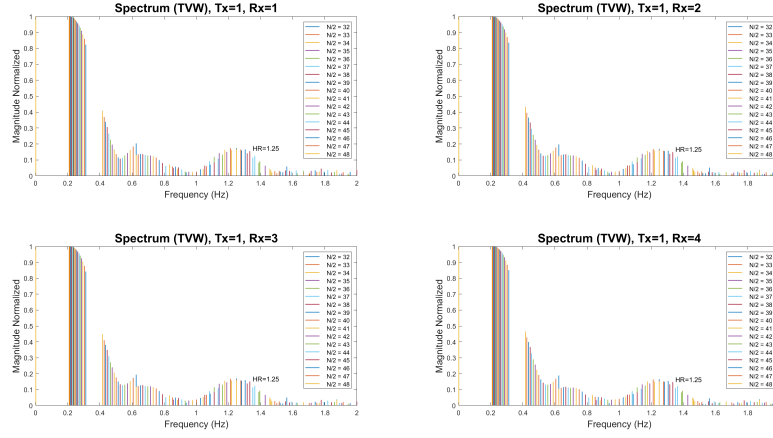


Figure 5.15: TVW-AD Results @60GHz

Figure 5.16 shows TVW-CSD Results for one set of Tx-Rx channels. It appears the harmonic was picked up as the peak estimate. Alternatively, to try to improve the CSD estimate, the window length can be reduced to decrease the breath rate and its harmonics. By reducing the window size to 50 points (2.5 seconds), the fundamental breathing frequency is decreased, however it is still not convincing enough to choose the correct frequency of 1.27Hz. In the work from [4], the estimate would choose 1.21Hz since it is known that the breath harmonic is strong around 0.85-9Hz. The smearing of the breathing harmonic completely covers the 0.6-1.2Hz range so a fair estimate cannot be made. The adjusted TVW result is shown in Figure 5.17. Some of the later TVW results do show improvement by adjusting the window time.

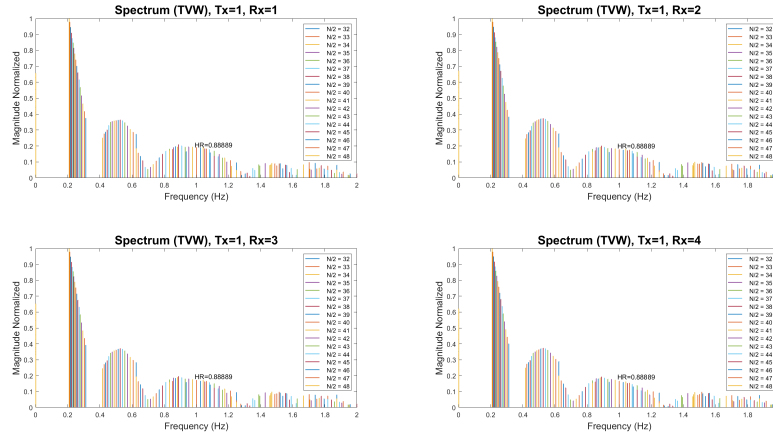


Figure 5.16: TVW-CSD Results @60GHz

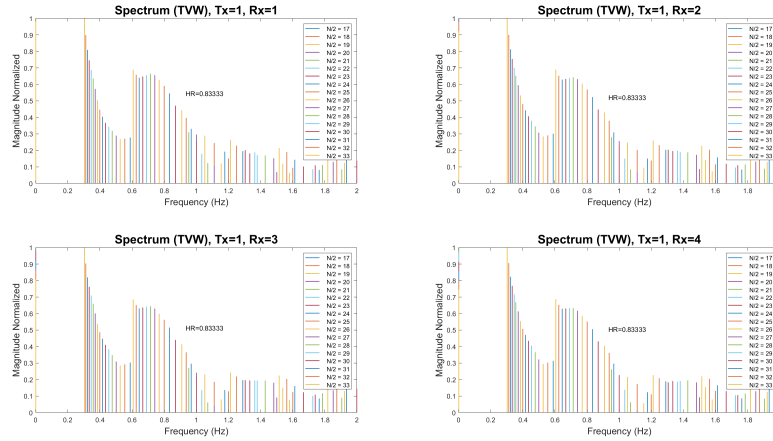
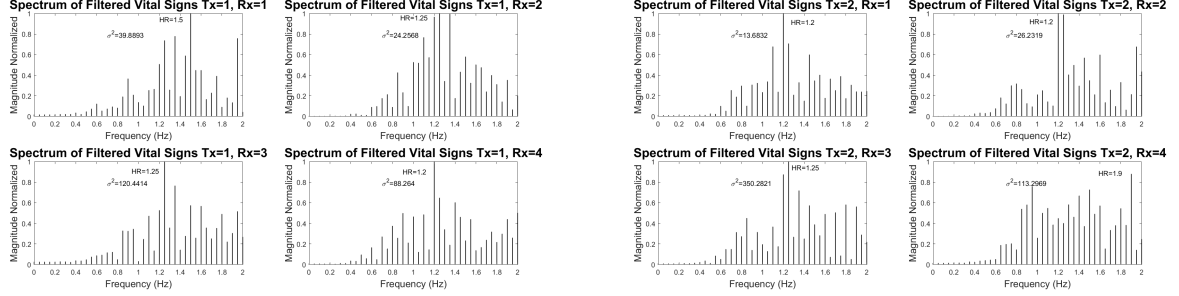


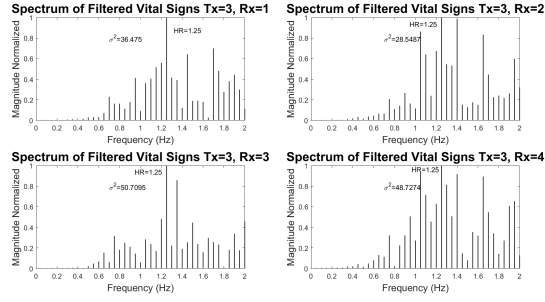
Figure 5.17: TVW-CSD Results @60GHz, 2.5s Window

For the Texas instruments algorithm processed results, the offline processor which extracted the algorithm from AWR1642 chip was used to process the data that was collected in Mmwave Studio. Figure 5.18 shows TI results for the processed cardiac waveform with the addition of an FFT.



(a) Tx 1

(b) Tx 2



(c) Tx 3.

Figure 5.18: Vital Signs TI Processed @60 GHz

Table 5.4 shows the results for one subject using the 60GHz system. The best transmit and receive pair as well as the worst pair results are shown. Each channel estimate was then averaged and also included in the table. Combinations of the channels will be shown in Section 5.3. It was decided to show the 60GHz and 77GHz results for the same test separately for clarity. BP stands for bandpass and TI-EVM represents the estimate reported from the TI process during each chirp processing cycle. This is averaged over all of the cycles to report the estimation error. The estimation error reported adheres to the frequency resolution result with no FFT padding. So the frequency resolution considering the number of sampled points and the sampling rate is $\frac{f_s}{N} = 0.05\text{Hz}$. This means the minimum achievable accuracy is 1.57% for all algorithms single channel estimates except for TVW, which adjusts the frequency resolution and could possibly have a lower minimum error. That said, SSM also has additional frequency padding shown in the graphs that is part of the code for running

the test. This was left alone, but the estimates were rounded to an appropriate frequency estimate (0.05Hz intervals) to be fair to the other methods. The TI process uses a 1024 point FFT for estimates so the results were also rounded to maintain accurate frequency resolution.

The TI-FFT BP result is from the spectrum of the cardiac waveform constructed using the TI processing method. It should be noted that the TI-EVM method takes 10-15 seconds to start making confident estimates since it takes time to fill the circular buffer. Also, The TI-FFT BP method still had an average error of 3.5% even with one bad channel estimate with a 50% error. Channel selection is not considered here, but removing the bad channel would greatly improve the average estimate. Overall, all of the methods appear to perform well, except CSD and TVW-CSD, and the error percentages are on par with the best results from lower frequency systems. However, the distance is 0.6m for experiment one, while the reference literature is between 0.8m to 1.5m. TVW-CSD did not perform nearly as well as predicted, however, from the literature it seems the results ignored peaks below 60bpm since the estimated breathing rate harmonic was below a reasonable heart rate estimate. This was not done in this work for all the algorithms to fairly choose a peak outside of the breathing harmonic range. The average channel estimates can show a % error below 1.57% which makes sense if the estimates were both above and below the reference sensor value of 1.27Hz (76bpm) and evenly distributed.

Table 5.4: HR % Error For One Subject Results @60GHz

Method	Distance	Duration	HR Best % Error	HR Worst % Error	Avg.	%Error Lit.
AD	0.6m	20s	1.57%	19.6%	3.5%	2.6% [1]
CSD	0.6m	20s	33%	37%	33.3%	2.6%[1]
SSM-AD	0.6m	20s	1.57%	19.6%	3.3%	1.7% [1]
SSM-AD BP	0.6m	20s	1.57%	4.2%	3.7%	NR
SSM-CSD	0.6m	20s	2.3%	5.5%	1%	1.7% [1]
TVW-AD	0.6m	4s	1.57%	6.3%	1.9%	NR
TVW-CSD	0.6m	4s	16.5%	34.4%	25.6%	3.4% [4]
TI-FFT BP	0.6m	20s	1.57%	50%	3.5%	NR
TI-EVM	0.6m	20s	10.9%	26.2%	19.5%	NR

Tests with the 77GHz system were conducted at the same time and will now be presented. Figure 5.19 shows AD results for 77GHz. From the figure, it is clear that the SNR for the 77GHz system appears to be lower than the 60GHz system. This suggests that SSM may be able to improve the confidence of the estimates.

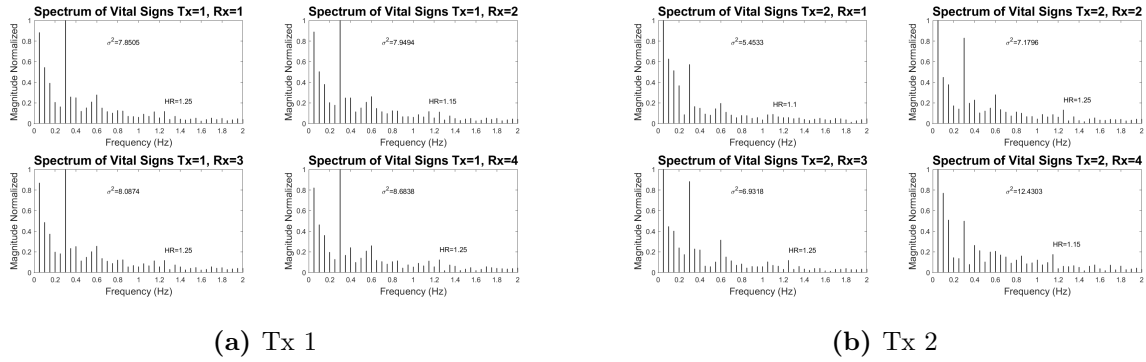


Figure 5.19: Spectrum of Vital Signs Using AD @77GHz

Figure 5.20 shows AD results with SSM. The SNR does seem to improve, however most of the results from SSM appear to be badly scaled or near singular matrices and the results are not good. Tx1-Rx1, Tx1-Rx2, Tx2-Rx1 and Tx2-Rx4 all make close estimates with a noticed improvement in SNR. Tx1-Rx3 is discarded for choosing a value in the BR harmonic range. SSM corrected the estimates made by Tx1-Rx1 and Tx1-Rx2, however, it drastically changed the Tx2-Rx2 result.

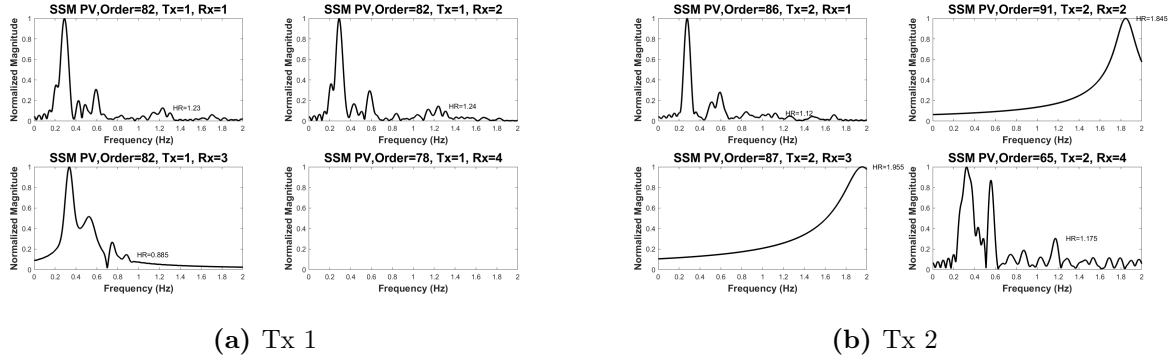


Figure 5.20: Spectrum of Vital Signs Using SSM-AD @77GHz

Figure 5.21 shows AD results with SSM and bandpass filtering with a low SSM order. All Tx-Rx pair estimates SNR have been significantly improved and the estimates are accurate.

