Th3C-3

Convolutional Neural Network-Based MIMO Radar Channel Selection for Improving Robust Remote Heart Rate Estimation Accuracy

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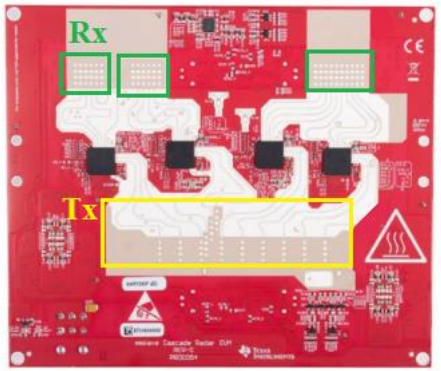
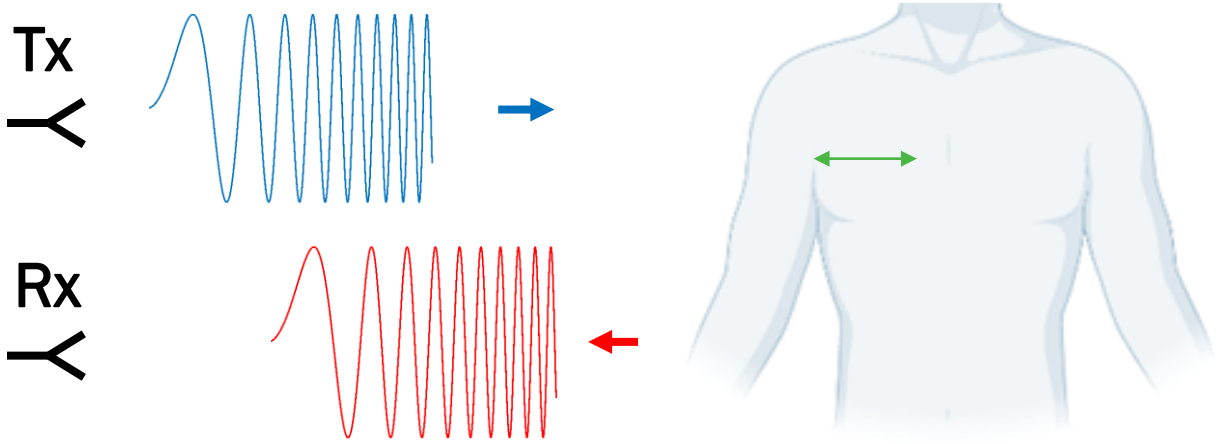
Outline

- Background + Motivation
- Methods
- Experiments
- Results
- Conclusion

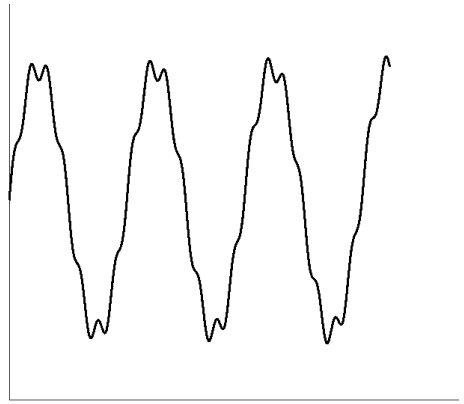
Background

- Frequency modulated continuous wave (FMCW) radar can be used to get vital sign information remotely



