Compressive Wireless Pulse Sensing

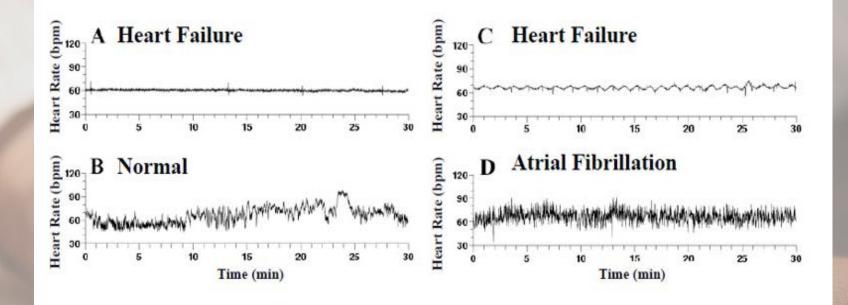
CTS 2015 – Internet of Things

Harvard University Kevin Chen Harnek Gulati HT Kung Surat Teerapittayanon



Tracking reliable pulse waves for long term health diagnostics

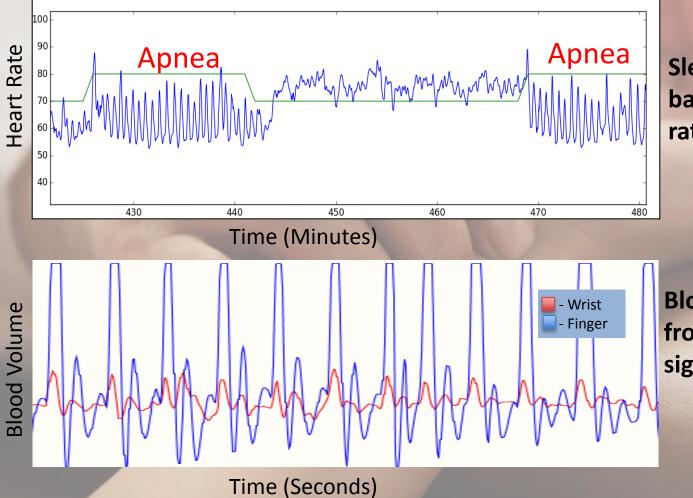
Motivation Classification of Heart Health



Classification of heart conditions derived from heart rate over time

[1] Peng, Chung-Kang. "Toward a General Principle of Health and Disease." Toward a General Principle of Health and Disease. Harvard Medical School, Cambridge. 26 Mar. 2015. Lecture.

Motivation Diagnostics based on pulse



Sleep apnea diagnosis based on changes in heart rate

Blood pressure calibration from phase change of PPG signals in two locations

Message

With the recent availability of low-power wireless chips, for the first time, we can monitor pulse waves over a long period of time for applications such as measuring heartrate variability. However, we are still limited by the power budget available on wearables. In this paper, we will show how we can use compressive sensing to reduce power consumption.

Problem to Solve Power Consumption of Wearables

12

Battery life of heartrate watches

Apple Watch Mio Link Mio Alpha Garmin Forerunner 0 2 4 6 8 10

Lifetime (hours)

Battery consumption of wearables restricts its ability to continuously monitor pulse wave

Bluetooth[™] 4.

Low Energy

With new low-power wireless chips like BLE and additional power-saving compressive sensing techniques of this paper, it is now feasible for batterypowered wearables to monitor pulse wave continuously for days or even weeks.