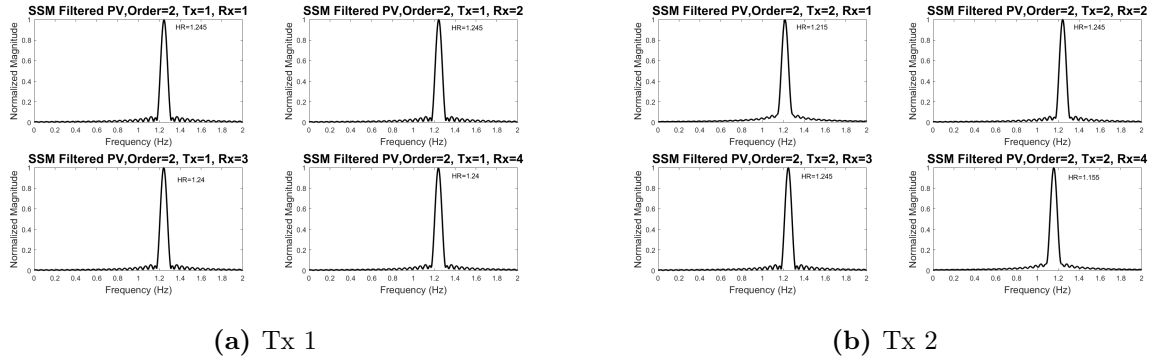


Figure 5.21: Spectrum of Vital Signs Using SSM-AD-BP @77GHz

The CSD results are plagued by the harmonics associated with the demodulation process. Clearly the breathing harmonic is interfering with the peaks in the heart rate spectrum. It is hard to tell if notch filtering could resolve this complication, since the perfect notch filter requires a high order filter which introduces significant delay. Figure 5.22 shows CSD results.

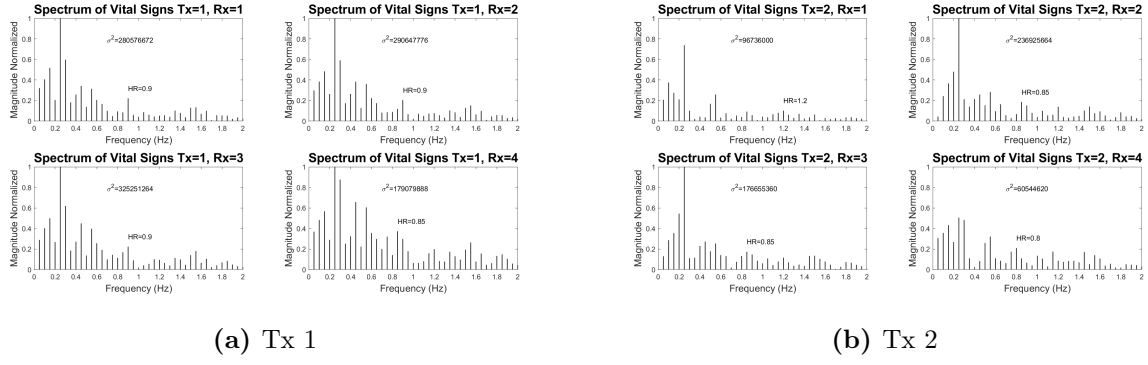


Figure 5.22: Spectrum of Vital Signs Using CSD @77GHz

Using SSM with CSD in these cases does not improve the estimation results due to the harmonics associated with the breathing rate. Figure 5.23 shows CSD results with SSM.

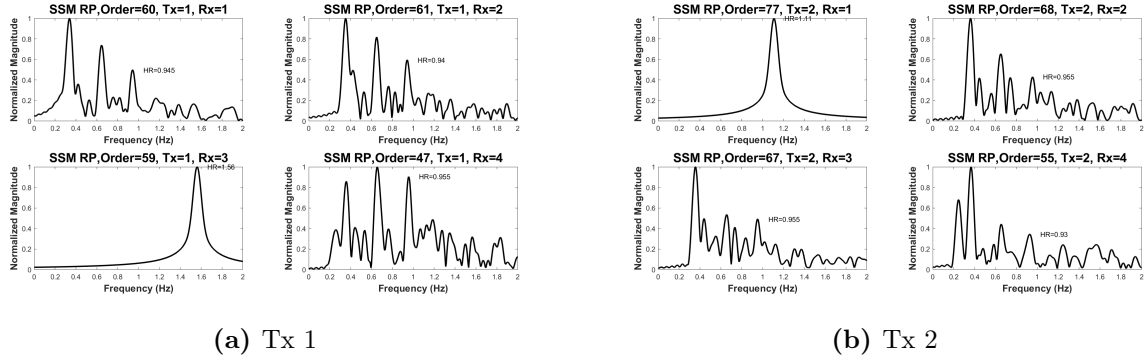


Figure 5.23: Spectrum of Vital Signs Using SSM-CSD @77GHz

The time varying window technique with AD shows good estimates, however it is slightly worse than the estimates made with the 60GHz system. CSD cannot choose the next highest peak outside of the harmonic range due to the frequency content between 0.9-1Hz. Figure 5.24 shows TVW-AD results for one set of Tx-Rx channels and Figure 5.25 shows TVW-CSD results.

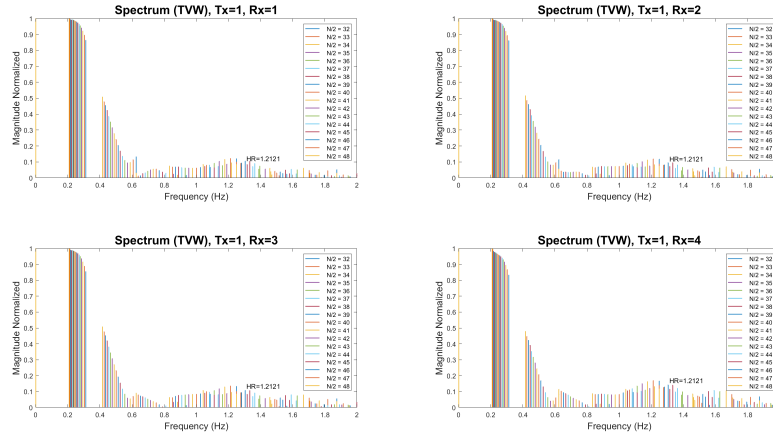


Figure 5.24: TVW-AD Results @77GHz

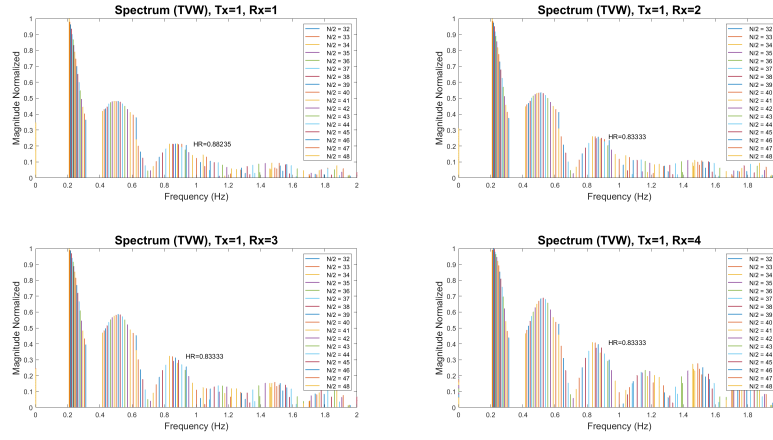
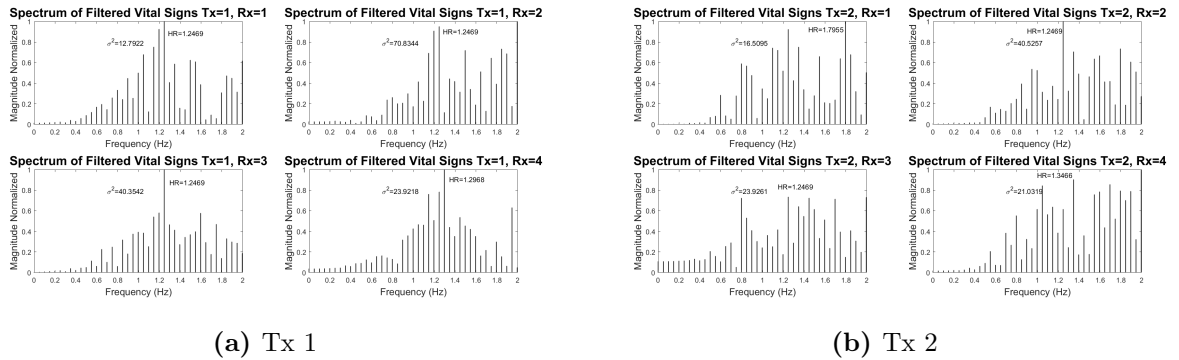


Figure 5.25: TVW-CSD Results @77GHz

TI processing for the cardiac waveform in combination with an FFT shows excellent results for 6 out of the 8 channel pairs. For Tx2-Tx1, the result could be improved with narrower bandpass filtering. *This could be done adaptively as estimate confidence increases to further improve the results.* Figure 5.26 shows TI processed results.



(a) Tx 1

(b) Tx 2

Figure 5.26: Vital Signs TI Processed @77 GHz

Table 5.5 shows the results for one subject using the 77GHz system. AD, SSM-AD, SSM-AD BP and TI-FFT BP are comparable to the 60GHz results and on par with the current best results from literature. TVW-AD performed slightly worse. This is believed to be because the 77GHz system is slightly more sensitive to random body motion than the 60GHz system. Overall, it appears the 77GHz system is capable of reporting vital signs accurately and confidently with the addition of SSM and filtering methods.

Table 5.5: HR % Error For One Subject Results @77GHz

Method	Distance	Duration	HR Best % Error	HR Worst % Error	Avg.	%Error Lit.
AD	0.6m	20s	1.57%	13.3%	5%	2.6% [1]
CSD	0.6m	20s	5.5%	29.1%	26.2 %	2.6% [1]
SSM-AD	0.6m	20s	1.57%	54%	12.86%	1.7% [1]
SSM-AD BP	0.6m	20s	1.57%	13.1%	4%	NR
SSM-CSD	0.6m	20s	13%	25.1%	17.8%	1.7% [1]
TVW-AD	0.6m	4s	4.7%	29%	9.7%	NR
TVW-CSD	0.6m	4s	10.3%	34.2%	25.9%	3.4% [4]
TI-FFT BP	0.6m	20s	1.57%	41.7%	5.3%	NR
TI-EVM	0.6m	20s	9.2%	26%	19.7%	NR

Finally, the comparison of both systems with a target distance of 0.6 meter is shown in Table 5.6. Overall, the 60GHz radar performed better, but 77GHz makes comparable estimates for most of the methods.

Table 5.6: HR % Error One Subject Result Comparison

Method	60GHz Avg. %	77GHz Avg. %	%Error Lit.
AD	3.5%	5%	2.6% [1]
CSD	33.3%	26.2%	2.6% [1]
SSM-AD	3.3%	12.8%	1.7% [1]
SSM-AD BP	4.2%	4%	NR
SSM-CSD	1%	1.8 %	1.7% [1]
TVW-AD	1.9%	9.7 %	NR
TVW-CSD	25.6%	25.9 %	3.4% [4]
TI-FFT BP	3.6%	5.3%	NR
TI-EVM	19.47%	19.7%	NR

Results for the subject at 0.6m seem adequate to claim both systems can accurately detect vitals at that distance. Next, the experimental results at a farther distance will test the systems abilities with increased path loss and an inherent decrease in SNR. It will be seen that SSM methods with filtering can extract the vital information, but estimate confidence can be improved with MIMO techniques such as diversity selection or combining.

5.2.2 Single Subject at 1 Meter Distance

Both radar systems will now be tested at a subject distance of 1m to see if the processing algorithms for vital sign detection can still compete with the best estimate results from lower frequency systems. It will be seen that this is still the case, but that there is a drop in estimation accuracy; although it is slight. This degradation is worse for the 77GHz system. The cardiac estimate for the subject is shown in Figure 5.7. The contact sensor HR of 74bpm means that the minimum error achievable is 1.57% just as in the first test at 0.6m.

Table 5.7: Subject Heart Rate

Distance	Heart Rate
1m	74 (bpm) $\approx$ 1.23 Hz

Figure 5.27 shows AD results for 60GHz. All channels make similar estimates.