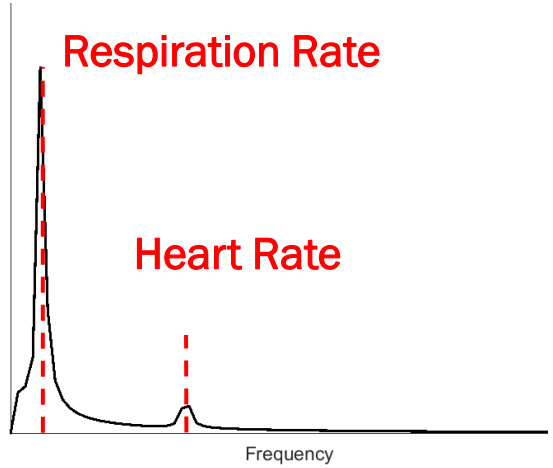


Phase Extraction



FFT

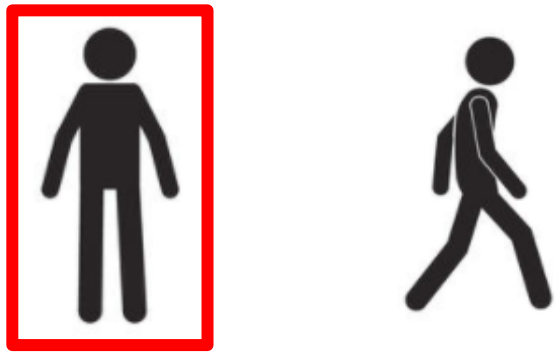
Ideal Scenario

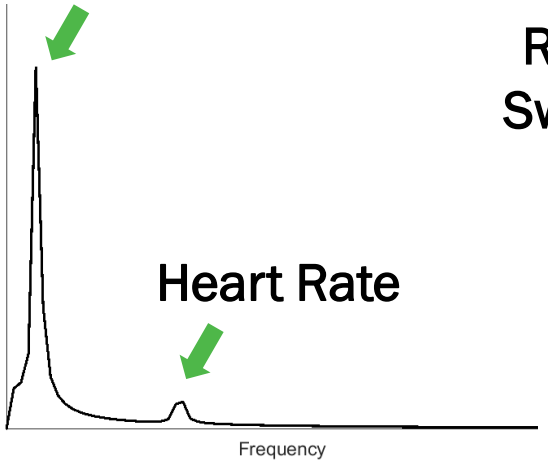


Motivation

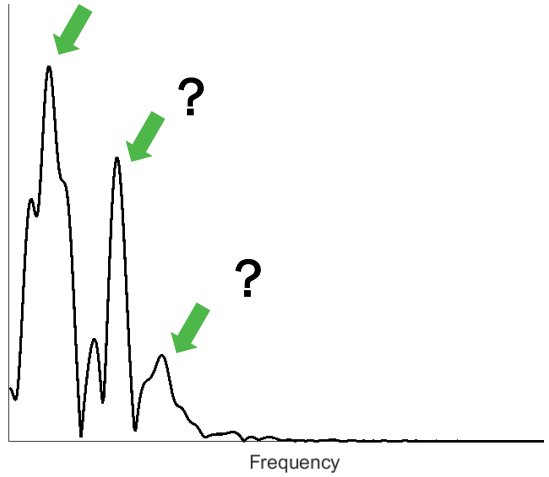
- Simple:

- <u>More Complicated:</u>





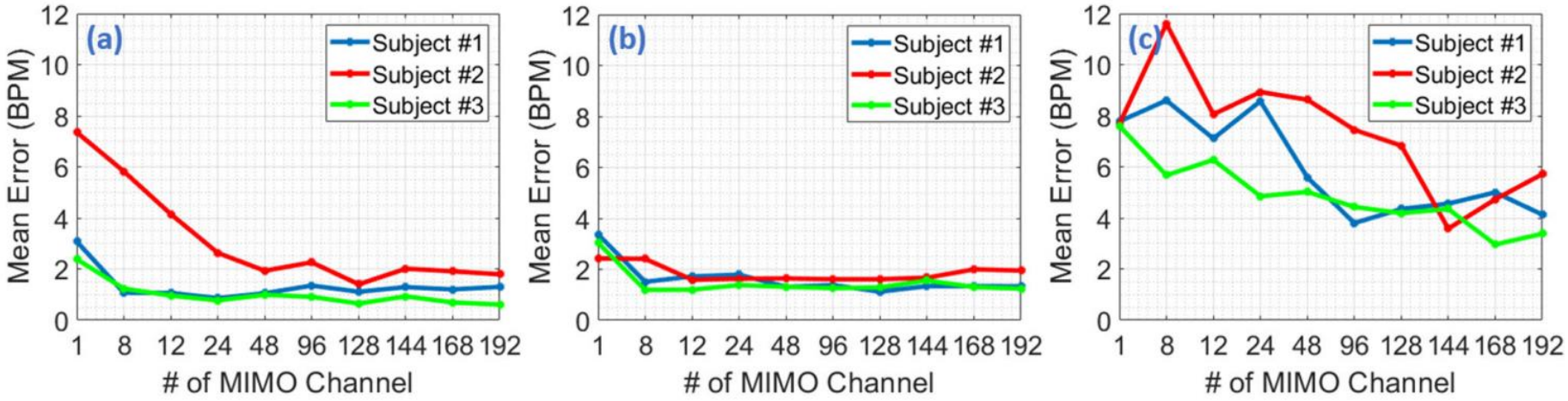
Random Body Swaying Motion (RBSM)



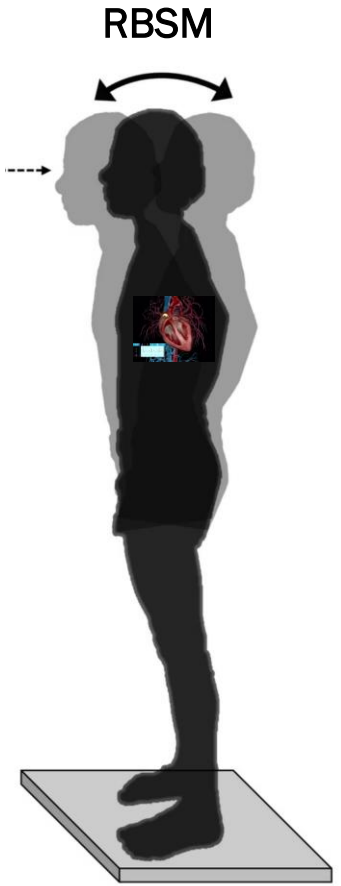
- How do we deal with this RBSM?
- How to deal with respiration harmonics?

Motivation

- Has been shown that performance improves as the number of MIMO channels used increases when addressing RBSM in standing subjects
- With more channels comes the need to optimally combine information (and increased computation time)



0.5m 1m 1.5m



Motivation

- Maximal Ratio Combining (MRC) is a signal processing technique used to combine data from multiple channels to increase the signal-to-noise ratio (SNR)
- Channel selection as a preprocessing step to MRC is a way to further improve results
  - Only include “good channels” in the final summation
  - Difficult to classify good channels vs. bad channels automatically

