Synchrosqueezing an Effective Method for Analyzing Doppler Radar Physiological Signals

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***Abstract*— Doppler radar can monitor vital sign wirelessly. Respiratory and heart rate have time-varying behavior. Capturing the rate variability provides crucial physiological information. However, the common time-frequency methods fail to detect key information. We investigate Synchrosqueezing method to extract oscillatory components of the signal with time varying spectrum. Simulation and experimental result shows the potential of the proposed method for analyzing signals with complex time-frequency behavior like physiological signals. Respiration and heart signals and their components are extracted with higher resolution and without any pre-filtering and signal conditioning.**

I. Introduction

Doppler radar has been used for non-contact physiological sensing [1]-[2]. There has been a tremendous effort in the past decades to reduce the size and cost of the sensor and overcome challenges facing wireless physiological sensing [3]-[6]. Vital signs are low frequency in nature usually in the range of 0.1 Hz to 1.5 Hz [7]. Vital signs carry crucial information about a patient's health status. Abnormal respiratory rates and changes in respiratory rate are a broad indicator of major physiological instability, and in many cases, respiratory rate is one of the earliest indicators of this instability [8]. Furthermore, monitoring heart rate and heart rate variability (HRV), which refers to beat-to-beat alternation in heart rate, reflects the manner in which the cardiovascular system responds to demands, stress, and illness [1].

There is a need for a time-dependent rate analysis tool to monitor time-varying behavior of cardiovascular systems. Respiration signal is an order of magnitude higher than heart signal making the heart signal extraction impossible without filtering and additional processing. Different time-frequency (TF) transforms exist for analyzing signals with time-varying

This work was supported in part by National Science Foundation under grants ECS-0702234, ECCS-0926076, STTR-1417308, by the University of Hawaii Renewable Energy and Island Sustainability (REIS) Program, and by Department of Energy grant DE-OE0000394.

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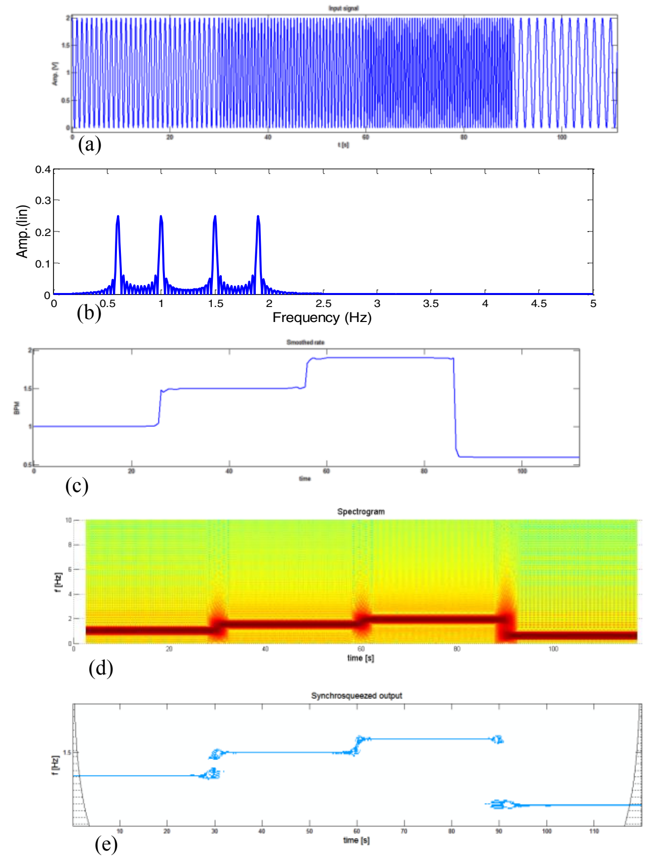

Figure 1. Comparison of Synchrosqueezing with DFT method and Spectrogram; (a) time-domain signal *s(t)*; (b) Spectrum of the signal; (c) DFT rate; (d) Spectrogram (e) Synchrosquezd output.

behavior [9] providing information about their constituent components. However these methods such as Short Time Fourier Transform (STFT), Wavelet Transform can fail to capture key short-range characteristics of the signal. The Empirical Mode Decomposition (EMD) method is another method that allows analyzing time–frequency analysis of multi-component signal [10]. EMD decomposes the signal into several intrinsic mode functions (IMF) which are essentially amplitude modulated-frequency modulated (AM-FM) signals [11]. In [12] EMD is used to remove fidgeting from Doppler radar signal. However, the EMD algorithm contains a number of heuristic and ad-hoc elements which makes it hard to guarantee its accuracy and limit its applicability.