Overview of System

Tracking reliable pulse waves for long term health diagnostics

Data Transmission

Wireless

signal Analysis

Signal Acquisition



Video Demo of Pulse Wave Reconstruction

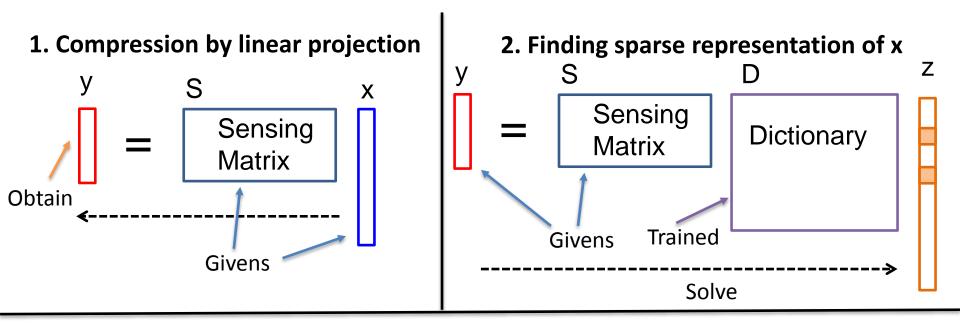
Outline of Presentation

- 1. Signal Acquisition
 - Compressive sensing for pulse waves
- 2. Wireless Data Transmission
 - Forward error correction by interleaving and randomization
 - Adaptations in response to channel quality
- 3. Signal Recovery
 - Reconstruction of pulse wave through sparse coding
 - Noise removal