$$\phi_{MRC}(t) = \sum_{i=1}^{N} w_i \phi_i(t)$$

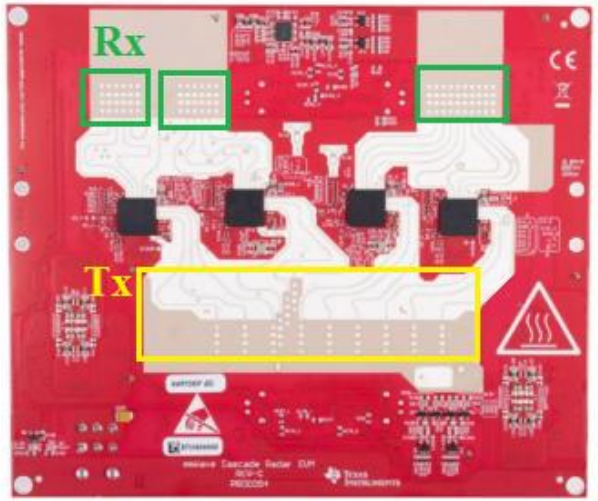
Goal

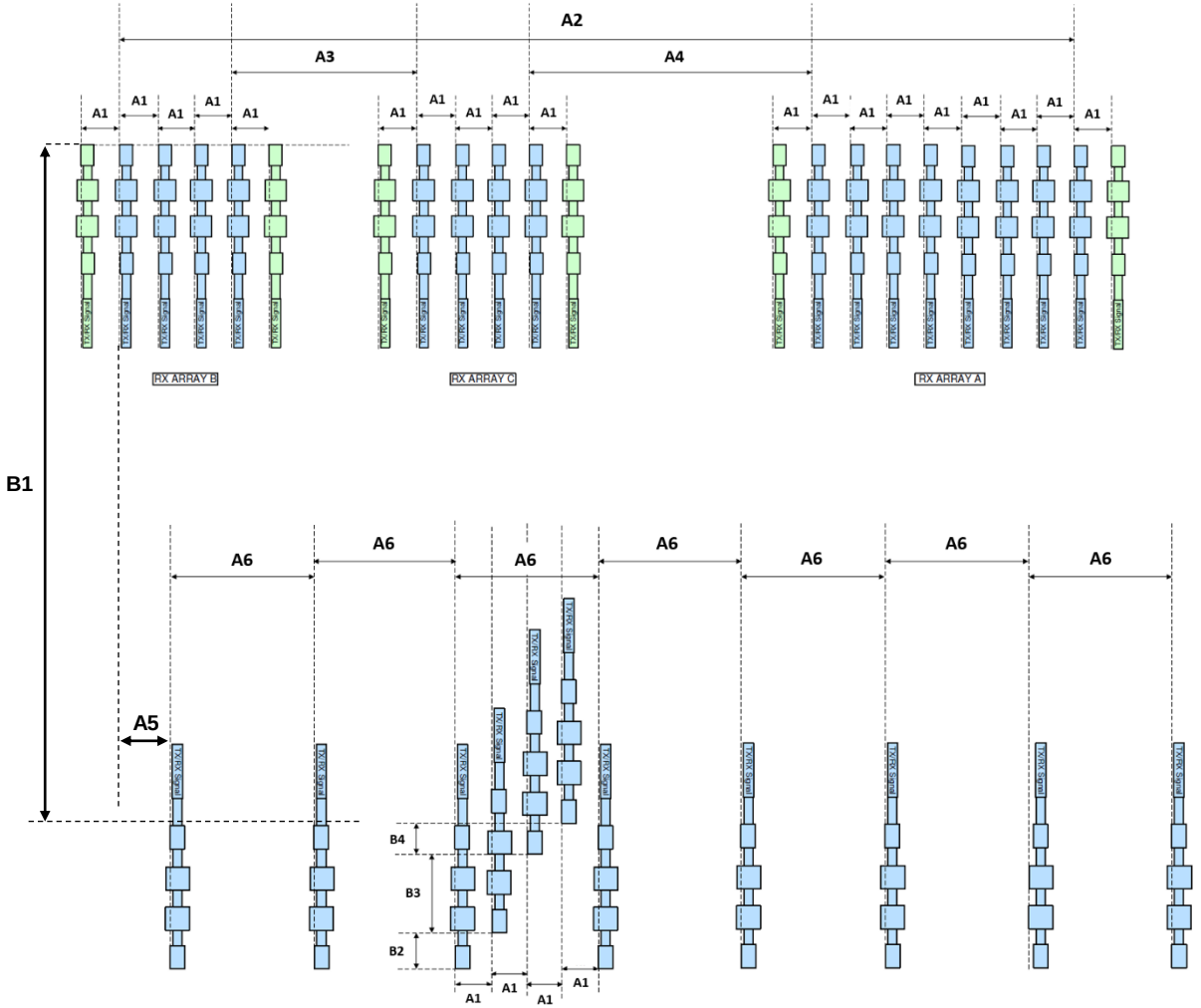
- Develop a convolutional neural network (CNN)-based framework to automatically classify the MIMO channels of a 192 channel 77GHz FMCW radar as either good or bad based on both time and frequency information

- This will aid MRC in the summation of phase variation signals with the goal of improving heart rate estimation accuracy of standing subjects

Methods - Hardware

- MMWCAS-RF-EVM from TI used in this study
- 192 Total Tx/Rx Channels





Methods – Chirp Configuration

Chirp Parameters	
Start Frequency, f_c (GHz)	77
Frequency Slope, S (MHz/μs)	98
Idle Time (μs)	250
TX Start Time (μs)	1
ADC Start Time (μs)	10
ADC Samples	64
ADC Sampling Frequency (MHz)	2.2
Ramp End Time (μs)	40
Number of Chirp Per Frame	8
Slow-time Sampling Frequency, $f_s = 1/T_s$ (Hz)	20

Detectable Range & Velocity Parameters	
Maximum detectable range (m)	3.3
Range resolution (cm)	3.83
Maximum detectable velocity (m/s)	31
Velocity resolution (m/s)	7.9