In this paper, Synchrosqueezing transform [13], an invertible time-frequency tool is analyzed for physiological signals. It is a powerful tool to extract and compare oscillatory components of the signal with time varying spectrum. It also allows individual reconstruction of the components. The transform stability make it an ideal candidate for non-uniformly sampled and noisy time series which are common in Doppler radar sensing.

II. Back Ground

Synchrosqueezing is a tool for extracting and comparing oscillatory components of signals. It can give insight into the complex structure of a multi-layered signal consisting of several components [9],[11]. Such signals *f(t)* have the general form:

$$f(t) = \sum_{k=1}^{k} f_k(t) + e(t) \qquad (1)$$

where $f_k(t) = A_K(t)\cos(\phi_k(t))$is and oscillating component, possibly with smoothly time varying frequency and amplitude, and *e(t)* is noise. We need to extract the instantaneous frequency $\phi'_k(t)$ and amplitude factor $A_K(t)$ for each *k*.

Synchrosqueezing has three steps. First we calculate the continuous wavelet transform (CWT) $W_f(a,b)$ of *f(t)*. Then, an initial estimate of the FM-demodulated frequency, $w_f(a,b)$ is calculated on the support of W_f. Lastly, the estimate is used to squeeze W_f via reassignment. The final representation is $T_f(w,b)$.

III. Simulations

To demonstrate the accuracy of Synchrosqueezing a set of simulations are conducted. The first simulation is a signal with single frequency at a given time slot. Fig. 1(a) shows the time domain representation of the signal. The signal frequency changes every 30 seconds. Signal *s(t)* contains abrupt transitions:

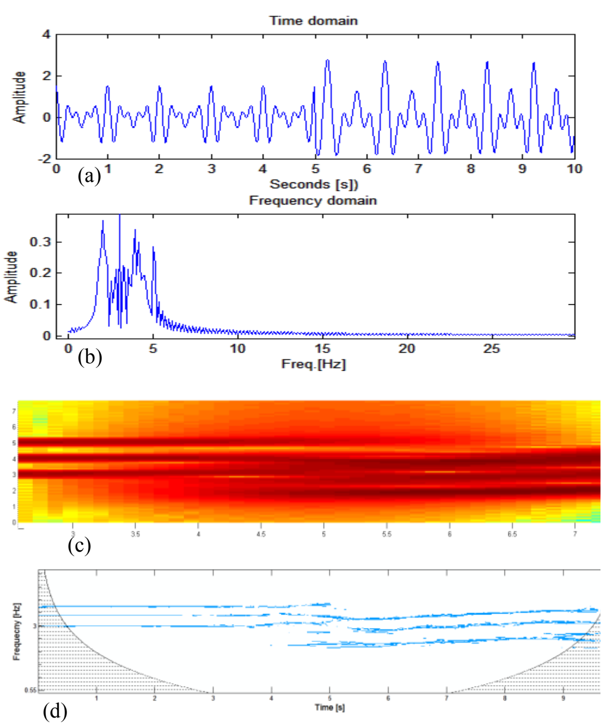

Figure 2. A more complex signal for perfromance comparsion; (a) time-domain signal *s(t)*; (b) Spectrum of the signal; (c) Spectrogram; (d) Synchrosquezd output.

$$s(t) = 1 + \begin{Bmatrix} \cos(2\pi t) & 0 \le t < 30 \\ \cos(2\pi(1.5t)) & 30 \le t < 60 \\ \cos(2\pi(1.9t)) & 60 \le t < 90 \\ \cos(2\pi(0.6t)) & 90 \le t < 120 \end{Bmatrix} \qquad (2)$$

