MIT 6.829: Computer Networks Fall 2017

Lecture 7: Physiological Signals from Wireless

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1 Overview

This lecture is on

1. Extracting breathing and heart rate from Radio Frequency (RF) signal.
2. Using RF signal to detect sleep stages.

Monitoring breathing and heart rate are especially important for health care because wearable devices are uncomfortable or even unacceptable for kids and elderly. If we can develop device-free monitor system, we don't need wearable device anymore.

Reminder:

- FMCW resolution is $\frac{C}{2B}$, where C is the speed of light and B stands for bandwidth.
- The resolution of WiTrack [1] is about 8-10 cm.

2 Measuring Small Distances [2]

In order to increase the resolution, we first utilize FMCW to separate signals reflected off from different distances into voxels, so each voxel stands for signal reflected off from a specific distance from the transmitter. Once we have a voxel of interest, we can zoom-in the specific voxel, and analyze the phase shift in that voxel to determine relative movements within that voxel. Figure 1 illustrates the above process.

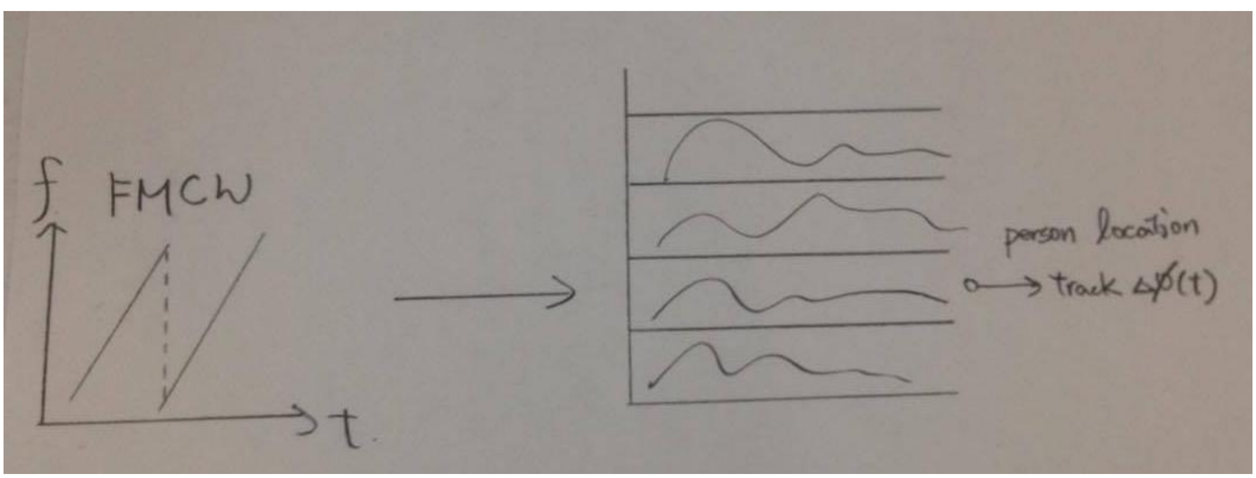

Figure 1: A 2-step procedure to extract relative small movements of a distance of interest.

Concretely, we perform the following steps to measure small distances:

First, since different frequencies corresponds to different distances in FMCW, we take FFT to the signal into different frequencies, and then select (zoom-in) the voxel of interest by only using the signal from a particular frequency in the FFT.

Second, we exploit the relation between distance and phase to determine movements within small distance. To elaborate, we have the following equation for the relation between distance d and channel h:

$$h(t) = \frac{1}{d} \exp(-j2\pi \frac{d(t)}{\lambda}), \tag{1}$$

where λ is the wavelength and $2\pi\frac{d(t)}{\lambda}$ stands for the phase $\phi(t)$ of the signal. As a result, the following equation holds for phase difference $\Delta\phi(t)$ and distance difference $\Delta d(t)$, which quantify the movement of interest.

$$\Delta\phi(t) = 2\pi \frac{\Delta d(t)}{\lambda}, \tag{2}$$

Since the wavelength λ is about 4.5 cm, a small distance shift $\Delta d(t)$ would cause a large phase shift $\Delta\phi(t)$, which demonstrate the sensitive nature of phase shift to measure small distance shift for movements.