Methods - MRC

- **Maximal Ratio Combining (MRC):** Weighted average of different MIMO channels

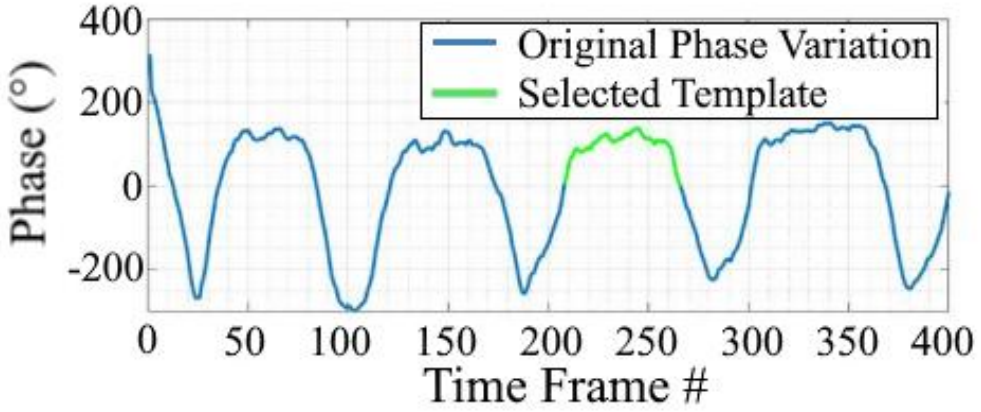
$$\phi_{MRC}(t) = \sum_{i=1}^{N} w_i \phi_i(t)$$

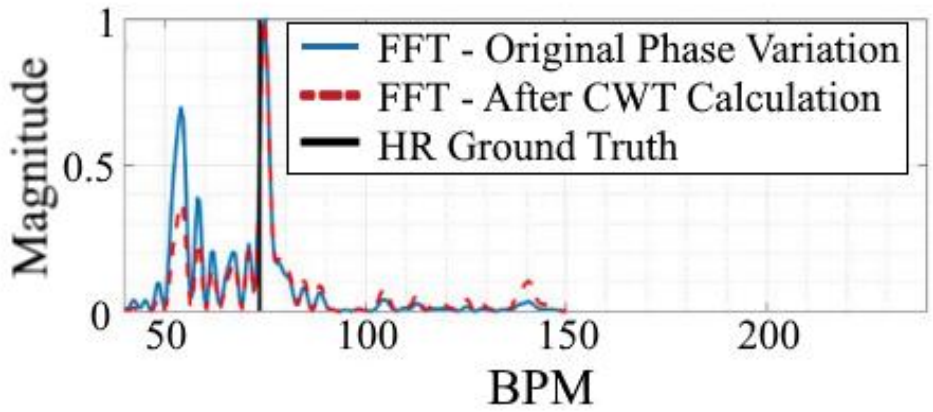
- To determine w_i, a cross−correlation matrix is formed based on the time domain signals channels $\phi(t) = [\phi_1(t), \phi_2(t), \ldots, \phi_N(t)]$

$$R_{ij} \simeq \int \phi_i(t)\phi_j^*(t)dt = [v_1 v_2 \ldots v_N] diag[\sigma_1 \sigma_2 \ldots \sigma_N][v_1^* v_2^* \ldots v_N^*]^T$$

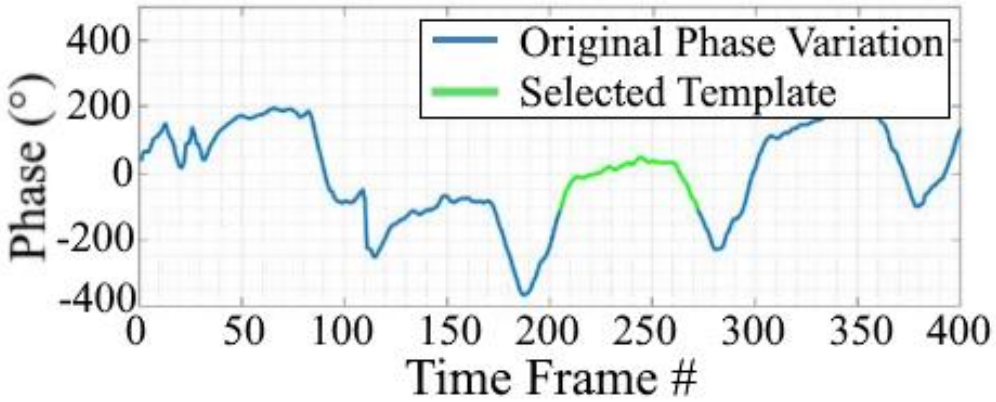
where σ_{1-N} are the eigenvalues and v_{1-N} are the eigenvectors for N channels. This MRC method uses the first eigenvector as weights for the received signal on all TX-RX pairs such that $\mathbf{w} = \boldsymbol{v_1^H}$