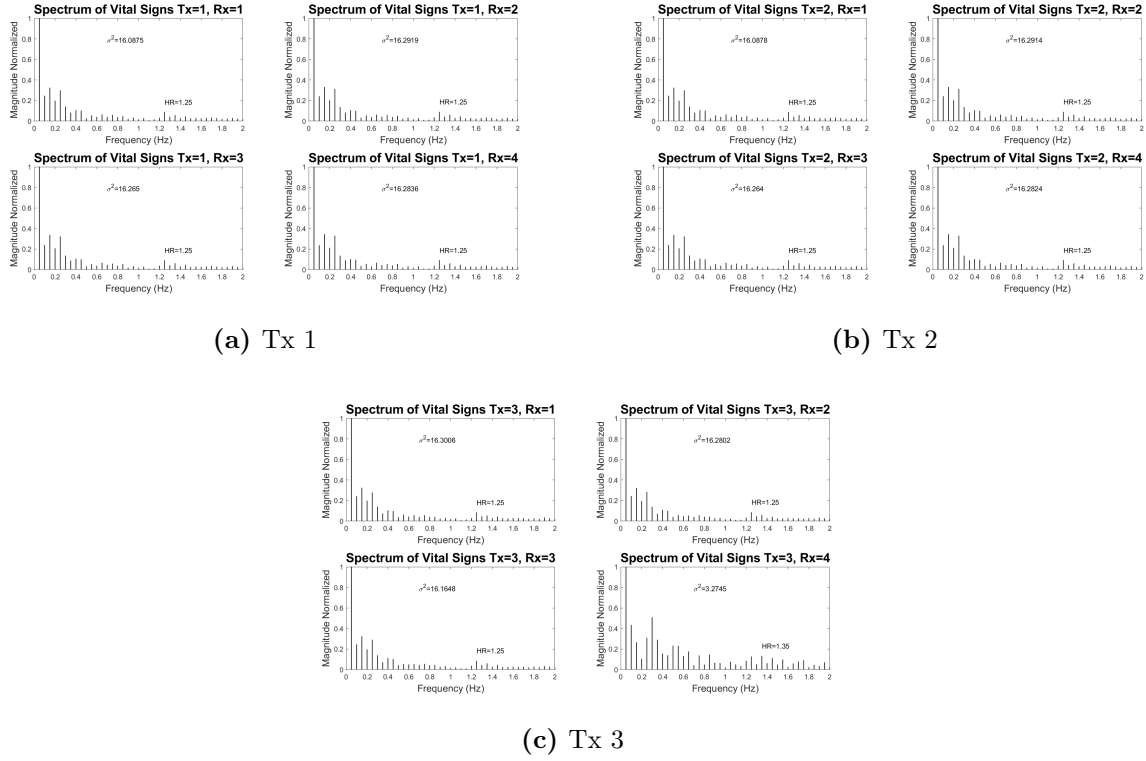
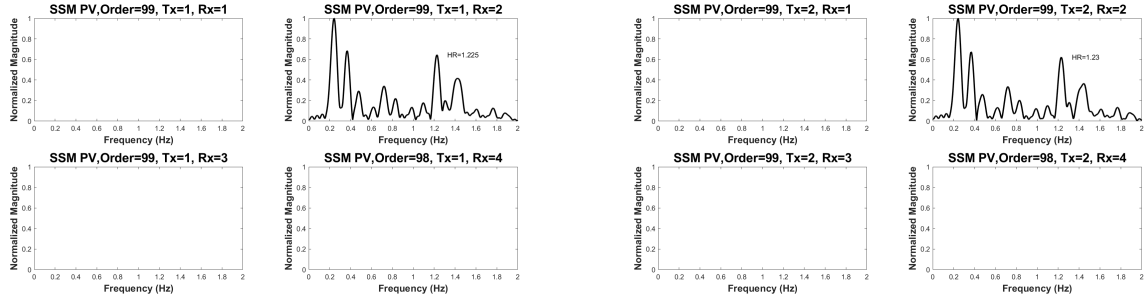


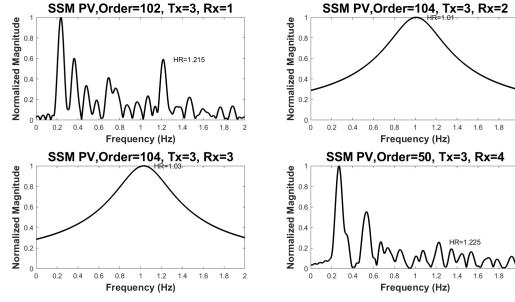
Figure 5.27: Spectrum of Vital Signs Using AD @60GHz, 1 meter

SSM results of the phase variation signal prior to filtering resulted in numerous badly scaled matrices where no result was reported. These are seen as null spectrum graphs or a wide band signal peak result. Of the channels that were processed correctly, four show high accuracy. The badly scaled matrices are disregarded. Figure 5.28 shows AD results with SSM.



(a) Tx 1

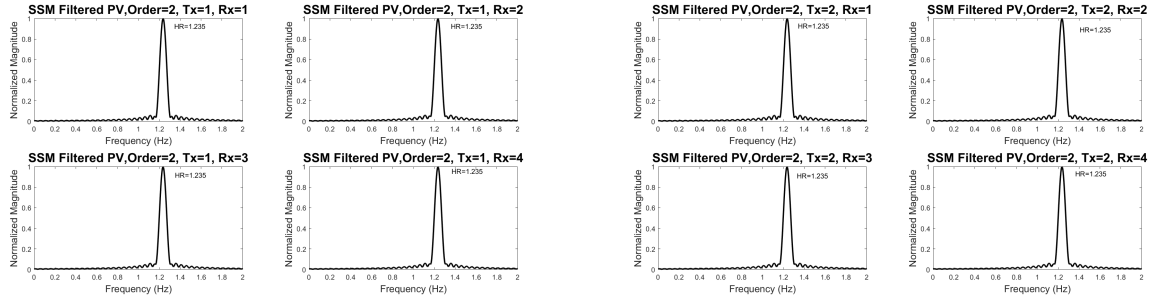
(b) Tx 2



(c) Tx 3

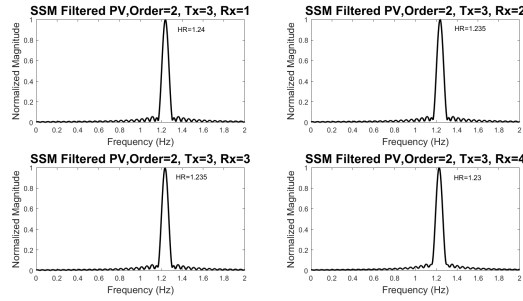
Figure 5.28: Spectrum of Vital Signs Using SSM-AD @60GHz, 1 meter

Filtering the phase variation signal again shows high estimation accuracy using a lower order for SSM for every channel. All channels report similar estimates. Figure 5.29 shows AD results with SSM and bandpass filtering.



(a) Tx 1

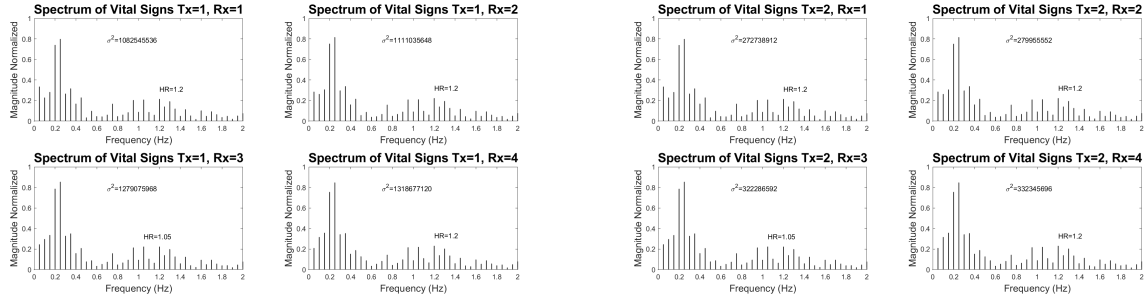
(b) Tx 2



(c) Tx 3

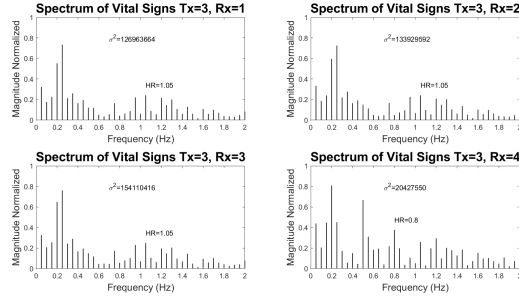
Figure 5.29: Spectrum of Vital Signs Using SSM-AD-BP @60GHz, 1 meter

For the 1 meter test, the CSD 2nd and 3rd harmonics do not appear to be as strong for all of the Tx-Rx pairs except for Tx3-Rx4. As a result, six of the channels make what appear to be good estimates, although they could still be 4th harmonics. Figure 5.30 shows the CSD results.



(a) Tx 1

(b) Tx 2



(c) Tx 3

Figure 5.30: Spectrum of Vital Signs Using CSD @60GHz, 1 meter

SSM-CSD results at 77GHz appear to be unreliable but could perhaps be improved with additional filtering and harmonic cancellation. Figure 5.31 shows CSD results with SSM.

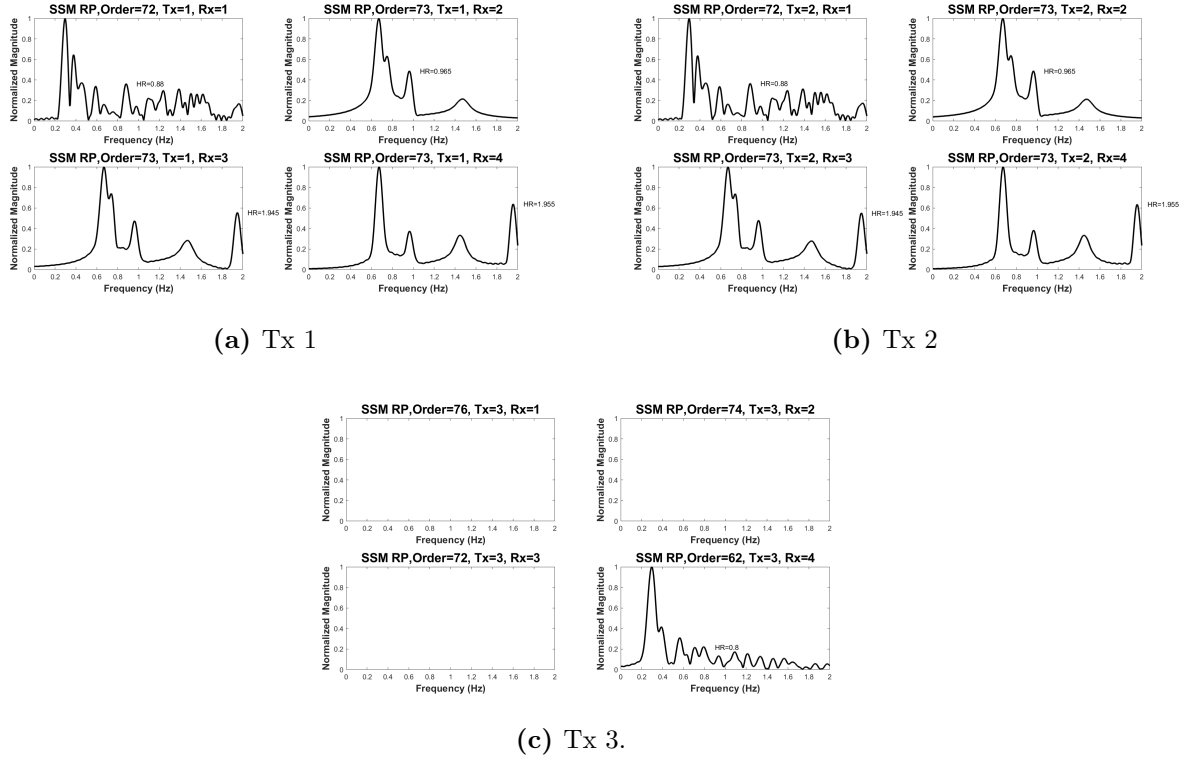


Figure 5.31: Spectrum of Vital Signs Using SSM-CSD @60GHz, 1 meter

TVW-AD method makes accurate estimates again at 1m for the 60GHz system but CSD does not. Figure 5.32 shows TVW-AD results for one set of Tx-Rx channels and Figure 5.33 shows TVW-CSD. Processing with the TI chain cardiac waveform and FFT show accurate results at 1m. Only one of the channels makes a bad estimate. Figure 5.34 shows TI processed results.

