BLIND SEPARATION OF HUMAN HEARTBEATS AND BREATHING BY THE USE OF A DOPPLER RADAR REMOTE SENSING

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ABSTRACT

The combined use of a Doppler radar with digital signal processing technique gives an effective non-invasive remote sensing of heart beat signals. Initial results have showed that the proposed technique is very promising in successfully isolating desired heart beat signals from other mobile objects and other distortion effects characterizing the wireless channel. We concentrate in this paper on the harder problem of separating at low SNR the signals from two subjects in the same room. We show that preliminary results obtained by the Real Analytical Constant Modulus Algorithm (RACMA from [6]) and the Independent Component Analysis (ICA from [8]) on experimental data are very promising into this goal.

***Index Terms*—** Blind Source Separation, Antenna Array, Doppler Radar, Remote Sensing, Heartbeat Detection, Real Analytical Constant Modulus Algorithm, Independent Component Analysis.

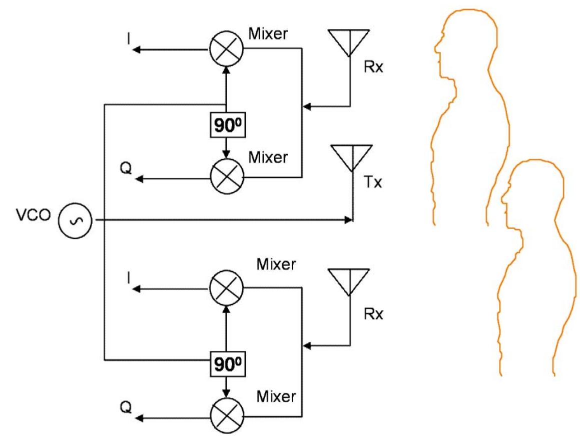

Fig. 1. System setup.

1. INTRODUCTION

Unobtrusive and non-invasive means for detection and monitoring of human physiological signals would provide a powerful tool in several areas including health care, critical responses in emergencies, surveillance, etc. [1, 2, 3, 4].

Although multiple antennae Doppler radar remote sensing of vital signs has shown promise to this end, its principle has not been developed yet to the level of practical implementation [1, 2, 3, 4]. The main problem is how to isolate the desired heart beat signal from other moving objects, other interference and distortion effects characterizing the wireless channel. With two or more subjects within the region of interest, it is even more challenging to isolate the signals from individual subjects [5].

The multiple antennae Doppler radar we have designed and implemented in University of Hawai'i is a one transmitter, two receivers system working at frequency of 2.4 Ghz (see Figure 1). The RF wave being reflected by a moving surface has its frequency modified by the Doppler effect. A person sitting still has his chest surface moving due to two mains causes: respiration and heartbeat. Theses two superposed movements will induce a Doppler shift, which will manifest itself as a phase shift in the received signal.

In this paper we focus on the separation of heartbeats and respiration of two subjects by the use of Blind Source Separation (BSS) algorithms (which have been successfully demonstrated in many biological applications [15, 16]). We mainly investigate the use of Real Analytical Constant Modulus Algorithm (RACMA [6]) and Independent Component Analysis (ICA [8]). We choose ICA, as it is one of the most robust model-free algorithm available for source separation.

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The paper is organized as follows: Section II is devoted to the problem formulation. Section III present some results based on semi-synthesized data, and enforce our choice on RACMA and ICA for the proposed solution. Promising experimental results are presented in Section IV, and finally we draw conclusions and highlight ongoing research in section V.

2. PROBLEM FORMULATION

Consider a typical heartbeat signal shown in Figure 2. The first approach to modeling this is to consider it to be a periodic signal. This has been used with some success in [5]. However, the heartbeat is not too acurately modeled by a periodic signal due to heart rate variability [10], and we therefore look for more robust properties to characterize it. Based on the modeling approach in [10], a reasonable model for the heart beat after lowpass filtering to remove harmonics is

$$s(t) = c(t)\cos(w_0 t + \varphi(t)) \tag{1}$$

Here $c(t)$ is a real scalar and $\varphi(t)$ is a phase component that can be modeled as a random walk on the unit circle. Unfortunately, $\varphi(t)$ is rather rapidly varying and the signal therefore cannot accurately be considered as periodic. On the other hand, $c(t)$ is nearly constant which means that $s(t)$ can be viewed as a real constant modulus signal. Figure 3 shows the plot of the pre-envelope of the reference ECG signal from Figure 2. The pre-envelope is obtained by taking the signal and adding in quadrature its Hilbert transform. The plot is almost circular indicating that indeed the heartbeat signals have a