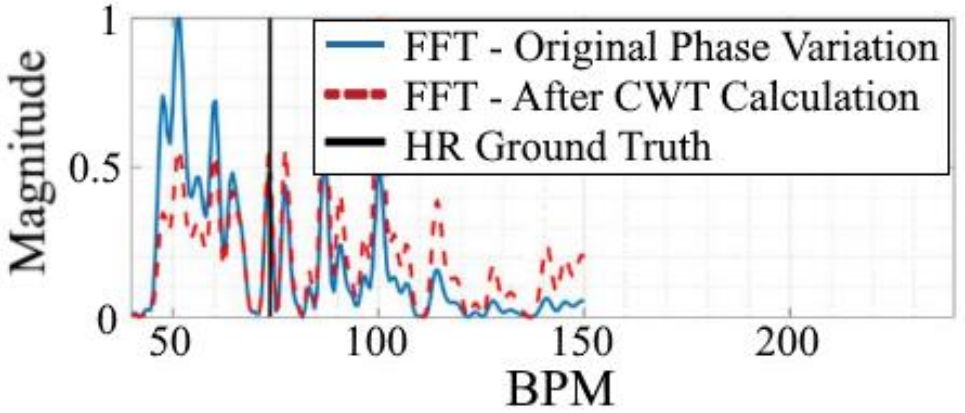
Methods – Channel Classification





Good Channel

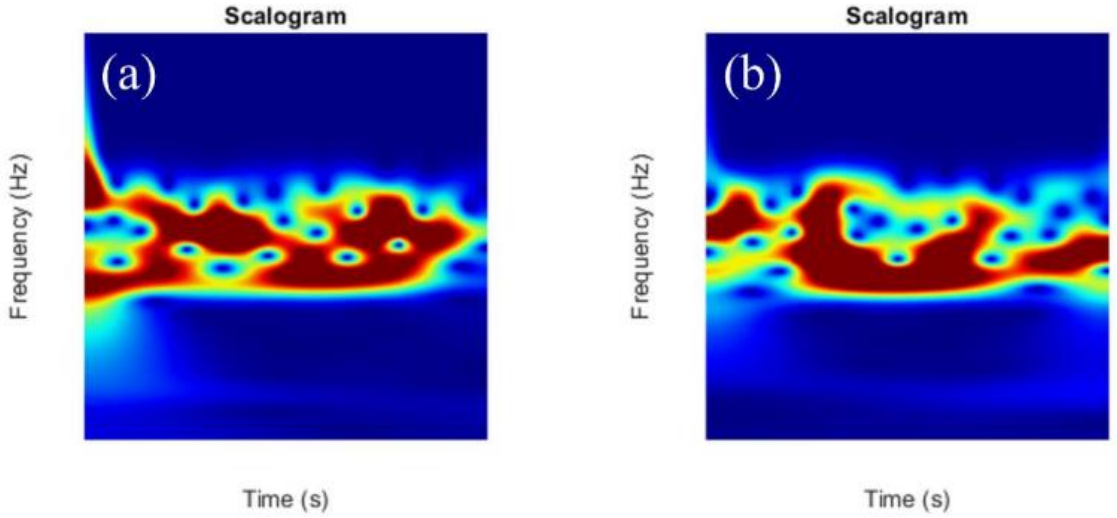




Bad Channel

Methods – Scalogram Creation

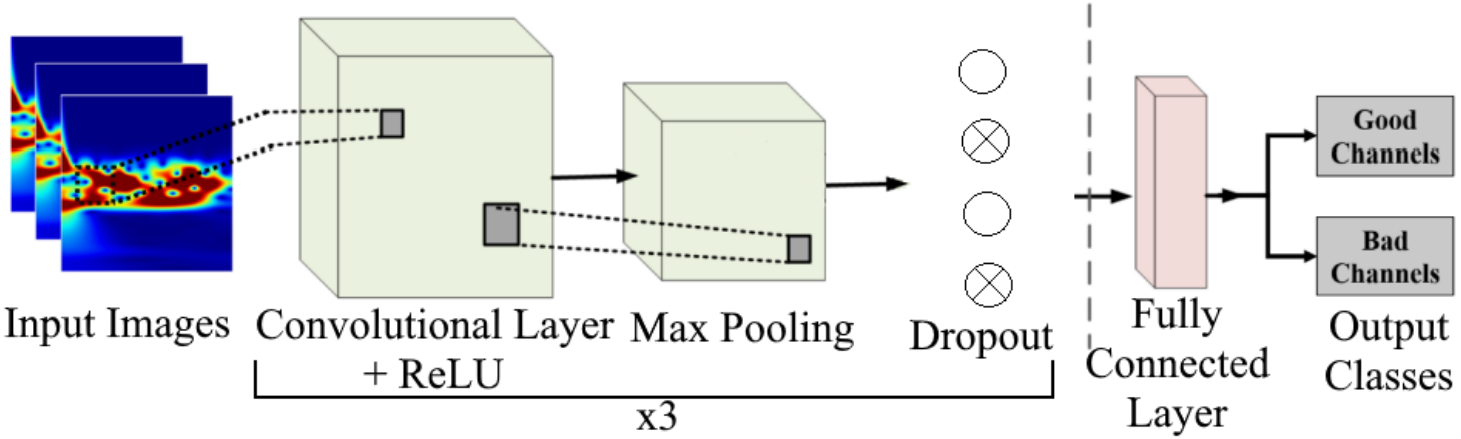
- Time-frequency features are extracted from the phase variation signals of each channel through scalograms using the continuous wavelet transform (CWT)
- Images are resized to be 224x224 pixels with 3 channels representing red, green and blue