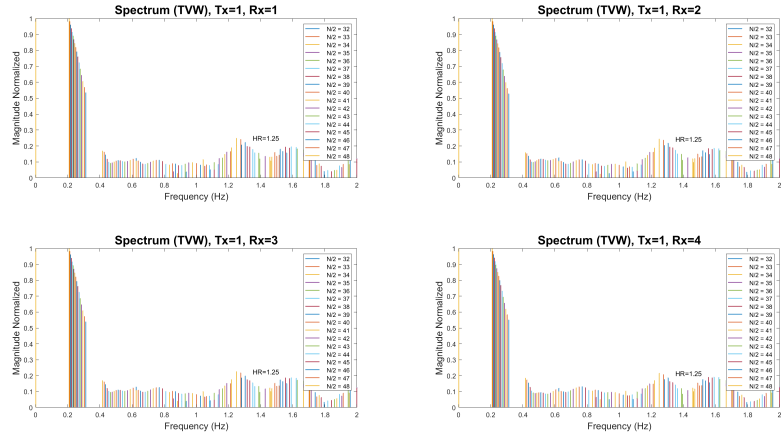


Figure 5.32: TVW-AD Results @60GHz, 1 meter

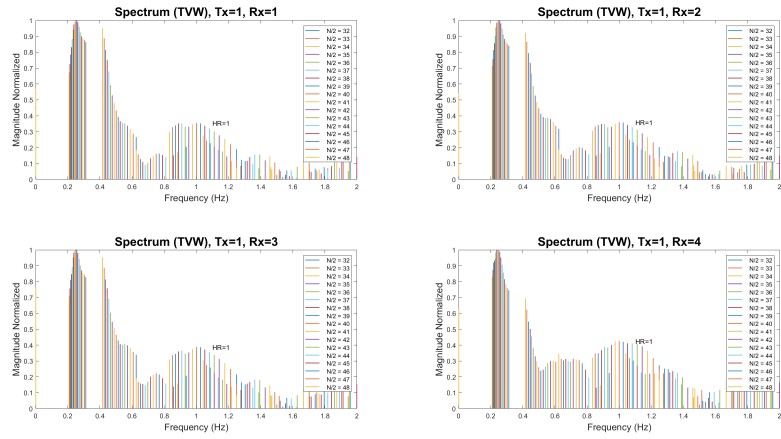
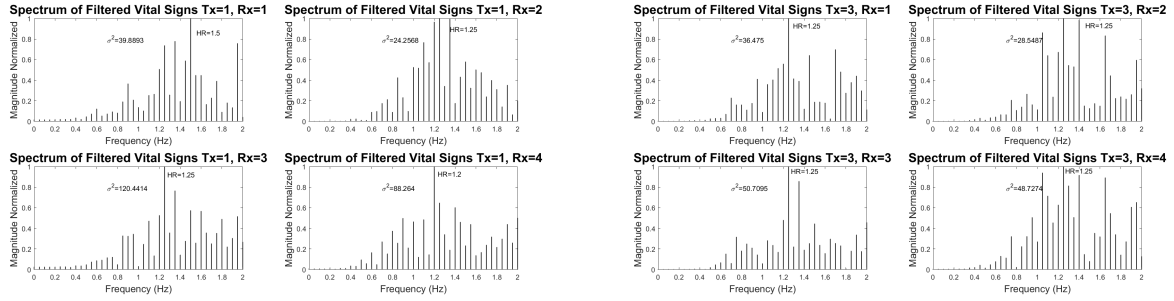
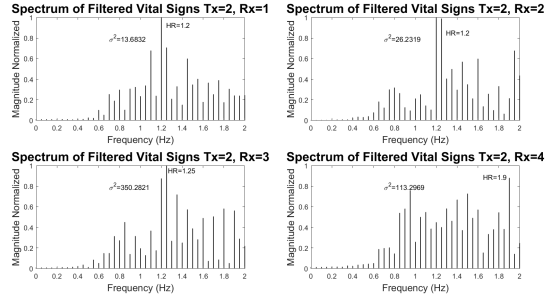


Figure 5.33: TVW-CSD Results @60GHz, 1 meter



(a) Tx 1

(b) Tx 2



(c) Tx 3.

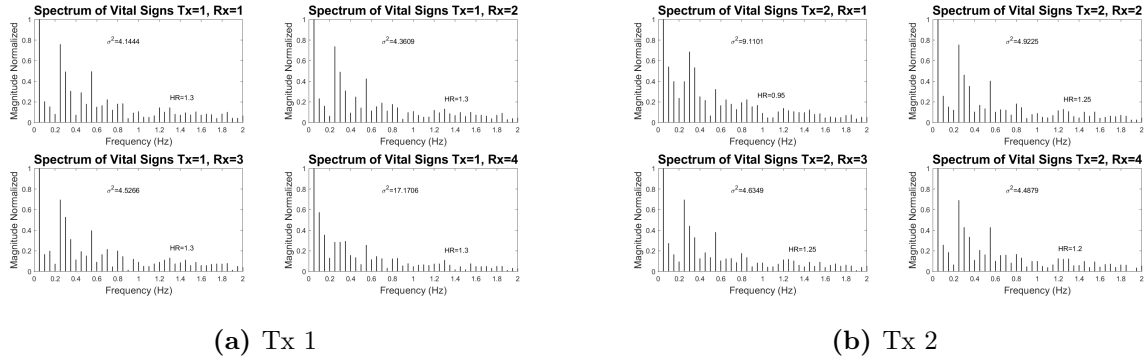
Figure 5.34: Vital Signs TI Processed @60 GHz, 1 meter

Table 5.8 shows the results for one subject using the 60GHz system with a target distance of 1m. SSM-AD BP, TVW-AD and TI-FFT BP are the best performing methods considering single channel estimates and the overall average. TI-FFT BP had only one bad channel and the removal of that channel would make its average accuracy about 1.57% for this particular experiment. *This was not done because channel selection needs to be determined in future works and the MIMO processing to be shown in the next section is a way of minimizing uncorrelated and noisy channels without biased selection.* The best single channel results are comparable to the literature. The TI 60GHz radar system is capable of making accurate vital sign estimations using multiple processing methods.

Table 5.8: HR % Error For One Subject Results @60GHz, 1 meter

Method	Distance	Duration	HR Best % Error	HR Worst % Error	Avg.	%Error Lit.
AD	1m	20s	1.57%	6.3%	2.3%	2.6% [1]
CSD	1m	20s	5.2%	36.8%	12.6%	2.6% [1]
SSM-AD	1m	20s	1.57%	18.6%	6.5%	1.7% [1]
SSM-AD BP	1m	20s	1.57%	2.4%	1.2%	NR
SSM-CSD	1m	20s	23.5%	54%	39%	1.7% [1]
TVW-AD	1m	4s	1.57%	20.3%	3.2%	NR
TVW-CSD	1m	4s	21%	22.9%	22.8%	3.4% [4]
TI-FFT BP	1m	20s	1.57%	54%	6.7%	NR
TI-EVM	1m	20s	15%	31.5%	24.4%	

Figure 5.35 shows AD results for 77GHz. Although peaks near the reference frequency of 1.21Hz are seen, there is strong spectral content below 1Hz, at what appears to be the 3rd harmonic of the respiratory signal. This is confirmed by the actuator experiment. Hence, all estimates with the FFT only using peak searching between 0.8Hz and 2Hz choose a low estimate for the heart rate. *These results are greatly improved by choosing the next peak that is not the breathing harmonic.*

**Figure 5.35:** Spectrum of Vital Signs Using AD @77GHz, 1 meter

SSM-AD reports close estimates to the reference for Tx2-Rx pairs as well as Tx1-Rx3 and Tx1-Rx4. Tx1-Rx2 and Tx1-Rx3 make bad estimates. It is clear that the 3rd harmonics

present in Figure 5.35 have been suppressed with the addition of SSM. Figure 5.36 shows AD results with SSM.

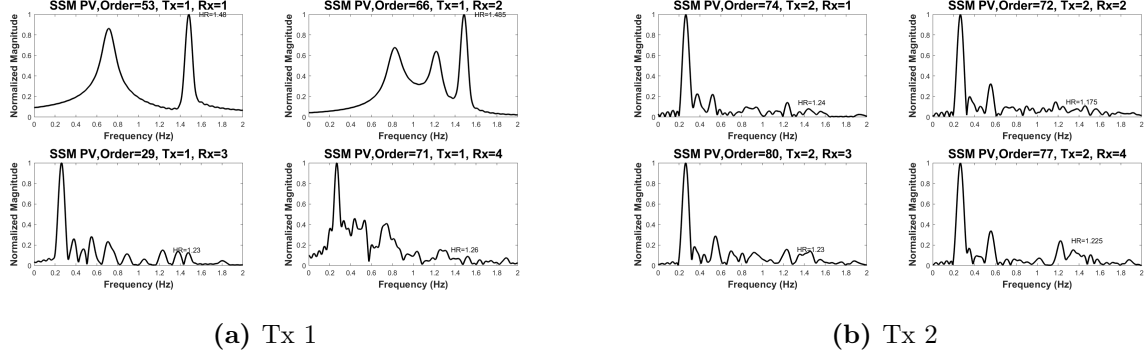


Figure 5.36: Spectrum of Vital Signs Using SSM-AD @77GHz, 1 meter

Bandpass filtering with low order SSM resolved all Tx-Rx pair estimations except for Tx2-Rx1. There are no other peaks to choose because of the low SSM order, however, noting that this appears to be the third harmonic, the estimate can be removed. Overall, it is seen that SSM-AD with filtering can produce high estimation accuracy with high SNR for the 77GHz system at a distance of up to 1m. Figure 5.37 shows AD results with SSM and bandpass filtering.

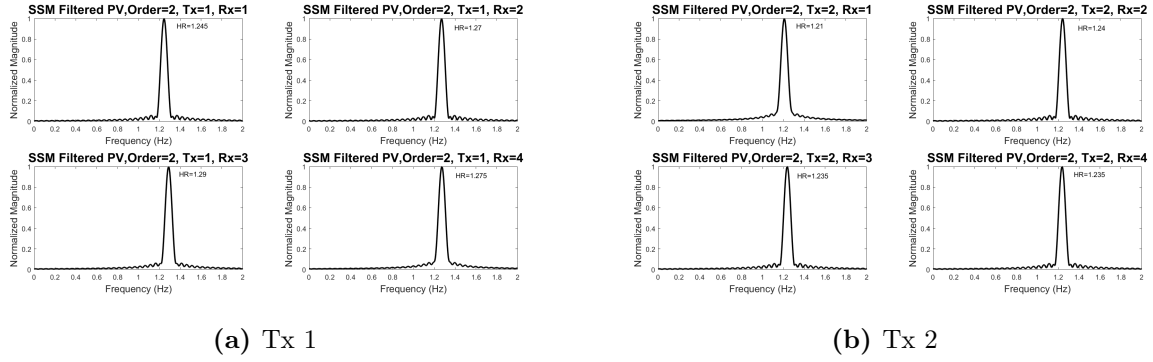


Figure 5.37: Spectrum of Vital Signs Using SSM-AD-BP @77GHz, 1 meter

Figure 5.38 shows the CSD results with expected behavior considering previous results.

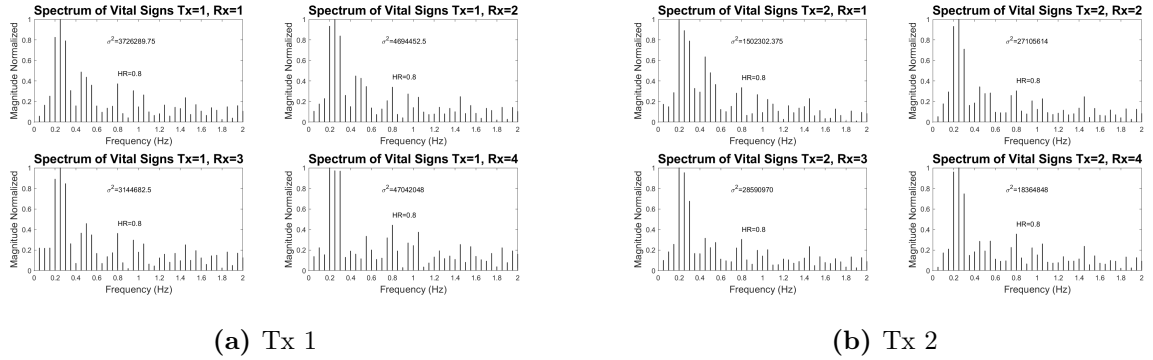


Figure 5.38: Spectrum of Vital Signs Using CSD @77GHz, 1 meter

Figure 5.39 shows CSD results with SSM which has significantly improved the results from CSD alone. Tx2-Rx4 can be disregarded since it picks the breathing harmonic and no other peaks are in the spectrum.

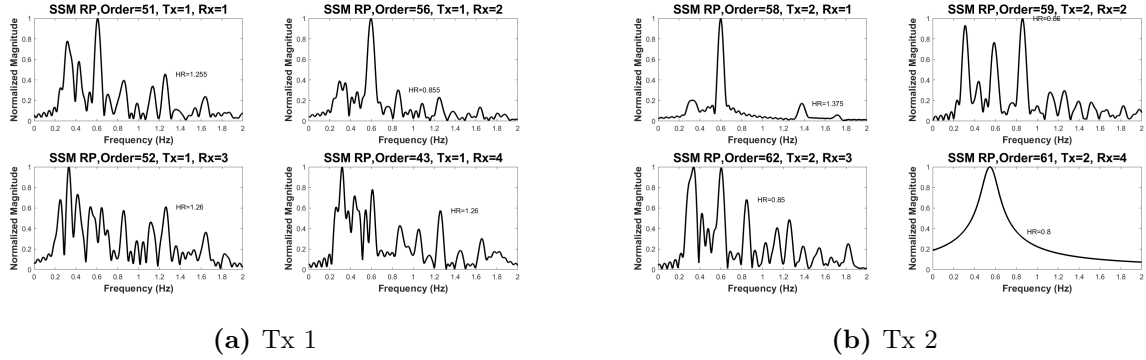


Figure 5.39: Spectrum of Vital Signs Using SSM-CSD @77GHz, 1 meter

TVW estimations degraded severely for the 77GHz test at 1m. The window size is 80 points in Figure 5.40 but it has been suggested that altering the window time can improve the results by suppressing the breath signal [4]. This is done in Figure 5.41 by reducing the window size to 55 points (2.75 seconds) and it can be seen that the harmonics are suppressed, however, there is a strong peak at a higher frequency than the reference signal, thus the results are not improved in this case. Sweeping for the optimal window which suppresses the breath harmonic and produces a correct estimate is doable in hindsight, but not for online processing.