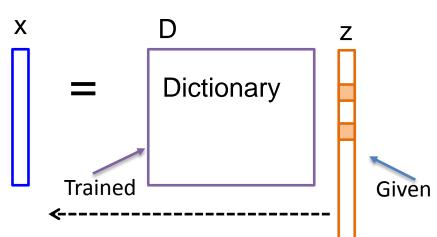
Part One: Signal Acquisition

Compressive sensing for pulse waves

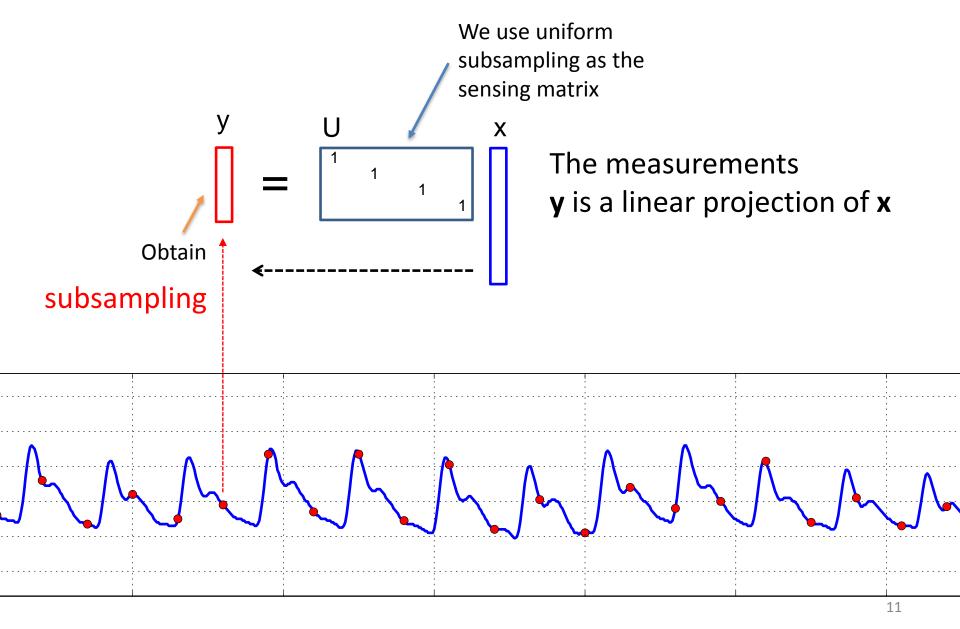
Compressive sensing formulation



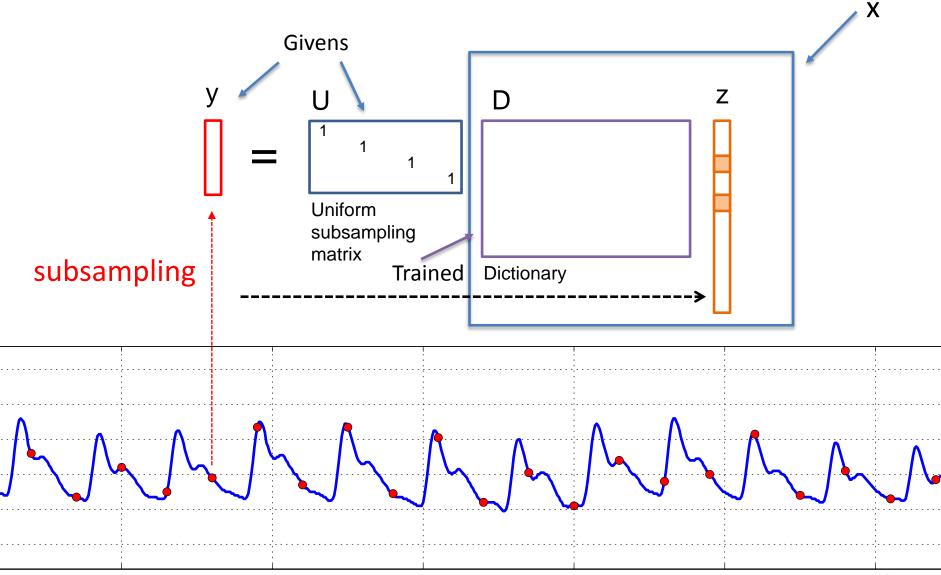
3. Reconstruction of x



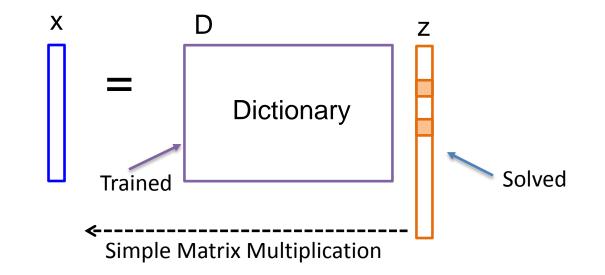
Uniform subsampling to reduce sensor wake-up time



Finding the sparse representation of x



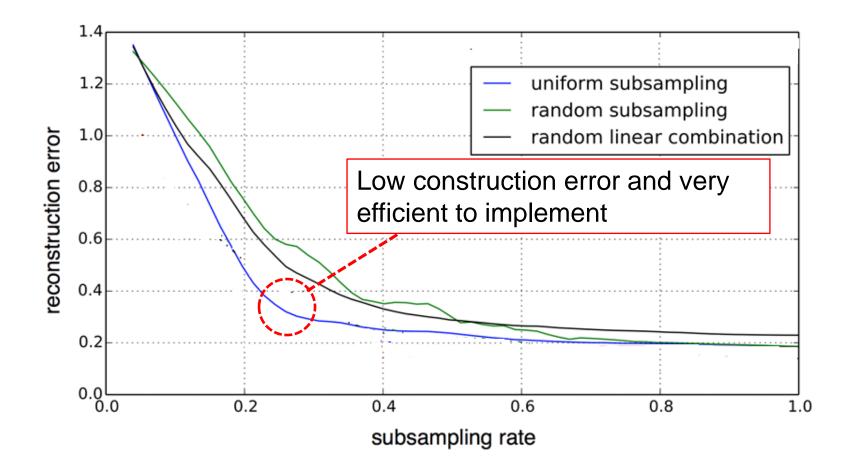
Reconstructing the signal from sparse representation





Experimental Results

With a dictionary trained on pulse waves, uniform subsampling performs better than classic compressive sensing methods.

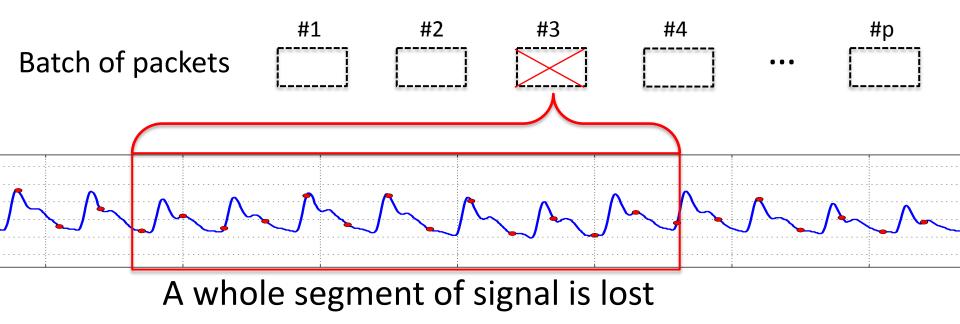


Wireless Data Transmission

- Forward error correction by interleaving and randomization
- Adaptations in response to channel quality