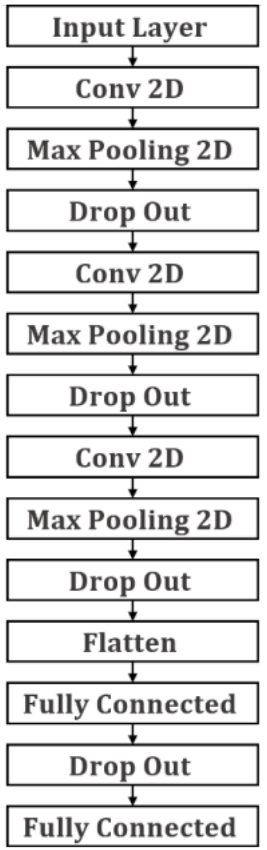


Good Channel Bad Channel

Methods - Network Architecture

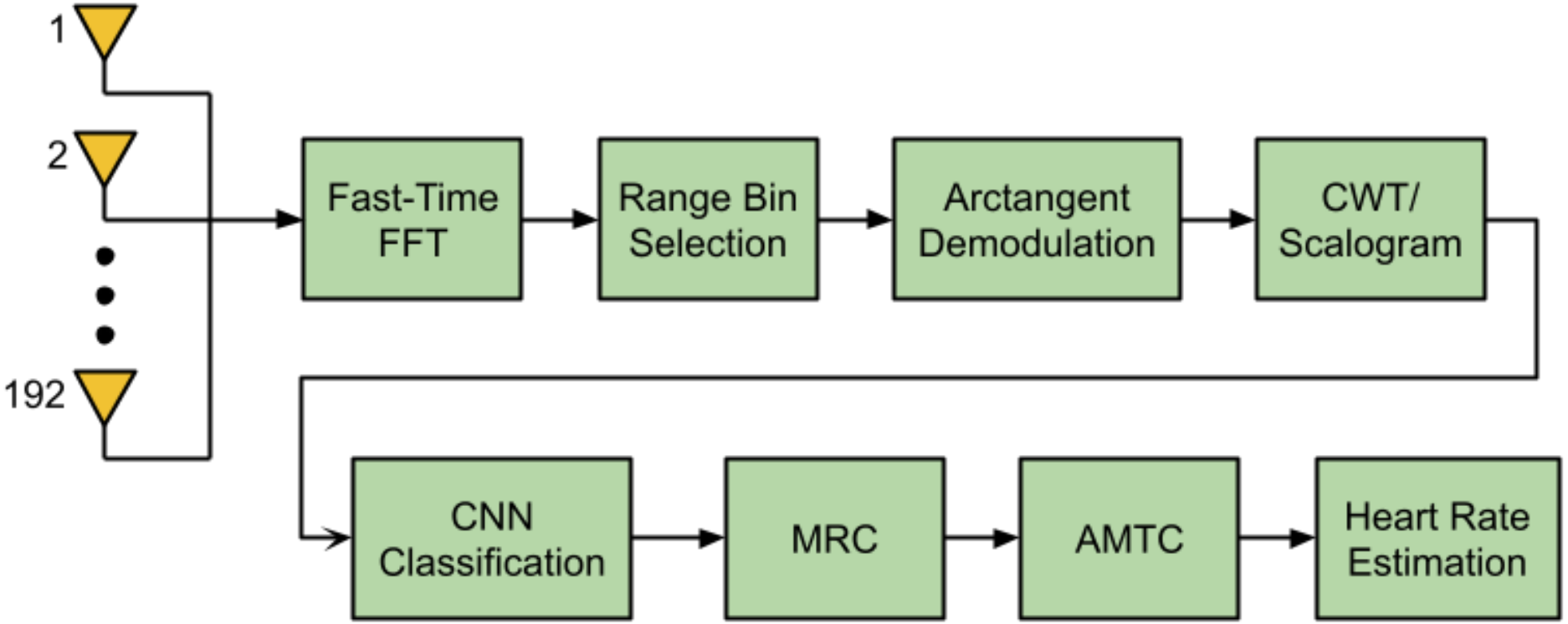
- A typical CNN such as the one proposed in [1] can be used.
- The input layer takes in a 224x224x3 image representing 20 seconds of radar data for a single transmit-receive channel.





[1] Andre Esteva et al. “Dermatologist-level classification of skin cancer with Deep Neural Networks”. In: Nature 542.7639

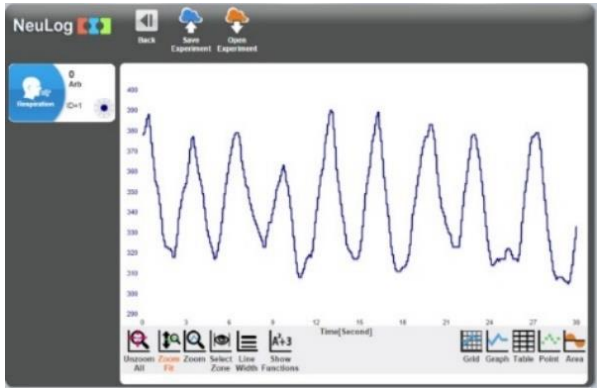
Methods – Signal Processing Chain



Experiments – Ground Truth Sensors

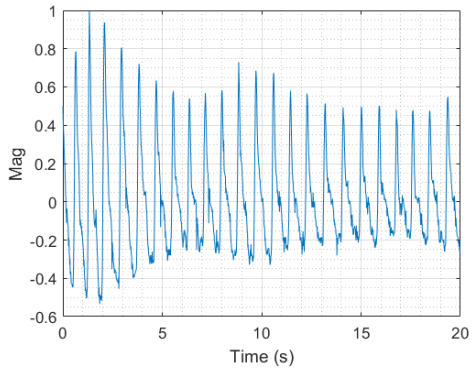
Belt Sensor NUL-236

Respiratory Waveform



Pulse Sensor SEN-11574

Heartbeat Waveform



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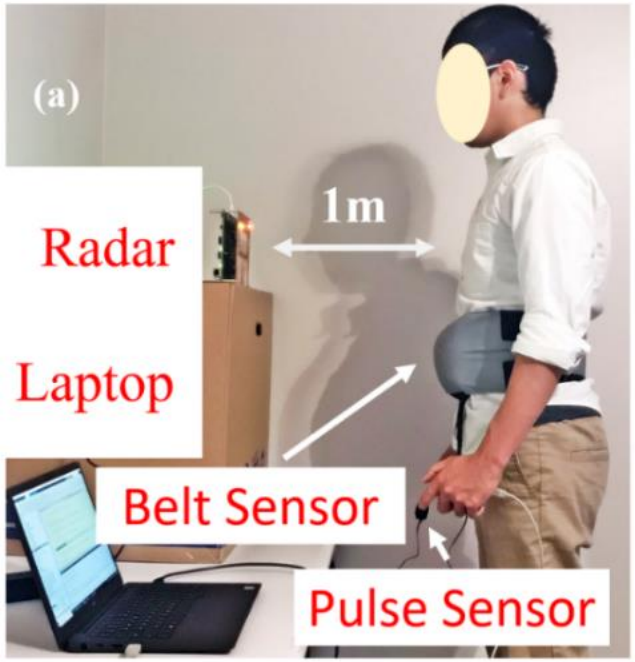
Experiments – Subjects and Scenario