Figure 5.42 shows TVW-CSD results for one set of Tx-Rx channels with a 4 second window. To improve these results and suppress the harmonic, the window time was changed to 2.25 seconds, producing a great improvement in estimation as shown in Figure 5.43. The reference heart rate is at 1.23Hz, so the window size of 2.25 seconds is just enough to contain a full cycle of the heart rate. This is one of the only cases where the iptimized window result was convincing and there was no ambiguity in the signal strength near the breathing harmonic. *More work needs to be done in regards to CSD harmonic suppression using the TVW for real time systems.*

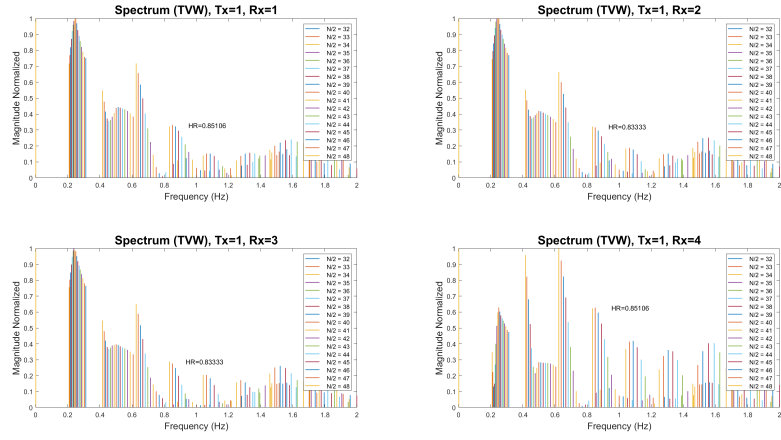


Figure 5.40: TVW-AD Results @77GHz, 1 meter, 4s Window

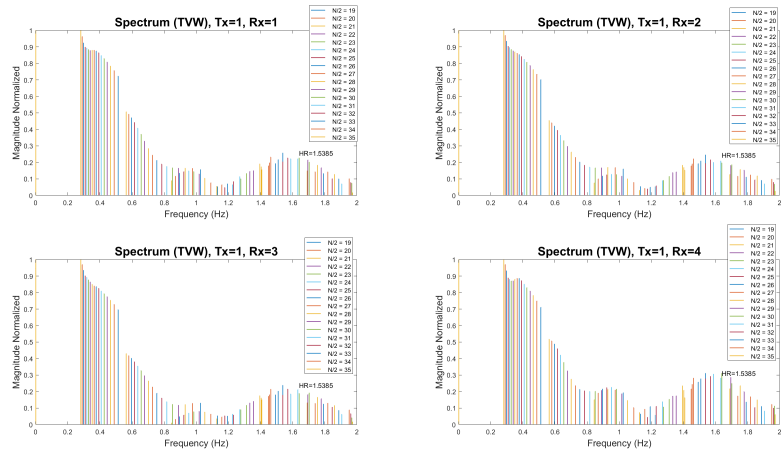


Figure 5.41: TVW-AD Results @77GHz, 1 meter, 2.75s Window

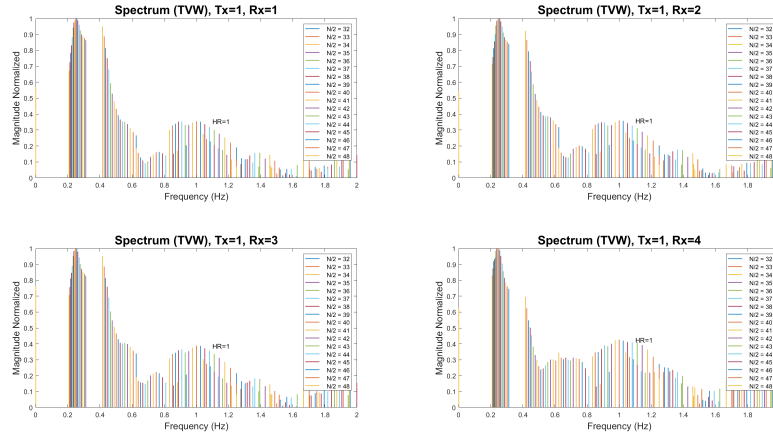


Figure 5.42: TVW-CSD Results @77GHz, 1 meter, 4s Window

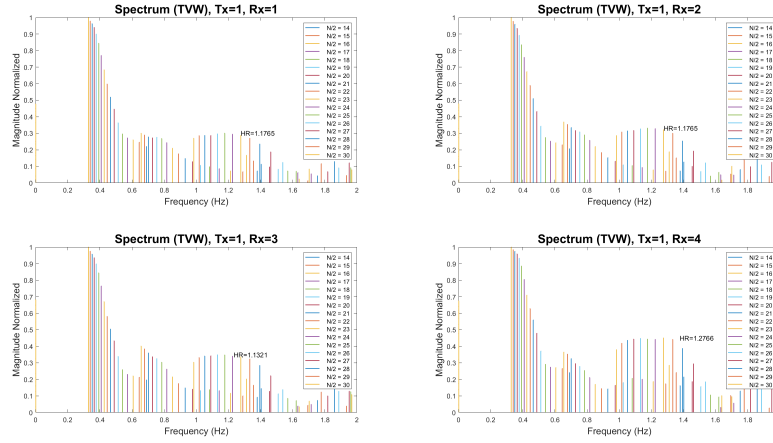


Figure 5.43: TVW-CSD Results @77GHz, 1 meter, 2.25s Window

Lastly, the TI processing results show a significant degradation from the results at 0.6m. Most of the estimates are above the reference of 1.22Hz. This is the first case showing the TI filtered cardiac spectrum being unanimously incorrect. Figure 5.44 shows TI processed results.

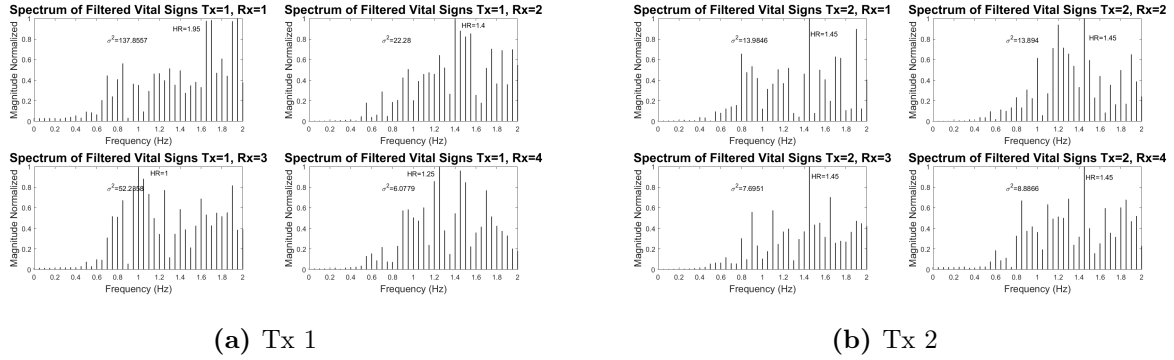


Figure 5.44: Vital Signs TI Processed @77 GHz, 1 meter

Table 5.9 shows the results for one subject using the 77GHz system. A comparison of the 60GHz and 77GHz performance averages compared to the literature is seen in Table 5.10. Just as the 0.6m case, the 77GHz system at 1m can make correct estimates with multiple methods. The noticeable change at 1m was that TVW-AD did not perform well, but TVW-CSD did. It should be noted that the TVW-CSD time varying window size needed to be adjusted in post-process. Overall, the 77GHz system performed worse at 1m than the 60GHz did, however, its best estimates are still competitive with the 60GHz system and the literature.

Table 5.9: HR % Error For One Subject Results @77GHz, 1 meter

Method	Distance	Duration	HR Best % Error	HR Worst % Error	Avg.	%Error Lit.
AD	1m	20s	1.57%	2.27%	<1%	2.6% [1]
CSD	1m	20s	36.8%	36.8%	36.8 %	2.6% [1]
SSM-AD	1m	20s	1.57%	17.8%	6.2%	1.7% [1]
SSM-AD BP	1m	20s	1.57%	3.6%	1%	NR [1]
SSM-CSD	1m	20s	1.57%	33%	15%	1.7% [1]
TVW-AD	1m	4s	32.8%	34.2%	33.8%	NR
TVW-CSD	1m	2.25s	3.3%	16.9%	7.3%	3.4% [4]
TI-FFT BP	1m	20s	1.57%	58.5%	15.9%	NR
TI-EVM	1m	20s	20%	49.3%	45.6%	NR

Although SSM-CSD shows a low error for channel averaging, the estimate distribution has a wide standard deviation.

Table 5.10: HR % Error One Subject Result Comparison 60GHz and 77GHz, 1 meter

Method	60GHz Avg. %	77GHz Avg. %	%Error Lit.
AD	2.3%	<1%	2.6% [1]
CSD	12.6%	36.8%	2.6% [1]
SSM-AD	6.5%	6.2%	1.7% [1]
SSM-AD BP	1.2%	1%	NR
SSM-CSD	39%	15 %	1.7% [1]
TVW-AD	3.2%	33.8%	NR
TVW-CSD	22.8%	7.3 %	3.4% [4]
TI-FFT BP	6.7%	15.9%	NR
TI-EVM	24.4%	45.6%	NR

It has been demonstrated that both the 60GHz and 77GHz radar systems are capable of extracting vital signs up to 1m with comparable accuracy to the best results from current literature. So far, channels have been viewed individually, however, it has been seen that not all channels agree, and in fact some appear to make bad estimates. The work in channel diversity selection and combining is a hot topic and presented next will be two methods which use MIMO channel combining. Diversity selection is left for future work but the results here should present a great start for the issues to solve when using multiple channels for estimations and how to combine them. The use of signal variance will play a part in channel selection and has been shown on all the previous graphs to give some insight into which channels may best work for combinations.

5.3 MIMO Results

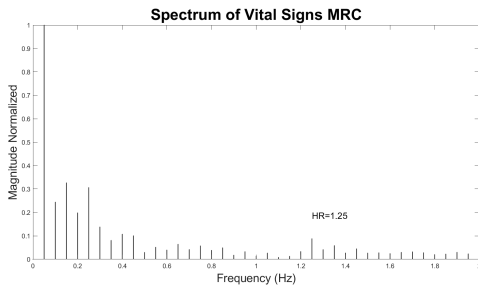
MIMO results will be presented for the subject at 1m, but it should be noted that the processed results for 0.6m show an improvement from the 1m results as expected. Two methods were used for MIMO channel combining. The first is from [3] where channel correlation is used to weight the more correlated channels heavier than the uncorrelated

channels prior to combining. This is titled as MRC in the results. The next method adjusts the channel gains according to their signal energy and total channel noise prior to combining and is titled MRCopt in the results. Both methods are a form of MRC which is used to operate on the time domain received signal. More details regarding the methods were presented in Section 4.6.

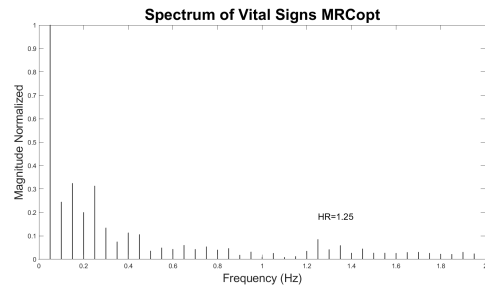
5.3.1 Single Subject at 1 Meter Distance

MIMO processing was done on the same data as previously shown for a subject at 1 meter. All of the same processing methods are compared, except for there is no TI processing method result for MIMO channel combinations. Only averages from previous results for all Tx-Rx pairs are reported for the TI processing results.

Figure 5.45a and 5.45b show the spectrum of the combined channels using MRC and MRCopt with AD. The reference HR is 1.23Hz so it is clear that the MIMO combining techniques produce an accurate result while maintaining the signal quality of all the channels. Both methods produce very similar results.



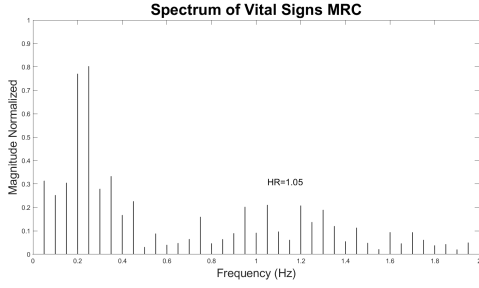
(a) MIMO MRC AD @60GHz



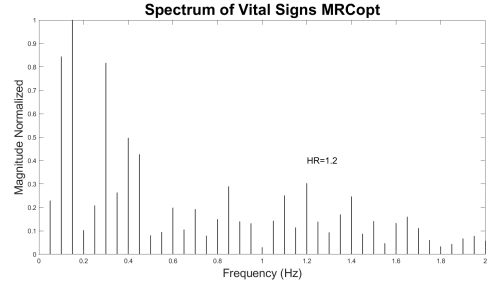
(b) MIMO MRCopt AD @60GHz

Figure 5.45: MIMO AD @60GHz, 1 meter

The CSD method appears to enhance undesired harmonics for both MRC and MRCopt, burying the correct estimation in the region between 1Hz to 1.4Hz. Figure 5.46a and 5.46b show MIMO results with CSD.