Finally, we make the following remarks.

- Phase wraps around, so movements larger than a wavelength λ would cause ambiguity.
- The above method measures displacement rather than distance, i.e. distance shift $\Delta d(t)$ rather than exact distance $d(t)$.
- Multi-path is mostly eliminated by FMCW, so we can just model single path phase.

3 Physiological Signals [2]

In this section, we will discuss about how to apply the above method to extract physiological signals reflected off from human boday.

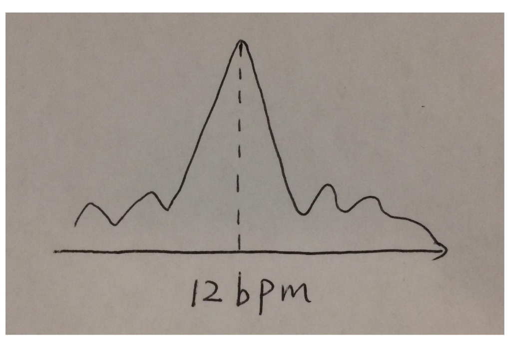

Figure 2: Breathing extraction based on FFT.

3.1 Breathing

To extract physiological movements from human body, we can take FFT again on the signal of interest determined by the first FFT taken in the last section, and correspond the biggest peak to breathing. The resulting signal (the biggest peak) should be around 12 beat-per-minute (bpm) as indicated in Figue 2.

3.2 Heart rate

To extract heart rate, we can also take FFT. However, due to the fact that the signal may be dominated by breathing, here are two solutions. On one hand, we can take FFT on smaller windows such that heart beat becomes the dominant signal. On the other hand, we can just eliminate breathing signals and do FFT again directly.

3.3 Applications

Monitoring breathing and heart rate can lead to several applications. To name a few, we may do

- Health monitoring.
- Security, such as panic for fear detection.
- Emotion recognition.
- Sleep staging.
- Drowsiness detection.

In the next section, we will discuss about the sleep staging application.

4 SleepRadio [3]

This part focuses on predicting sleep stages [3] from radio measurements without wearable sensors on subjects. The input and output are illustrated as in Figure 3. The input RF signal is a wave along time axis. According to the RF signal, we want to predict the sleeping stages every 30 seconds according to the RF signal, such as Awake, Light and Deep.

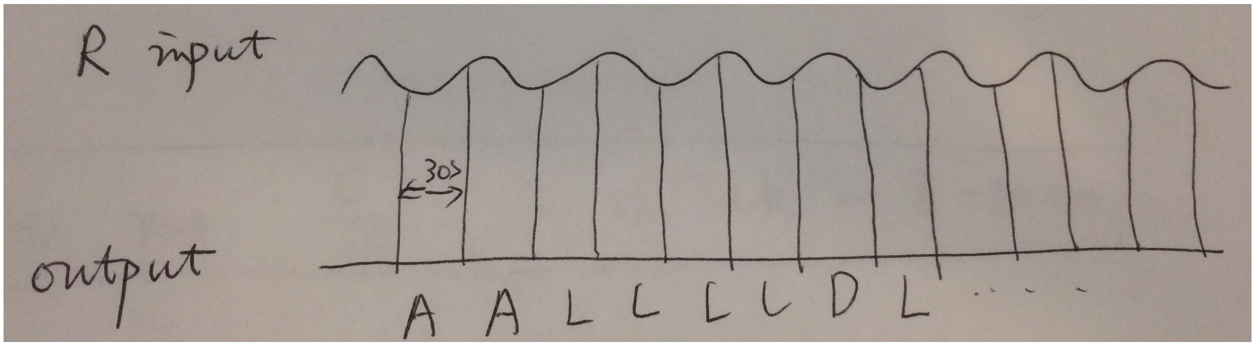

Figure 3: Input and output of SleepRadio.