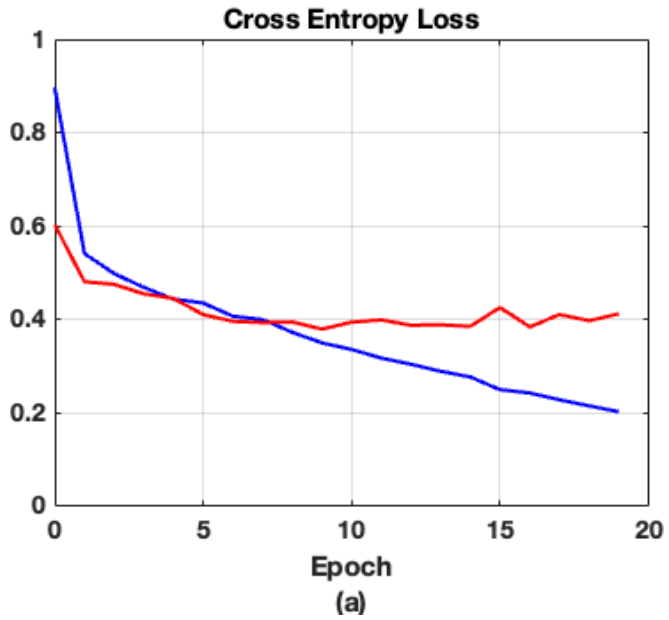
Experimental Setup

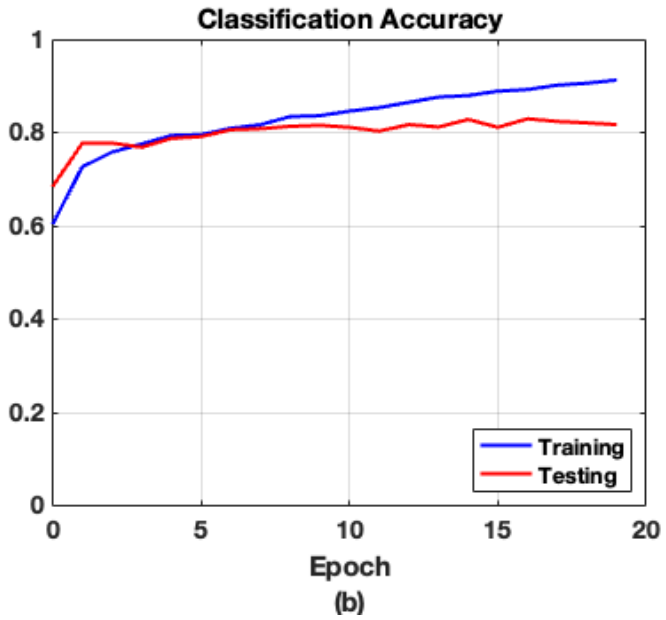
Participant #	Gender	Age	Weight (lbs)	Height (in)
1	Male	29	125	64
2	Female	30	110	62
3	Male	22	185	70
4	Male	26	150	69
5	Female	54	150	61
6	Female	65	110	64
7	Female	64	235	67
8	Male	23	170	72
9	Male	33	340	73
10	Male	27	125	66
Mean ± Std	-	37 ± 17	170 ± 71	66.8 ± 4

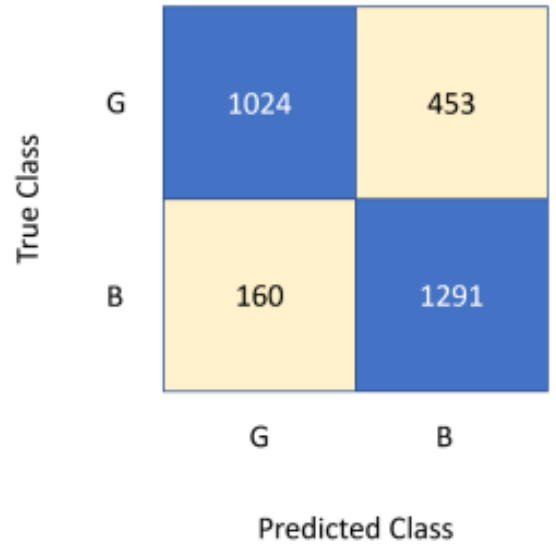
Results – Network Performance

Training Hyperparameters

Parameter	Value
Optimizer	Stochastic Gradient Descent
Learning Rate	0.001
Momentum	0.9
Mini Batch Size	16
Epochs	20