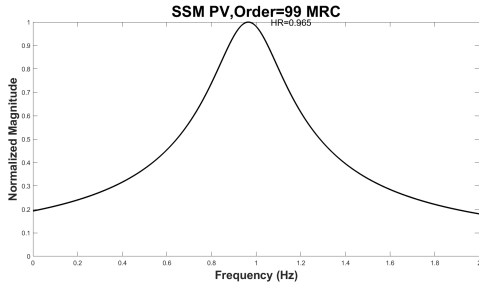
(a) MIMO MRC CSD @60GHz



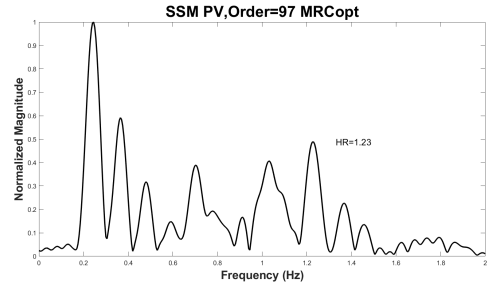
(b) MIMO MRCopt CSD @60GHz

Figure 5.46: MIMO CSD @60GHz, 1 meter

The MRCopt method shows great results for SSM-AD of the phase variation signal but MRC did not. Figure 5.47a and 5.47b show MIMO results with SSM-AD with order estimation.



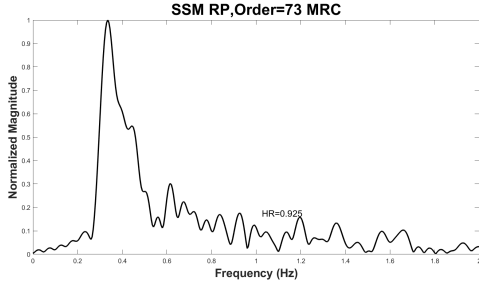
(a) MIMO MRC w/ SSM-AD Order Est.
@60GHz



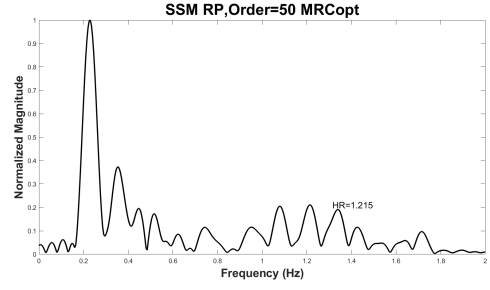
(b) MIMO MRCopt w/ SSM-AD Order Est.
@60GHz

Figure 5.47: MIMO SSM-AD @60GHz, 1 meter

Figure 5.48a and 5.48b show MIMO results with SSM-CSD with order estimation. The MRC method is inaccurate as it seems to have introduced unwanted signal energy between 0.8-1.2Hz. The MRCopt method on the other hand now has three peaks near the reference frequency and the breathing harmonics seem to have been greatly reduced.



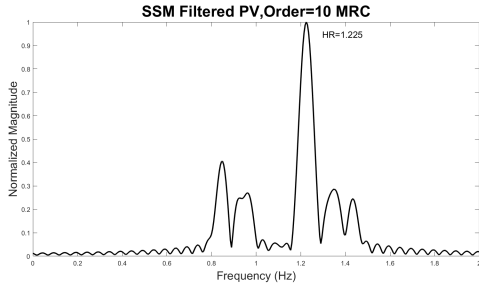
(a) MIMO MRC w/ SSM-CSD Order Est.
@60GHz



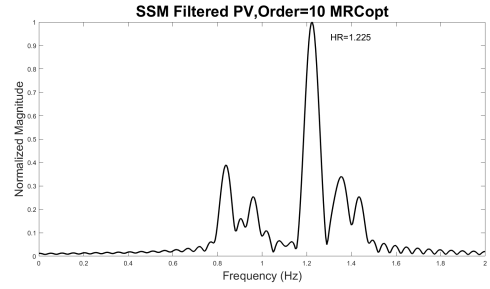
(b) MIMO MRCopt w/ SSM-CSD Order Est.
@60GHz

Figure 5.48: MIMO SSM-CSD @60GHz, 1 meter

The SSM-AD BP method shows great accuracy and similar performance for both MIMO processing techniques. SNR is greatly enhanced and a very confident estimate can be made. Figure 5.49a and 5.49b show MIMO results with SSM and bandpass filtering.



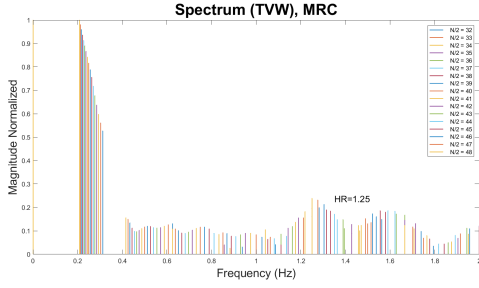
(a) MIMO MRC w/ SSM-AD BP @60GHz



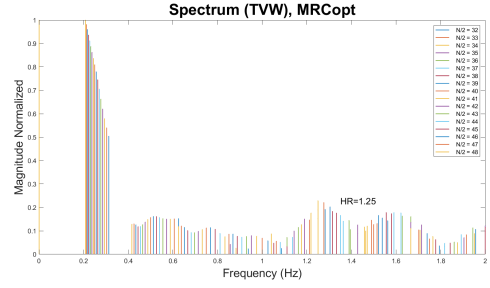
(b) MIMO MRCopt w/ SSM-AD BP @60GHz

Figure 5.49: MIMO SSM-AD-BP @60GHz, 1 meter

TVW for both techniques produce similar and accurate results. Figure 5.50a and 5.50b show MIMO results with TVW-AD.



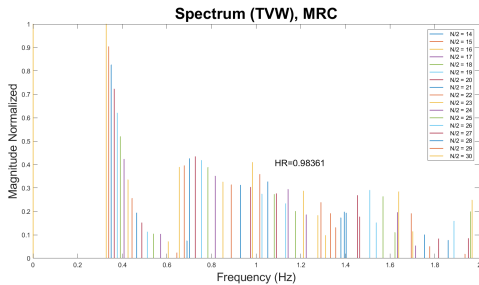
(a) MIMO MRC TVW-AD @60GHz



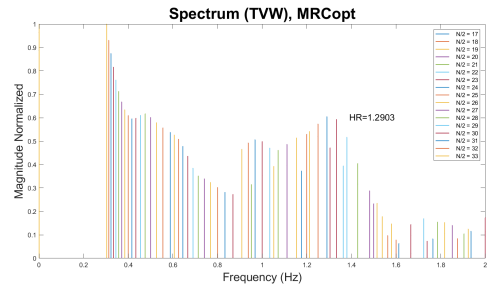
(b) MIMO MRCopt TVW-AD @60GHz

Figure 5.50: MIMO TVW-AD @60GHz, 1 meter

Even after adjusting the TVW size to suppress the breathing harmonic using CSD, the heart rate is still difficult to extract using MRC, however, the estimation is greatly improved for the MRCopt method. Figure 5.50a and 5.50b show MIMO results with TVW-AD.



(a) MIMO MRC TVW-CSD @60GHz



(b) MIMO MRCopt TVW-CSD @60GHz

Figure 5.51: MIMO TVW-CSD @60GHz, 1 meter

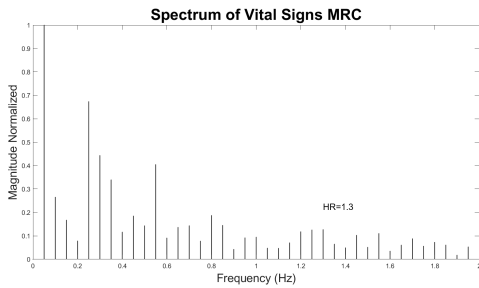
A summary of the results for MRC and MRCopt are shown in Table 5.11 for 60GHz. Estimation accuracy has been improved compared to the overall average for each Tx-Rx pair except for SSM-AD BP. MIMO combining can achieve the same accuracy as the best SISO results, meaning the combination did not degrade the signal quality. TVW-CSD seems to

work better with MRCopt and window size adjustment for this case. Interestingly, MRC performed poorly using SSM-AD and SSM-CSD but MRCopt had excellent performance.

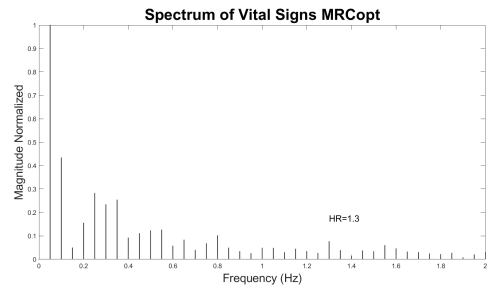
Table 5.11: HR % Error MIMO Results @60GHz, 1 meter

Method	Dist.	MRC	MRC opt.	Averaging	Best SISO
AD	1m	1.57%	1.57%	2.3%	1.57%
CSD	1m	14.6%	2.4%	12.6%	5.2%
SSM-AD	1m	1.57%	1.57%	6.5%	1.57%
SSM-AD BP	1m	1.57%	1.57%	1.2%	1.57%
SSM-CSD	1m	22.7%	2.4%	39%	23.5%
TVW-AD	1m	1.57%	1.57%	3.2%	1.57%
TVW-CSD	1m	18.6%	4.8%	22.8%	21%
TI-FFT BP	1m	NR	NR	6.7%	1.57%
TI-EVM	1m	NR	NR	24.4%	15%

Next, the 77GHz MIMO results will be compared to see if improvements have also been made with the addition of MRC processing techniques. Figure 5.52a and 5.52b show MIMO results with AD. MRC and MRCopt both make slightly high estimates.



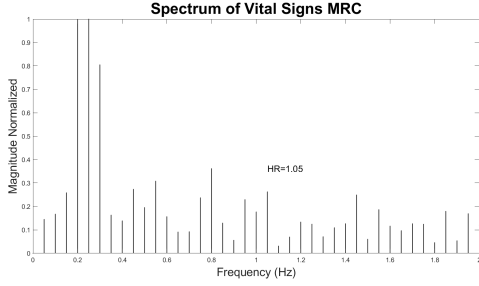
(a) MIMO MRC AD @77GHz



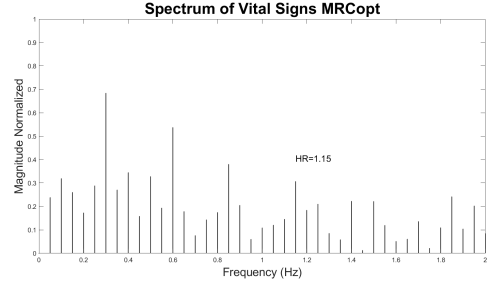
(b) MIMO MRCopt AD @77GHz

Figure 5.52: MIMO AD @77GHz, 1 meter

The CSD method with MRC again has introduced high energy spectral content between 0.8Hz and 1.2Hz resulting in a poor estimate. The MRCopt method has the same issues. Figure 5.53a and 5.53b show MIMO results with CSD.



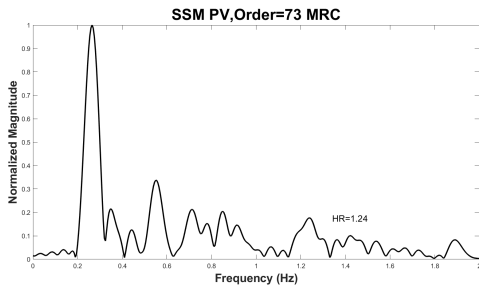
(a) MIMO MRC CSD @77GHz



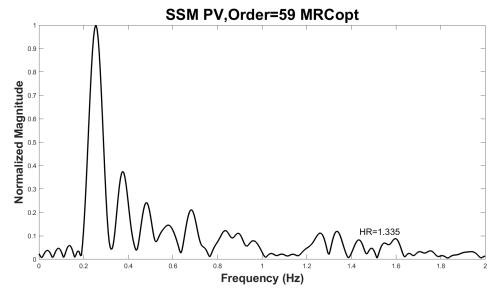
(b) MIMO MRCopt CSD @77GHz

Figure 5.53: MIMO CSD @77GHz, 1 meter

SSM-AD has improved the SNR around 1Hz and made a good estimate for MRC. The MRCopt estimate is a bit high. Figure 5.54a and 5.54b show MIMO results with SSM order estimation.