The spectrum of the signal in Fig. 1(b) is not very informative since it has the information for the entire 120s. Since an instantaneous rate is desired, the data is divided into different chunks depending upon the window length. Then, the Discrete Fourier Transform (DFT) is calculated for each window. The peak of the FFT is found for each segment of data, which represents rate in that specific window. Then, the window moves to the next chunk of data based on predefined steps. The window length is determined by FFT resolution, as well as the degree of averaging for instantaneous rate. In this example the window size is 5s and the step size is 0.5s. The result is shown in Fig. 1(c). The spectrogram of the signal is shown in Fig. 1(d). The temporal resolution of Spectrogram is significantly lower than DFT and Synchrosqueezing. The Synchrosqueezed output is illustrated in Fig. 1(e) which shows its precision in time and frequency.

Another example for showing superior precision of Synchrosqueezing in both time and frequency at identifying componenets of some quasi-harmonic signals is depicted in Fig. 2. Signal *s(t)* this contains an abrupt transition at *t=5 s*, and time-varying AM and FM modulation. It can be described as:

$$s(t) = \begin{Bmatrix} 0.5\cos\big(2\pi(3t)\big) + 0.5\cos\big(2\pi(4t)\big)0.5\cos\big(2\pi(5t)\big) & t < 5 \\ \cos\big(2\pi(0.5t^{1.5})\big) + e^{-\frac{t}{20}}\cos\left(2\pi(0.75t^{1.5}) + \cos(2\pi t^{1.5}\right) & t \ge 5 \end{Bmatrix} \qquad (3)$$

The spectrum of the signal is not very informative due to complexity of the signal. For $t < 5$ the harmonic components of *s(t)* are clearly identified in the Synchrosqueezing plot. Spectrogram also illustrates that; however, the frequency estimate is not as precise as Synchrosqueezing. For $t \ge 5$ the frequency components are better estimated in Synchrosqueezed output than Spectrogram with higher resolution. A shorter window in Spectrogram provides higher temporal resolution but lower frequency resolution and more smearing between the three components.

IV. Component Extraction

feature of Synchrosqueezing is the ability to extract oscillating components of time-varying frequency and amplitude from sampled time series. It provides a tool for analyzing signals with time-varying nature and give insight into the structure of their components. To show the ability to analyze, identify, and extract the curves and to reconstruct their associated components, a complex heart and respiration in Doppler radar receiver is discussed.

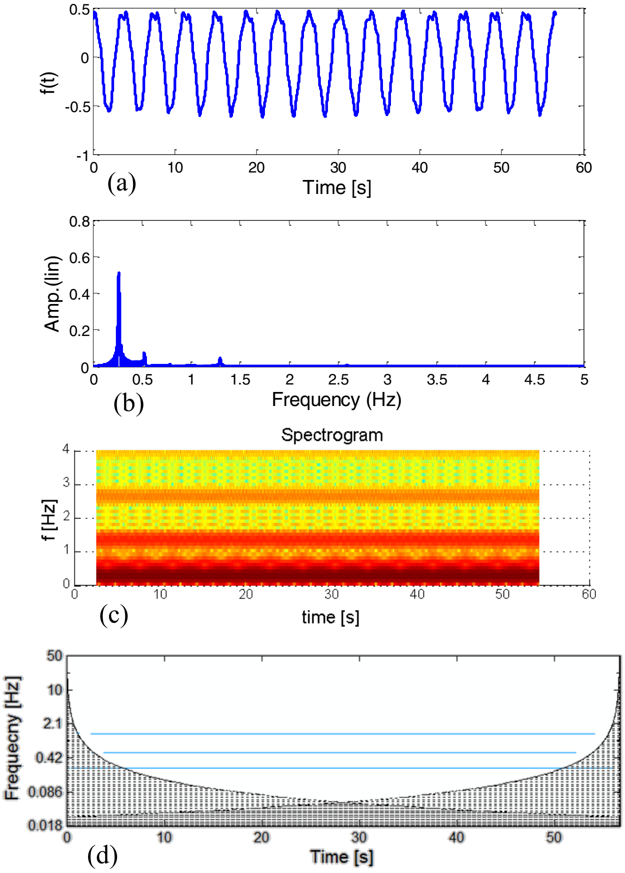

Figure 3. (a) Heart and respiration complex signal; (b) Spectrum of the signal; (c) Spectrogram; (d) Synchrosqueezed output.