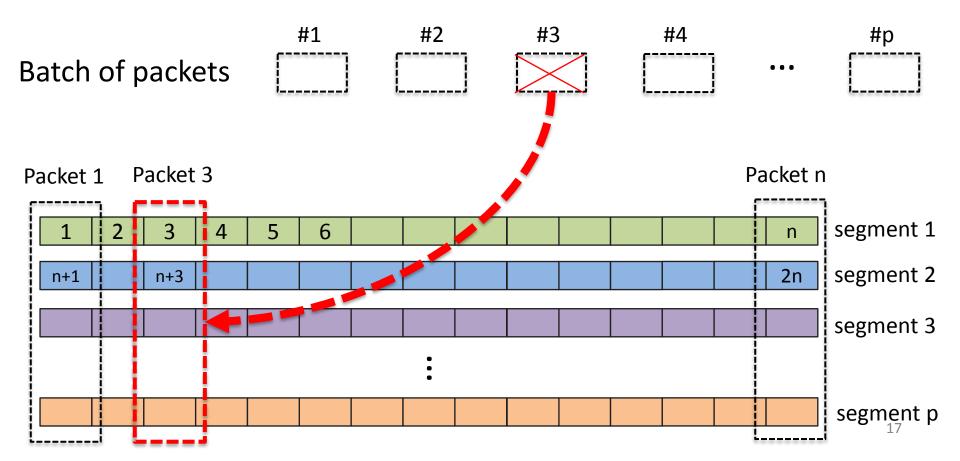
Naïve transmission scheme

Putting a whole signal segment in one packet is not ideal, because there is no way to recover information without resending



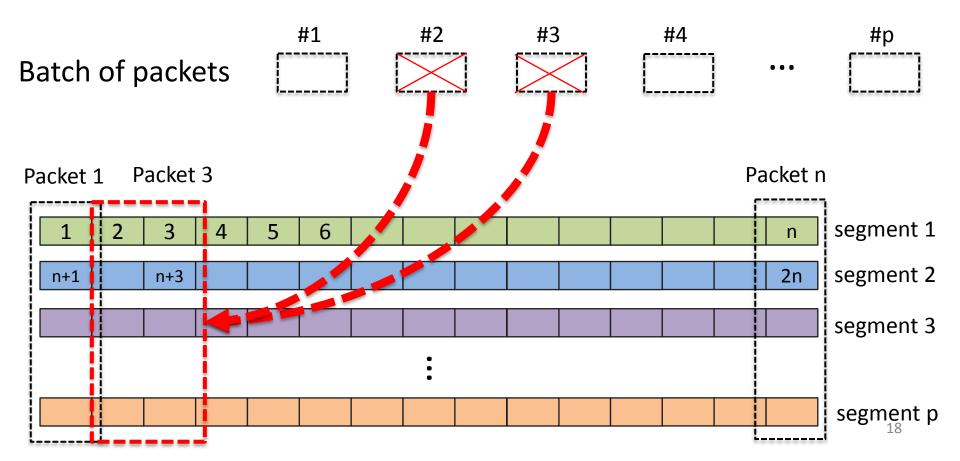
Packet interleaving

By interleaving packets, we can recover the information of lost packet from neighboring received packets.