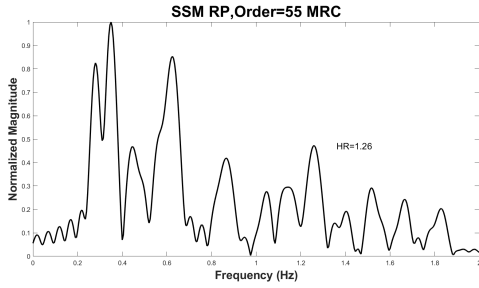
(a) MIMO MRC w/ SSM-AD Order Est.
@77GHz



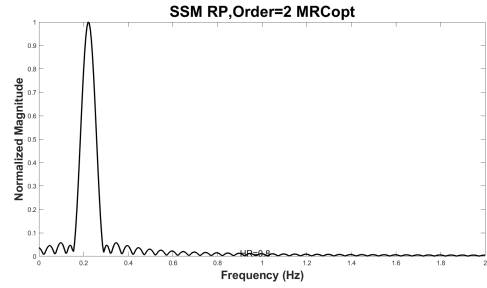
(b) MIMO MRCopt w/ SSM-AD Order Est.
@77GHz

Figure 5.54: MIMO SSM-AD @77GHz, 1 meter

MRC performs well with CSD, however, MRCoPt only estimates the breathing frequency since the order estimation was too low to include higher spectral content. In practice, this might be resolved with noting that the overall signal energy could suddenly change to an unrealistic value based on previous estimates. Figure 5.55a and 5.55b show MIMO results with SSM order estimation.



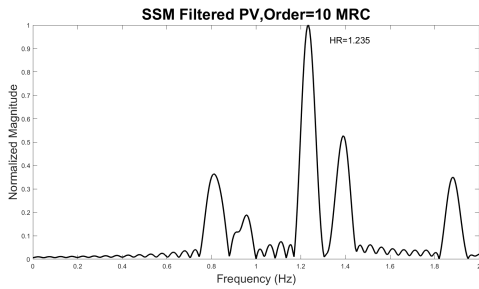
(a) MIMO MRC w/ SSM-CSD Order Est.
@77GHz



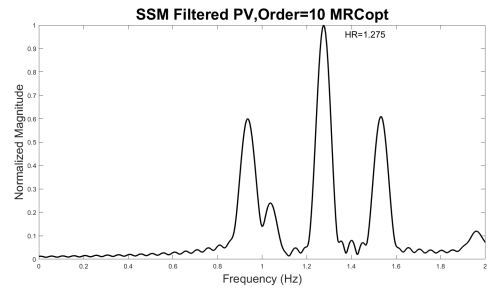
(b) MIMO MRCoPt w/ SSM-CSD Order Est.
@60GHz

Figure 5.55: MIMO SSM-CSD @77GHz, 1 meter

The final SSM example using SSM-AD BP shows excellent results again for both MRC and MRCoPt. Figure 5.56a and 5.56b show MIMO results with SSM and bandpass filtering.



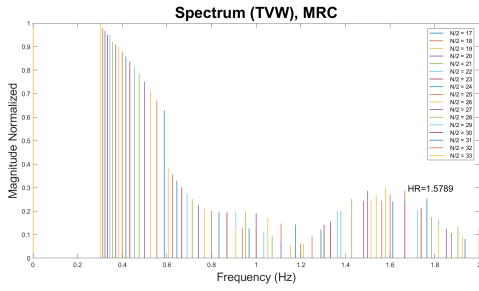
(a) MIMO MRC SSM-AD-BP @77GHz



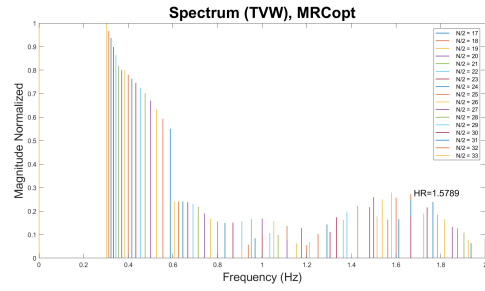
(b) MIMO MRCoPt w/ SSM-AD BP @77GHz

Figure 5.56: MIMO SSM-AD BP @77GHz, 1 meter

Figure 5.57a and 5.57b show MIMO results with TVW-AD. The correct cardiac rate could not be extracted with TVW-AD for both processing techniques, even with adjusting the time window.



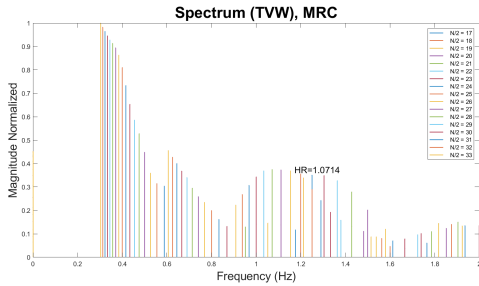
(a) MIMO MRC TVW-AD @77GHz



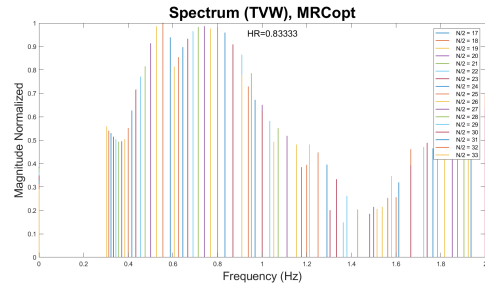
(b) MIMO MRCopt TVW-AD @77GHz

Figure 5.57: MIMO TVW-AD @77GHz, 1 meter

TVW-CSD also produced poor results for MRC and MRCopt for the 77GHz system. This is not entirely surprising since the TVW-AD method for single Tx-Rx pairs also gave poor results. The TVW method needs improvement to be more robust and report more confident estimates. Figure 5.58a and 5.58b show MIMO results with TVW-CSD.



(a) MIMO MRC TVW-CSD @77GHz



(b) MIMO MRCopt TVW-CSD @77GHz

Figure 5.58: MIMO TVW-CSD @77GHz, 1 meter

Table 5.12 summarizes the MIMO processing results at 77GHz. Clearly, SSM-AD BP again shows the best performance and shows an improvement from averaging the individual channels. For the 77GHz system, AD and CSD were significantly improved which is a good sign since both methods require the least computation time of the methods compared in the table.

As a final comparison between the 60-77GHz systems, Table 5.13 has the MRC and MRCopt results for all of the methods. MIMO has shown to improve the overall channel accuracy and cut down on processing time for all of the channels. In fact, the best SISO results have been achieved using MRC methods with SSM-AD BP. This means less SSM processing needs to occur, saving computation time for other pertinent tasks. TVW-AD had great results for the 60GHz system, but not for 77GHz. After reviewing all the results, what seems best is a mixture of the techniques. This will be elaborated on further in the conclusion in Chapter 6.

Table 5.12: HR % Error MIMO Results @77GHz, 1 meter

Method	Dist.	MRC	MRC opt.	Averaging	Best SISO
AD	1m	5.7%	5.7%	<1%	1.57%
CSD	1m	14.6%	6.5%	36.8%	36.8%
SSM-AD	1m	1.57%	9.7%	6.2%	1.57%
SSM-AD BP	1m	1.57%	1.57%	1%	1.57%
SSM-CSD	1m	1.57%	×	18%	1.57%
TVW-AD	1m	28.3%	28.3%	33.8%	32.8%
TVW-CSD	1m	13%	32%	7.3%	3.3%
TI-FFT BP	1m	NR	NR	15.9	1.57%
TI-EVM	1m	NR	NR	45.6%	20%

Table 5.13: HR % Error MIMO Results 60GHz and 77GHz, 1 meter

Method	Dist.	60GHz	60GHz	70GHz	77GHz
		MRC	MRC opt.	MRC	MRC opt.
AD	1m	1.57%	1.57%	5.7%	5.7%
CSD	1m	14.6	2.4	14.6%	6.5%
SSM-AD	1m	18.6%	1.57%	1.57%	9.7%
SSM-AD BP	1m	1.57%	1.57%	1.57%	1.57%
SSM-CSD	1m	22.7%	2.4%	1.57%	×
TVW-AD	1m	1.57%	1.57%	28.3%	28.3%
TVW-CSD	1m	18.6%	4.8%	13%	32%
TI-FFT BP	1m	NR	NR	NR	NR
TI-EVM	1m	NR	NR	NR	NR

Now that all of the offline processing techniques have been compared for all Tx-Rx pairs for both systems including MIMO combining techniques, the realization of these methods in a real-time system making estimates every 20fps will be demonstrated. The results are preliminary and are meant only to demonstrate future possibilities using the AW1642 and IWR6842 chips for vital sign processing.

5.4 Real-Time Results

The previous results have all been found from post processing. This gives a good picture of what methods will work and why, however, the reason time duration and time complexity was mentioned is because real-time operating systems have time and memory constraints.

This is what defines them as being real-time. Operating and completing the required tasks given the constraints of the system, such as reporting a measurement in a certain time or transferring data and processing before the next chirp takes place. Here, the AWR1642 was programmed as discussed in Chapter 4. *For the previous results shown, MIMO combining techniques were used, but they have yet to be programmed on the chip and are not reported here.* However, this could be a great addition for future contributors. Also, the results use the pre-filtered TI cardiac and breath waveforms, since the data transfer was done in MATLAB. This needed to be done for time constraints and since this is proof of concept, it suffices. Several frames were dropped, but this could be resolved with sending a subset of the packet, processing more on board or using the QtCreator GUI for vital signs which is written in C++. For the purposes of programming the board, adjusting the MATLAB parser was quicker and shows the results in an adequate manner.

Shown in Figure 5.59 are the real-time measurements taken over 30 seconds. The frame rate was 50ms. It is clear that over 5 seconds worth of data was dropped over the course of the experiment, however, the overall picture can still be seen. The results show on-chip TI processing estimates as well as breath and cardiac filtering with a FFT. Additionally, the time-varying window with a 4 second sliding window is used and SSM is used with a 20 second sliding window. For the processing done in MATLAB after data transfer, each processing type had a circular buffer depending on the size of data needed for a high resolution frequency estimation. The TVW buffer was only 4 seconds, or 80 points, whereas the FFT and SSM estimates had 20 second buffers, or 200 points. This effect can be seen as the FFT and SSM estimates become more accurate as more frames are acquired. At first, all buffers are filled with zeros, so the FFT and SSM methods have quite a bit of padding for their respective spectrum until the buffers are filled. Once the buffers are filled, it is a first-in-first-out philosophy such that the frequency resolution remains constant for each estimation type. Breath rate estimates are also included for two methods. Lastly, the TI cross-correlation (X-Corr) estimate is also included.

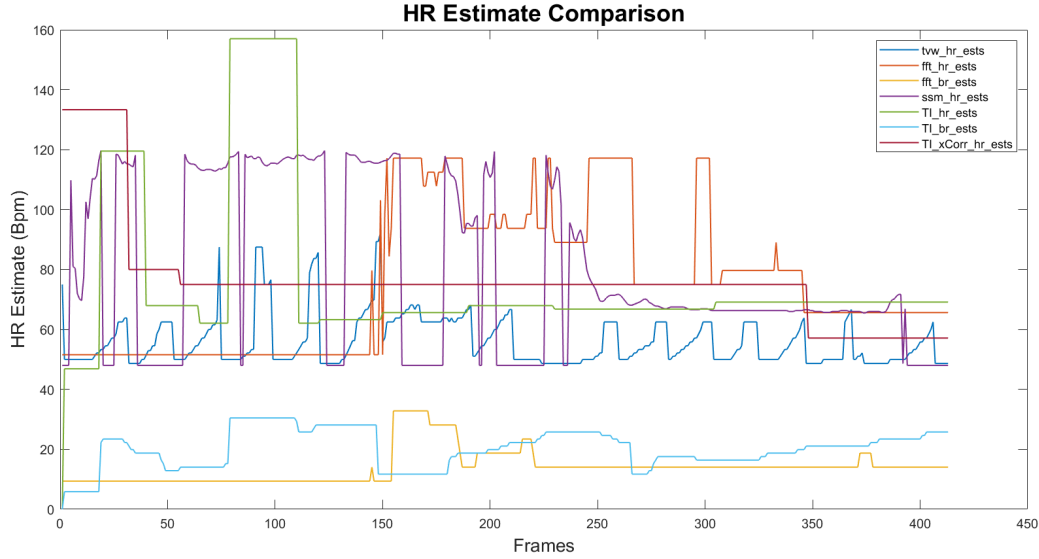


Figure 5.59: AWR1642 Real-time Comparison

Table 5.14 compares the estimate averages over the whole test. Also included is the last 100/200 frames of the measurement when the measurement buffers had time to fill. It is not surprising that these measurements are more accurate, as most of the bad estimates take place at the beginning while the buffers have mostly zeros. This is the case for all the estimation types except for the TVW. It is capable of making good average estimates with a limited number of samples. However, it is noted that it is prone to jumping around in regards to the estimates. In fact, all of the methods show that they are not robust enough for frame by frame accurate measurements, even though a median filter of the last twenty estimates was used for each new estimate. This method was adopted from the TI processing chain and used such that all methods had similar estimation reporting. The subjects common vital signs are a breath rate of 10-13bpm and heart rate of 66-70bpm however verification could not be used at the time of real-time operation. The goal here is to show the ability and further experiments can be conducted to verify the accuracy. Only one of the processed channel results are shown due to time constraints with the additional MATLAB processing.