In Doppler radar physiological sensing, heart and respiration signals are desired information. Since the amplitude of heart signal is two orders of magnitude smaller than respiration signal, frequency difference is small and harmonics of respiration can be strong, extraction of heart signal can be challenging.

In Fig. 3 baseband Doppler radar complex heart and respiration signal is illustrated with strong respiration harmonics [14]. The respiratory signal frequency is 0.26 Hz and heart signal frequency is 1.29. Fig. 3(b) shows the spectrum of the complex model. The spectrogram and synchrosquezed output is illustrated in Fig. 3(c) and 3(d) respectively. Respiration signal, first harmonic of respiration, and heart signal are clearly visible in Fig. 3(d).

Fig. 4 shows the time-frequency transform with components extracted on the TF of Fig. 3. First three extracted components are illustrated in Fig 4. The second component contains the exact heart signal. Component extraction is one of the great features of Synchrosqueezed transform. First and third components contain respiration signal and its first harmonics.

V. Experimental Result

An experiment is conducted to confirm the simulation results. The block diagram of a quadrature Doppler radar that is used to make the measurements is depicted in Fig. 5; 2.4 GHz continuous wave signal is generated with HP E4433B signal generator. Minicircuits ZFSC-2-2500 coupler is used to split the signal source into transmit and local oscillator paths Antenna Specialist (ASPPT2988) antenna is used with 8 dBi gain and 60 degree E-plane beamwidth for transmitting and receiving antenna.

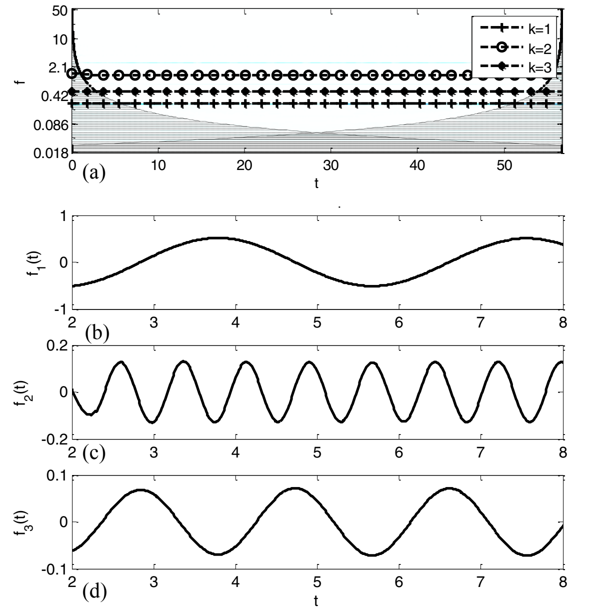

Figure 4. (a) Synchrosqueezed output with marked components of TF plot; (b)(c)(d) First three components of the complex signal

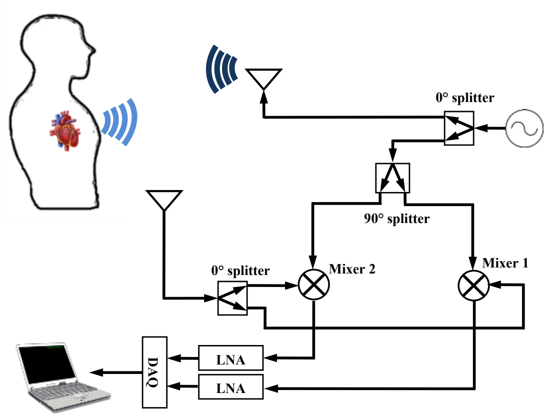

Figure 5. Doppler radar quadrature reciever experimental setup

The backscattered signal is down converted; after filtering and amplification with standard research low noise amplifier model SR-560, the data is recorded with 100 Hz sampling rate. A human subject is employed for measuring heart and respiration rate sitting 1.5 m away from the radar.