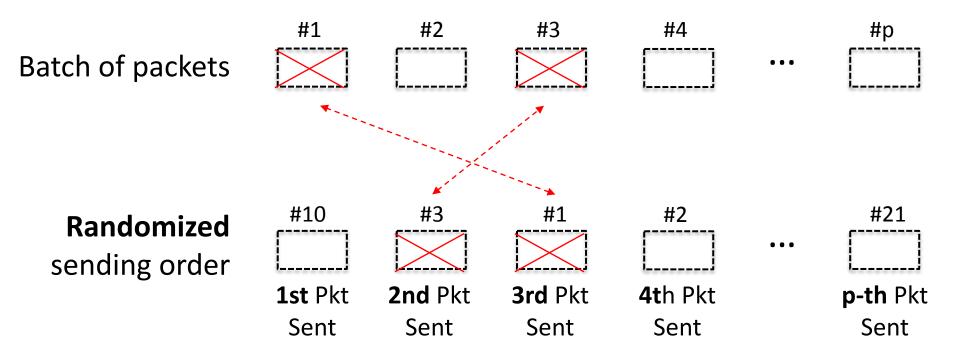
Problems with burst packet loss

However, consecutive packet loss still results in consecutive sample loss in each segment

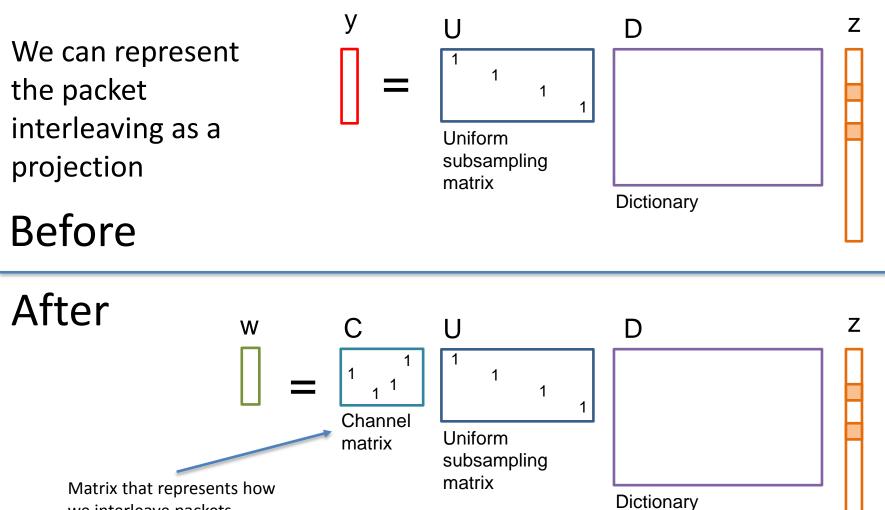


Randomizing packet sending order

We can avoid consecutive sample loss by sending packets in randomized order



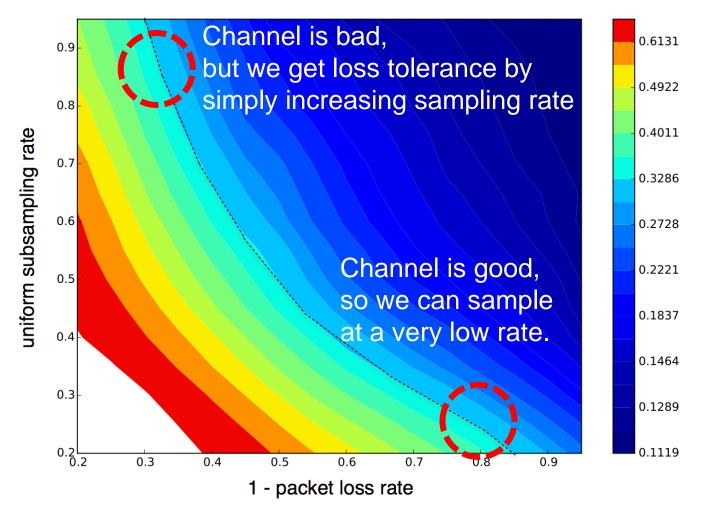
Reconstruction with updated packet transmission scheme