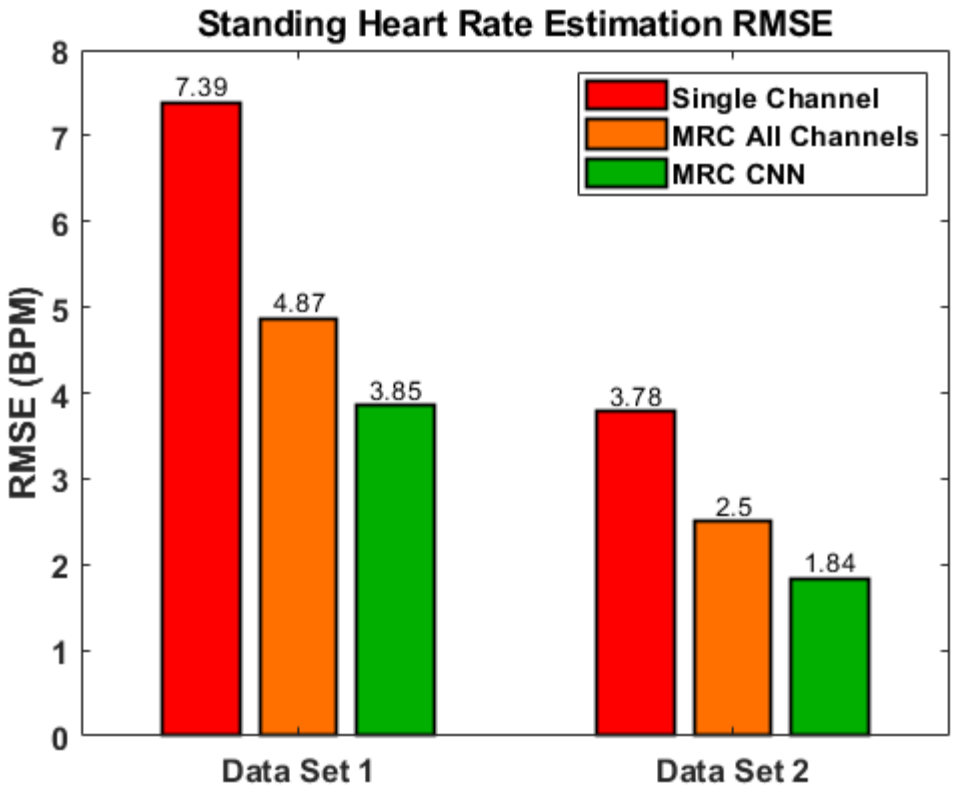






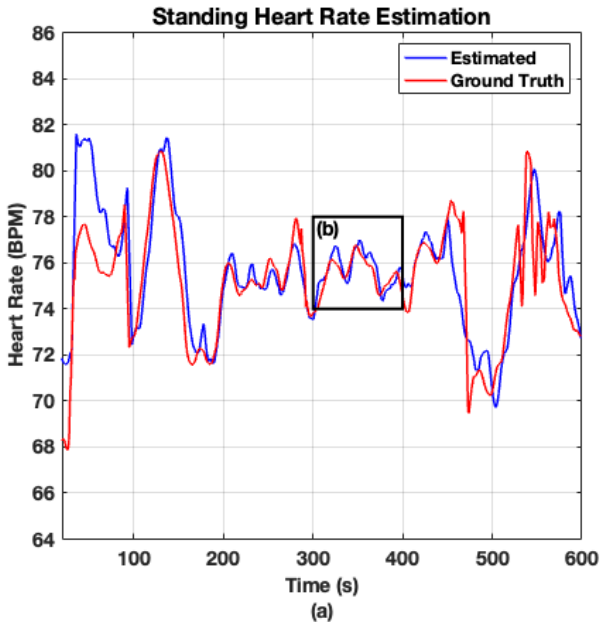
Results

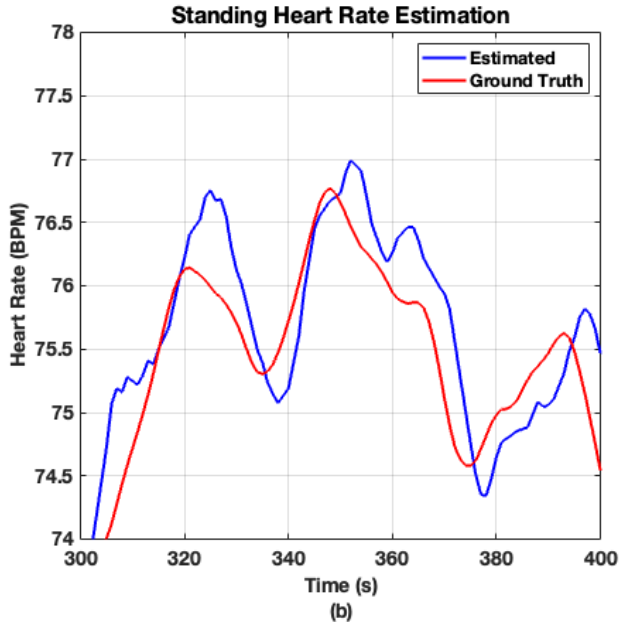
- Results show an improvement in heart rate estimation error when only including “good channels” in the MRC summation
- Over 20% improvement when compared to using all channels
- Much greater improvement compared to using a single channel radar



Results

- An example of the estimation accuracy over time is shown for Data Set 2
- It can be seen that the highly varying heart rate of a person standing for 5 minutes can be accurately tracked over the entirety of the experiment.





Limitations and Future Challenges

- It is desired to improve the channel classification accuracy through network improvements
- Apply this technique to a wider range of highly challenging scenarios (walking)
- Possibility of feeding raw I and Q data rather than scalogram images

Conclusion

- A CNN-based method for an automatic process of MIMO channel selection for a mmWave radar was presented to improve remote heart rate estimation accuracy in scenarios containing RBSM
- A channel classification accuracy of over 80% was obtained, allowing for the improvement of the channel summation done by MRC and outperforming the single-channel radar technique
- The heart rate estimation accuracy results of two long-duration standing subject data sets were shown to improve after the use of the trained CNN model by over 20%

Questions?

Contact:

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