Human data is processed with Synchrosqueezing method. Subject is seated on a chair and breathing normally. Fig. 6(a) shows combined respiration and heart signal after linear demodulation for 90s. It contains both respiration and heart signal however, the heart amplitude is an order of magnitude smaller than respiration. Since the respiration amplitude is much larger than heart without accurate filtering it is impossible to retrieve heart signal. Fig. 6(c) shows heart signal after bandpass filtering (0.5 Hz-3 Hz). Synchrosqueeze can extract oscillating components with one round of processing without additional filtering stage. Fig. 6(f) illustrates the synchrosqueezed output. Both respiration and heart signal are visible in time-frequency plot. Fig. 6(b) and 6(d) shows first and fifth extracted oscillating components which are heart and respiration components. Fig. 6(e) shows the extracted component (red) versus reference finger pulse sensor for measuring heart rate.

VI. Conclusion

Doppler radar physiological sensing is a promising tool for wireless vital sign detection. However common time-frequency transforms such as windowed Fourier transform and Wavelet transform are unable to capture key components of the signal. Synchrosqueezing is a powerful tool to analyze time-frequency multi component signals. Simulation results illustrate the potential of this technique for a wide range of complex time-varying signals. Experimental results confirm the effectiveness of this method and give a better insight to constituent components of the signal.

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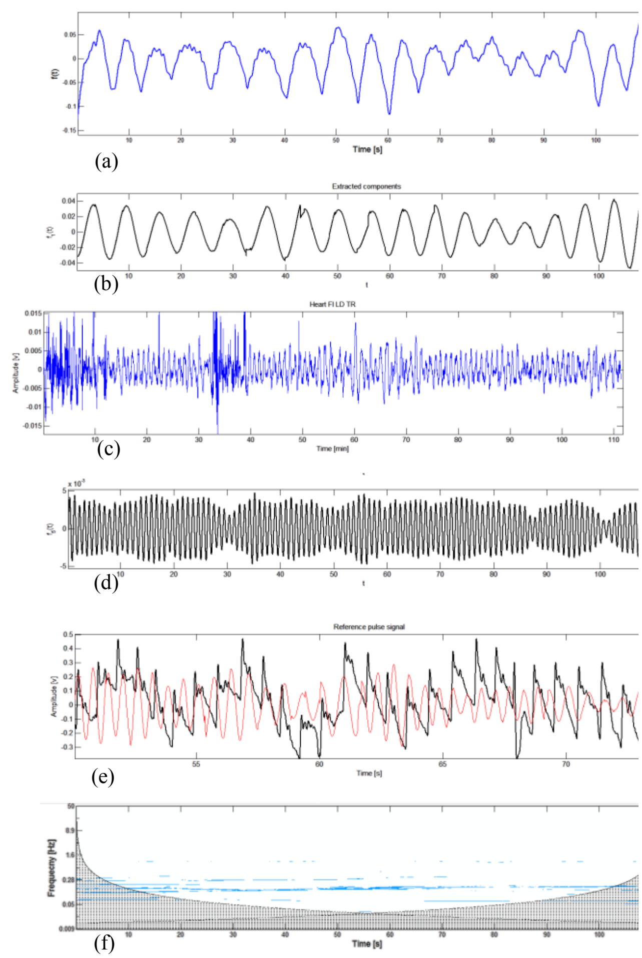

Figure 6. Experimental results (a) Radar baseband output contains both respiration and heart signal; (b) First extracted oscilating component which represent respiration signal; (c) Heart signal after bandpass filtering; (d) Fifth extracted oscilating componenet which represent heart signal. (e) extracted fifth compoenet versus reference finger pulse for heart signal; (f) Synchrosqueezed output