we interleave packets

Reconstruction error with varying packet loss rates

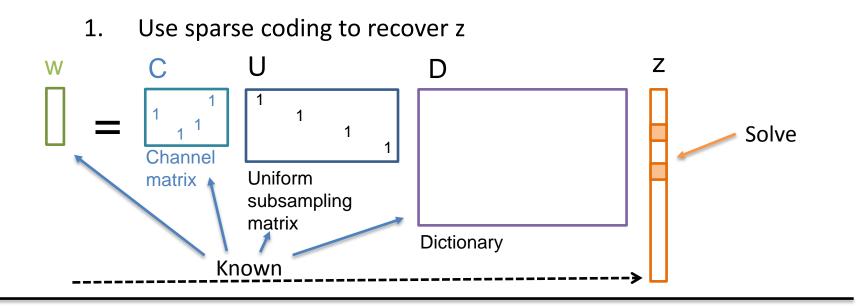
Transmission rate is adaptive to packet loss



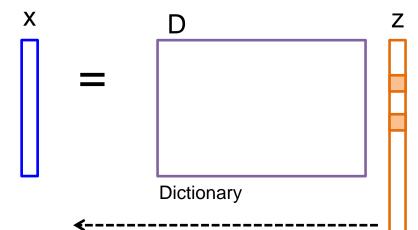
Signal Recovery

- Reconstruction of pulse wave through sparse coding
- Noise Removal

Reconstructing the signal

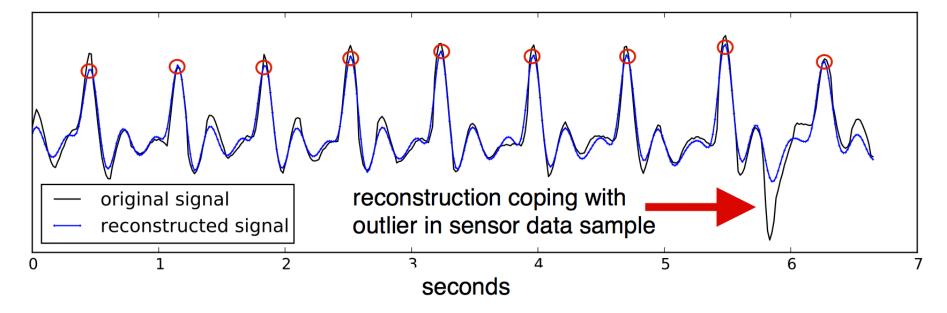


2. Reconstruct x



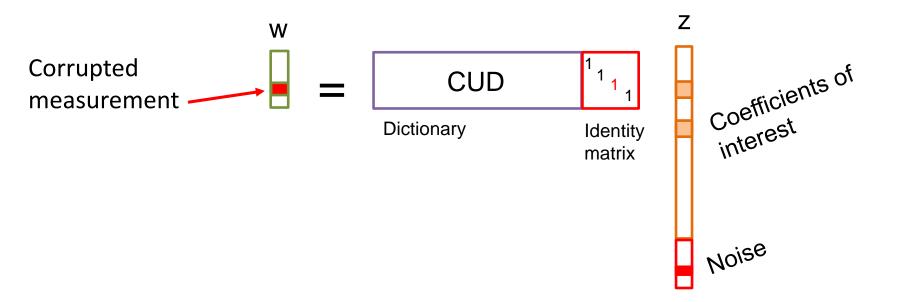
Cleaning the signal from outliers

There can be outliers caused by movements, sensor voltage change, etc.