This problem has two aspects:

- Predict sleep stages
- Generalize to new people and new environments

We need a classifier to decide which sleeping stages corresponds to different time intervals of the RF signal. Instead of using a classifier like SVM, we will use deep neural networks under a new adversarial training framework.

Why not SVM?

- How to design the features? We do not know what types of features are proper enough to represent the problem. Besides, hand-crafted features are usually not the optimal way for a classification problem, because the feature extraction stage and classification stage are optimized separately.
- How to generalize across different people and environments? SVM can not model this type of generalization explicitly. All you get out of SVM is a linear classifier based on hand-crafted features.

Why Deep Neural Networks?

- Deep neural networks can automatically extract hierarchical features from the raw data. The feature extraction stage and classification stage are embedded into one single framework, and therefore the two stages can be jointly optimized.
- We can use adversarial training to eliminate information that are irrelevant to this task, such as a particular person or specific environment.

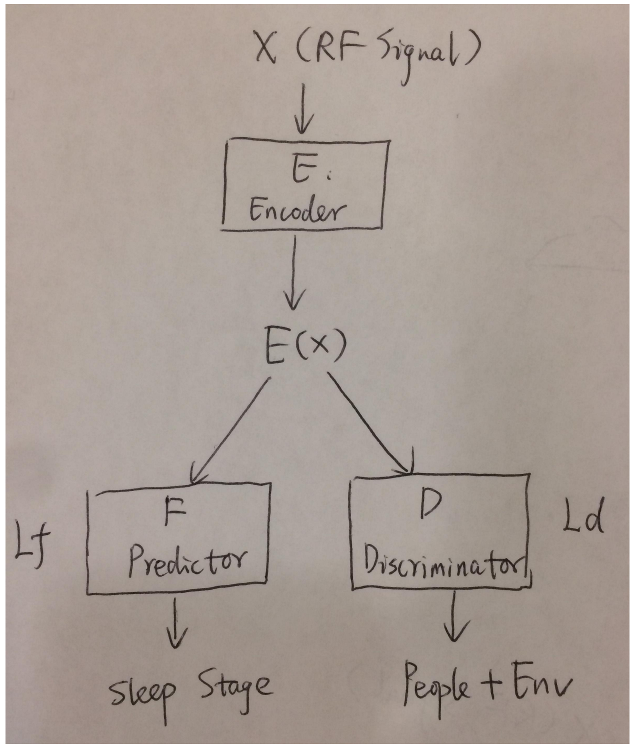

Figure 4: Frame work of the deep model.

The high-level structure of the model has three parts, as illustrated in Fig 4.

- **Encoder.** Encoder gradually encodes the raw input into a compressed representation $E(x)$.
- **Predictor.** Predictor tries to predict the sleeping stages according to the compressed representation $E(X)$
- **Discriminator.** Discriminator tries to predict which people and environment the signal belongs to. Then it back-propagates adversarial gradient to help encoder eliminate the information relevant to people and environment, and thus improving generalization ability.

The objective function of the model is $maxmin(Lf, Ld)$, where Lf and Ld represent the loss of predictor and discriminator, respectively. The model is trained with stochastic gradient decent.

References

[1] Fadel Adib, Zachary Kabelac, Dina Katabi, and Robert C Miller. Witrack: motion tracking via radio reflections off the body. In *Proc. of NSDI*, 2014.

[2] Fadel Adib, Hongzi Mao, Zachary Kabelac, Dina Katabi, and Robert C Miller. Smart homes that monitor breathing and heart rate. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 837–846. ACM, 2015.

[3] Mingmin Zhao, Shichao Yue, Dina Katabi, Tommi S. Jaakkola, and Matt T. Bianchi. Learning sleep stages from radio signals: A conditional adversarial architecture. In *Proceedings of the 34th International Conference on Machine Learning*, pages 4100–4109, 2017.