Table 5.14: Real-Time Estimation Averages

Method	Type.	Total Avg. (bpm)	Last 200 Avg. (bpm)	Last 100 Avg. (bpm)
X-Corr	HR	76.2	69	63
TVW	HR	56	53	53
SSM	HR	78.4	66.6	63
TI-FFT BP	HR	74.6	81	70.3
TI-EVM	HR	75.6	68	69
TI-FFT BP	BR	14	14.5	14
TI-EVM	BR	20	20	21

The IWR6843 MIMO output coding will take place in future works. The goal of this section was to demonstrate the capabilities with an example of a few processing methods estimation comparisons. The behavior of the estimations during each frame can be viewed, which is of great importance for overall HR and BR tracking as well as improving estimation accuracy. To improve vital signs processing algorithms even more, an ECG readout with the processing methods as shown in the above figure could give researchers a target goal for the algorithms. Of course, many subjects would have to be recorded to prevent over fitting.

Chapter 6

Conclusion

This work began with the fundamental explanation of mmwave systems and their uses. In particular the use of mmwave systems as radar systems was discussed and multiple types of radar systems were presented. Furthermore, mmwave system architecture, operation and design were presented specifically for the AWR1642 to show the promise of mmwave systems as a fully operational sensor equipped with antenna arrays and on-board signal processing. The use case for this work was for vital sign detection of the breath and heart rate, with a focus on the heart rate. Multiple options for signal processing techniques were presented in detail and their advantages/disadvantages were mentioned in regards to signal quality and computation time. Experiments were conducted with one subject at two different distances (up to 1m) to compare to state of the art results from lower frequency systems which reported high estimation accuracy for breathing and cardiac rates. Real-time abilities were explored and an AWR1642 chip was programmed to process MIMO channels for vital signs estimation, which has not been done with the AWR1642 chip in any literature to date that the author is aware of.

6.1 Summary of Results

It was shown that the 60GHz and 77GHz mmwave systems used in this work could accurately detect human vital signs for the breath and heart rate, however, significant work had to be done to improve the SNR for cardiac estimation whereas the breath rate can be

accurately predicted with filtering and a FFT. It was also shown that harmonics can plague estimation accuracy and harmonic cancellation should be used to try to suppress the breathing harmonics which are near the target cardiac signal frequency. There are great complications associated with this that must be addressed in future result processing. It was shown that AD, SSM-AD and SSM-AD with bandpass filtering consistently report high estimation accuracy for both systems and for MIMO processing. MIMO has also been shown to improve estimation accuracy for both systems compared to the overall channel averages. This has the advantage of less computation time, and improved estimation confidence since all of the channels are considered, but weighted according to MRC. Overall, both systems are capable of producing results on par with current literature reports at lower frequency. Occasionally, the TVW method could produce high estimation accuracy however this accuracy degraded as the subject was moved to 1m. The real-time results show the ability of the processing methods to make estimates given a time constraint. All of the methods relying on a single FFT must acquire an adequate number of samples prior to making an accurate estimation. On the slow-time axis scale of 20fps, this is usually between 10-20 seconds which corresponds to 200-400 data points. As more points are acquired, the accuracy can increase. The TVW method does not need a high number of samples, however it requires optimizing the window time based on the breath rate, which can be done considering the breath rate can be easily determined. The results for optimizing the window size were not as robust as predicted.

Mmwave systems are more sensitive to random body motions due to their operating frequencies. Also, due to increased path loss, the system accuracy will be significantly affected by the target distance, which limits the applications of the mmwave systems for vital sign detection. Not many hardware changes can be made to improve this since both systems already operate at maximum radiation power limits. The maximum distance which the systems can operate and accurately report vital signs has not been determined, although some experiments at 1.5m have been conducted with mixed results. Hardware changes to the system to improve performance could be done by cascading chips and antenna arrays for multiple sensors and increased MIMO capabilities, which may be useful future work although the additional antenna arrays must be spaced such that radiation power restrictions are met.

6.2 Contribution

The contribution of this work to the community is that it provides a detailed account of numerous processing techniques which may be more favorable in some scenarios than others and that it verifies reliable vital estimation for the breath and heart rate up to one meter using mmwave systems and advanced signal processing with 60GHz and 77GHz radar systems. In addition, the exploration of processing methods with a demonstration of real-time performance gives future researchers a foundation for developing adaptive algorithms, fusing results from multiple methods, or using certain methods results to decide which technique should be used. This could change dynamically if one defines a confidence level for each estimate, which could be verified by something like SSM. SSM is more taxing, but if a simpler technique is reporting similar estimations, SSM might not be required every iteration. For example, the TVW technique could be used until the buffer for SSM was full, which could then be used to verify the previous TVW estimates. Additionally, one method could be used for keeping an overall average bpm, while a method such as TVW tries to track the heart rate on a smaller time scale. The possibilities for fusing the algorithms shown are vast but this work gives some insight into starting that process.

Another contribution was the programming of the AWR1642 to process every virtual antenna for a vital estimation, as well as transferring the breathing, cardiac and range bin phase values during every processing cycle over UART. There was not enough time to program the MIMO processing techniques onto the chip, however, this could be done at a later date. MRCopt seems like a good place to start, although the chip seems to have enough available memory to perform eigendecomposition for implementing methods like MRC and SSM directly onto the chip. This work also explored MIMO for vital signs, which has only been done minimally in literature.

Lastly, an offline processor for the TI algorithm was created from the original code for the AWR1642 chip. This has been added to GitHub for future development for the vital signs processing for real-time systems using the AWR and IWR systems. It is also the only work of this kind to the author's knowledge. It is crucial for team development and testing processing methods without the hardware, which allows for multiple individuals to

be developing at the same time. The processing emulates the on-chip processing by using previously recorded data from Mmwave studio and emulating the chirp and frame processing steps done on the chip, then outputting the results to binary file following the UART packet structure defined by the EVM. Of course, code composer studio could be used for testing new code but the flashing, debugging process with the hardware was found to be troublesome. It was the hopes that this processing could also be used for non-TI systems by the research group and has shown some good results at 2.4GHz and 24GHz but the code needs some minor adjustments still to verify accuracy with results from different hardware systems.

6.3 Future Work

Additional work which would be complementary to the work presented here would be programming on the AWR1642 chip for MIMO processing, programming the IWR6843 to do the same and adjusting the QtCreator GUI to receive MIMO data. Since the current UART transmission goes to a host computer, it may be worthwhile to instead transmit the data over serial peripheral interface (SPI) to a microcontroller with a mini LCD display to make a truly portable system. The biggest task for future work will be beamforming of the transmission and digital beamforming on the receive end. The advantages of this are an increased SNR, and the ability to detect multiple subject vital signs which was not done in this work. With mmwave systems, it seems necessary that beamforming is used for multiple subject detection due to high frequencies sensitivity to tiny body motions. Preliminary tests with two subjects have been done but were not reported here as significant work for vital detection of multiple subjects needs to be completed. Beamforming seems like the necessary starting point before any further tests are conducted with multiple subjects.

6.4 Concluding Remarks

Although the focus here was on vital sign detection, it should be further stressed that the AWR1642 and IWR6842 systems are capable of a wide range of radar applications like people tracking, gesture recognition and multiple target detection. It is the hope that this work

can serve as a guide for future work in vital signs, but also exposes future researchers to the ability of already commercially available products from TI for prototyping signal processing algorithms or new radar applications for practical use cases. The ability to customize the chip operation should be exciting for anyone interested in embedded system work, computer science or signal processing with real-time systems. Lastly, the hopes of this project were to be a complete system top-down explanation and exploration of current mmwave system technology and their abilities to further guide future researchers interested in radar and signal processing.

Bibliography

- [1] L. Ren, H. Wang, K. Naishadham, O. Kilic, and A. E. Fathy. Phase-based methods for heart rate detection using uwb impulse doppler radar. *IEEE Transactions on Microwave Theory and Techniques*, 64(10):3319–3331, Oct 2016. 2, 3, 10, 31, 32, 38, 73, 79, 80, 88, 94, 95
- [2] Lingyun Ren, Hao-fei Wang, K. Naishadham, Q. Liu, and A. E. Fathy. Non-invasive detection of cardiac and respiratory rates from stepped frequency continuous wave radar measurements using the state space method. In *2015 IEEE MTT-S International Microwave Symposium*, pages 1–4, May 2015. 2, 3
- [3] T. Sakamoto. Noncontact measurement of human vital signs during sleep using low-power millimeter-wave ultrawideband mimo array radar. In *2019 IEEE MTT-S International Microwave Biomedical Conference (IMBioC)*, volume 1, pages 1–4, May 2019. 2, 5, 51, 52, 95
- [4] J. Tu and J. Lin. Fast acquisition of heart rate in noncontact vital sign radar measurement using time-window-variation technique. *IEEE Transactions on Instrumentation and Measurement*, 65(1):112–122, Jan 2016. 2, 3, 37, 38, 70, 73, 79, 80, 88, 91, 94, 95
- [5] T. Sakamoto, R. Imasaka, H. Taki, T. Sato, M. Yoshioka, K. Inoue, T. Fukuda, and H. Sakai. Feature-based correlation and topological similarity for interbeat interval estimation using ultrawideband radar. *IEEE Transactions on Biomedical Engineering*, 63(4):747–757, April 2016. 2, 3, 5
- [6] J. Lee and S. Park. A 14 ghz non-contact radar system for long range heart rate detection. In *2013 Proceedings of the International Symposium on Antennas Propagation*, volume 01, pages 204–206, Oct 2013. 3
- [7] M. Alizadeh, G. Shaker, J. C. M. D. Almeida, P. P. Morita, and S. Safavi-Naeini. Remote monitoring of human vital signs using mm-wave fmcw radar. *IEEE Access*, 7:54958–54968, 2019. 4, 5, 31

- [8] Zhicheng Yang, Parth Pathak, Yunze Zeng, Xixi Liran, and Prasant Mohapatra. Monitoring vital signs using millimeter wave. pages 211–220, 07 2016. 4, 5
- [9] Huey-Ru Chuang, Hao-Chung Kuo, Fu-Ling Lin, Tzuen-Hsi Huang, Chi-Shin Kuo, and Ya-Wen Ou. 60-ghz millimeter-wave life detection system (mlds) for noncontact human vital-signal monitoring. *Sensors Journal, IEEE*, 12:602 – 609, 04 2012. 4, 5
- [10] S. Wang, A. Pohl, T. Jaeschke, M. Czaplik, M. Köny, S. Leonhardt, and N. Pohl. A novel ultra-wideband 80 ghz fmcw radar system for contactless monitoring of vital signs. In *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 4978–4981, Aug 2015. 5
- [11] Jenshan Lin and Changzhi Li. *Microwave Noncontact Motion Sensing and Analysis*. John Wiley & Sons, Inc, Hoboken, New Jersey, 2014. 7, 8, 12
- [12] David M. Pozar. *Microwave and RF Design of Wireless Systems*. John Wiley & Sons, Inc, 2001. 9, 16, 17
- [13] Karthik Ramasubramanian. Using a complex-baseband architecture in fmcw radar systems. *Texas Instruments*. 19
- [14] Texas Instruments. Flip chip ball grid array package. *Texas Instruments*. 19
- [15] J. Tu and J. Lin. Respiration harmonics cancellation for accurate heart rate measurement in non-contact vital sign detection. In *2013 IEEE MTT-S International Microwave Symposium Digest (MTT)*, pages 1–3, June 2013. 30
- [16] K. Naishadham and J. E. Piou. A robust state space model for the characterization of extended returns in radar target signatures. *IEEE Transactions on Antennas and Propagation*, 56(6):1742–1751, June 2008. 32, 35, 36, 65
- [17] Donald E. Kirk. *Optimal Control Theory: An Introduction*. Prentice-Hall, Inc, Englewood Cliffs, New Jersey, 1970. 32, 33
- [18] R. Kalman. On the general theory of control systems. *IRE Transactions on Automatic Control*, 4(3):110–110, December 1959. 33

- [19] J.E. Piou. A state identification method for 1-d measurements with gaps. 08 2005. 33, 35
- [20] B. D. Rao and K. S. Arun. Model based processing of signals: a state space approach. *Proceedings of the IEEE*, 80(2):283–309, Feb 1992. 33
- [21] Alan Kaylor Cline and Inderjit S. Dhillon. *Computation of the Singular Value Decomposition*. CRC Press, 2006. 39
- [22] Alan V. Oppenheim and John. R. Schafer, Ronald. W. with Buck. *Discrete-Time Signal Processing 2nd ed*. Prentice-Hall,Inc, Upper Saddle River, New Jersey, 1999. 39, 40, 42, 43
- [23] R. G. Lorenz and S. P. Boyd. Robust minimum variance beamforming. *IEEE Transactions on Signal Processing*, 53(5):1684–1696, May 2005. 50
- [24] D. G. Brennan. Linear diversity combining techniques. *Proceedings of the IEEE*, 91(2):331–356, Feb 2003. 51

Vita

Kellen Oleksak grew up in Mentor, OH. He became a resident of Tennessee during his time in Nashville where he worked on music recordings for songwriters and artists. While working at a commercial country music facility, he became intrigued by audio electronics and eventually it led him towards the electrical engineering profession. His interests are vast and ever changing but his primary focus at this moment is in RF/Microwave engineering and digital signal processing. Kellen spends his free time in the mountains, on his bicycle or enjoying the pleasures of well orchestrated musical performances.