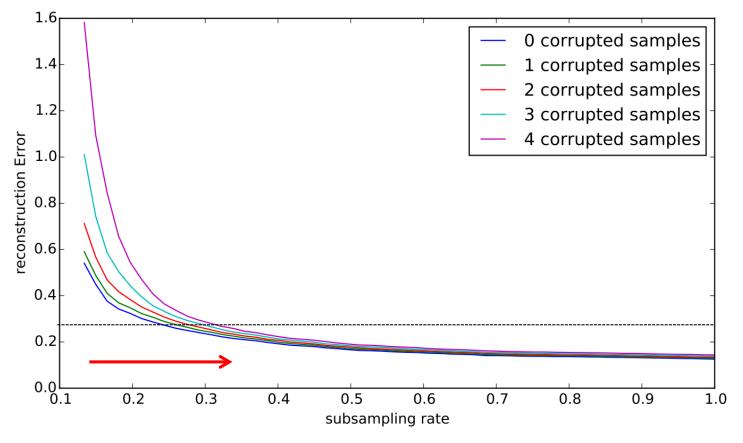


Augmenting the dictionary for noise removal

With a little tweak, we can even tolerate corrupted measurements



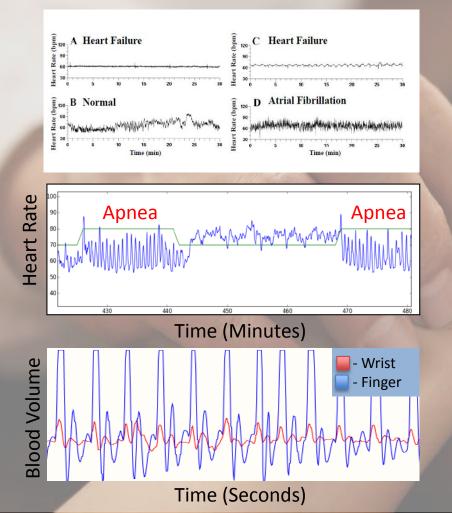
Reconstruction error at different noise levels



We can deal with corrupted samples by increasing sampling rate

Implications of Our Results Pulse Diagnostics Readily Available

Long term health monitoring made possible



Classification of heart conditions derived from heart rate over time

Sleep Apnea diagnosis based on changes in heart rate

Blood Pressure Calibration from phase change of PPG signals in two locations

Summary With new BLE chips, continuous health monitoring is possible for the first time

Data Transmission

Lower transmission rate

Resilience to channel loss

Wireless

Lower wakeup frequency Signal Acquisition



Reconstruction

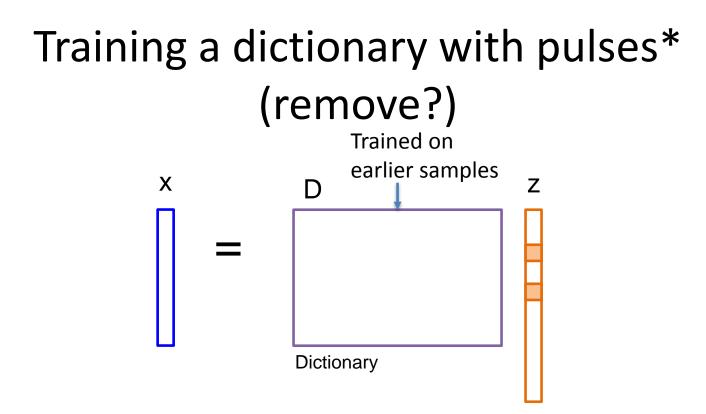
De-noising

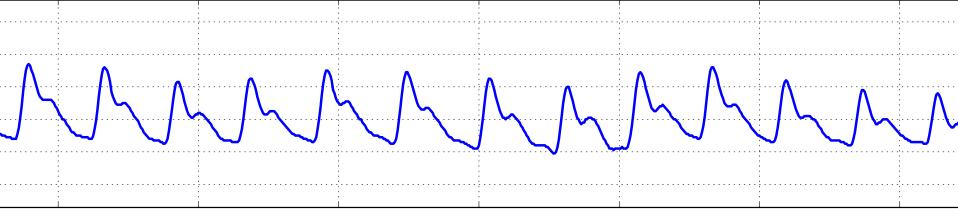
signal

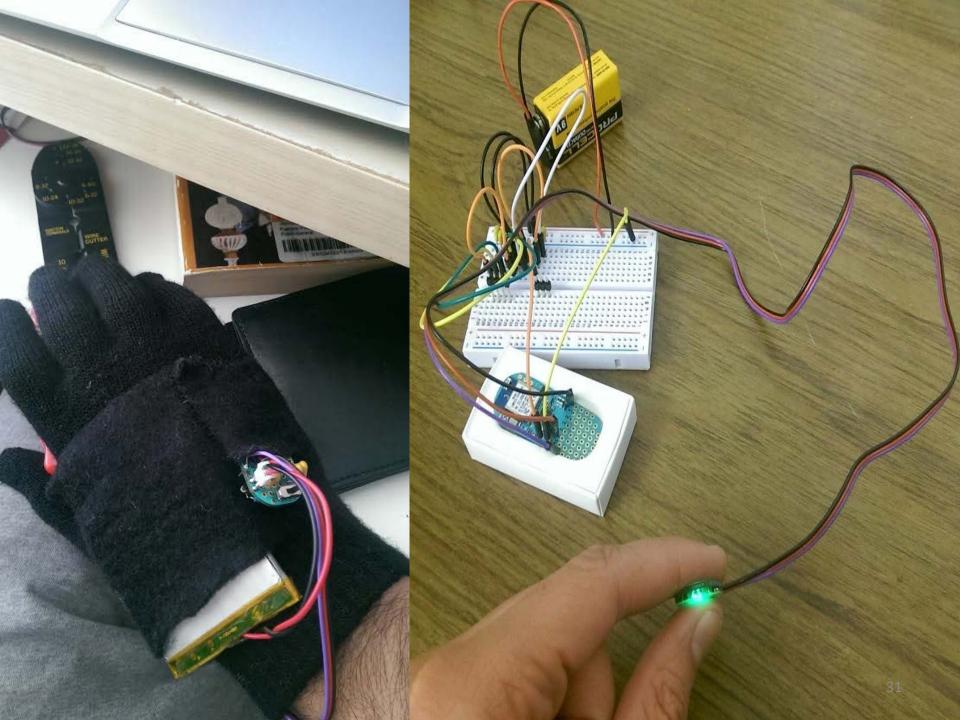
Analysis

Conclusion

Due to the recent availability of pulse sensing chips, and low-power wireless chips, for the first time we can monitor pulse waves over along period for applications such as measuring heartrate variations. But we have a challenge of coping with limited power budget available on wearables. We have shown in this paper that we can use compressive sensing to reduce power consumption.

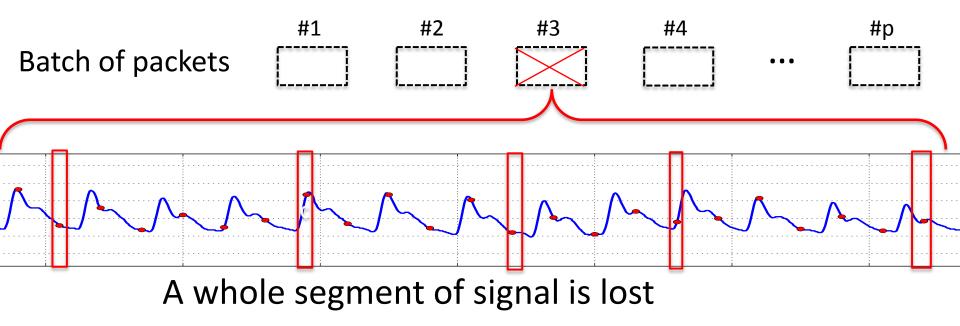


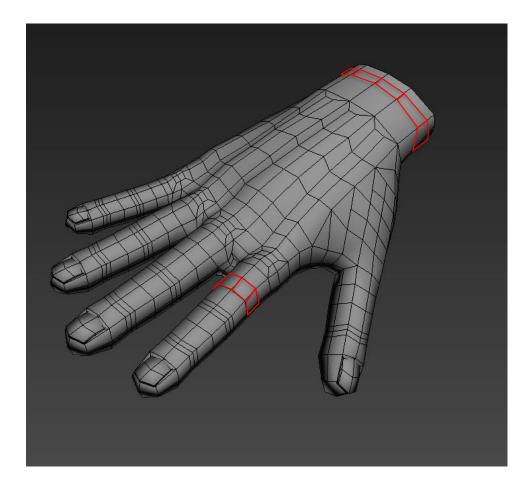




Naïve transmission scheme

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Signal Acquisition