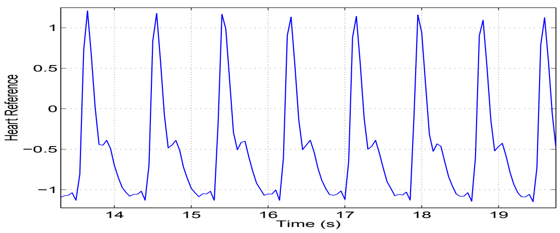

Fig. 2. ECG signal measured using a finger pulse sensor after bandpass filtering in the range 0.03-30 Hz.

nearly constant modulus envelope (after lowpass filtering, this property shows up even stronger).

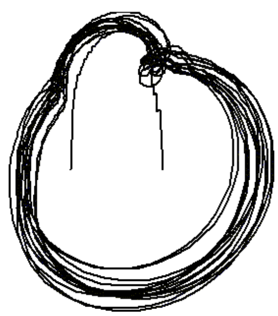

Fig. 3. Pre-envelope of a finger pulse sensor signal after bandpass filtering in the range 0.03-30 Hz.

When multiple subjects are present within range of the wireless system, the problem can then be described as a BSS problem consisting of recovering unknown sources (heartbeat signals) from their observed mixtures acquired by a number of sensors where each sensor receives signals from all subjects. The term "blind" is justified by the fact that the only a-priori knowledge that we have for the signals is their statistical independence. No other information about the signal distortion on the transfer paths from the sources to the sensors is available beforehand. Since, the sources involved are characterized by a constant modulus property as discussed above, the ACMA as a BSS algorithm introduced in [6, 7] seems a reasonable candidate to be pursued as a solution to this problem.

An alternative approach is to simply use the statistical independence of the different heartbeat signals for separation, for example using ICA [8]. ICA has indeed been used succesfully for separation of heartbeats in the context of fetal ECG [9]. However, in a real world application of Doppler Radar, there will be many independent sources (e.g., hand movements, a leaf flapping in the wind, vibrations from machines), and we are only interested in separating and detecting those that are heartbeats. The hope is that the constant modulus property will be sufficient to avoid most non-heartbeat sources.

ACMA can only be applied for cases when complex constant modulus signals are involved. When the source signals are real valued, the method has to be modified. One possibility is to apply a Hilbert transform prior to applying ACMA. Alternatively, the RACMA [6] algorithm can be used. Although the RACMA algorithm was developed for binary data, it turns out it also works for real constant modulus signals as defined in this paper.

To more formally state our problem, we will assume an M-element linear uniform antenna array system (distance d). We assume a continuous wave (CW) radar system transmitting a single tone signal at frequency w. This signal is reflected from a target at a nominal distance D_0, with a time-varying displacement given by $x(t)$, due to the heart-beat. Suppose at first that the signal from a given subject arrives from a single path. The sampled, passband received signal at the n-th antenna in a SIMO system with quadrature receivers can be written for each $n \in [0, M-1]$ as

$$\begin{aligned} r_n(t) &= A \exp\left(\jmath w \left(t + x(t - n\tau)/c - n\tau\right)\right) + w_n(t) \\ \tau &= \frac{d}{c}\sin(\nu) \end{aligned}$$

Where ν is the angle of incidence, and $w_n(t)$ the noise. The delay τ is of the order $1/(3.10^8)$, so that $x(t - n\tau) \approx x(t)$. Then after mixing, for each $n \in [0, M-1]$,

$$\begin{aligned} r_n(t) &= A \exp\left(\jmath \left(2\pi x(t)/\lambda - n\phi\right)\right) + w_n(t) \\ \phi &= \frac{2\pi d}{\lambda}\sin(\nu) \end{aligned}$$

If we collect the signal received at the M antennas into a vector, this can be written as

$$\begin{aligned} \mathbf{r}(t) &= A \exp\left(\jmath 2\pi x(t)/\lambda\right) \mathbf{s}(\phi) + \mathbf{w}(t) \\ \mathbf{s}(\phi) &= [1, \exp(\jmath\phi), \exp(2\jmath\phi), \ldots, \exp((M-1)\jmath\phi)] \end{aligned}$$

If the signal instead arrives through several paths with different angle of incidence, the received signal is

$$\begin{aligned} \mathbf{r}(t) &= \sum_{p=1}^{P} A_p \exp\left(\jmath 2\pi x(t)/\lambda\right) \mathbf{s}(\phi_p) + \mathbf{w}(t) \\ &= \exp\left(\jmath 2\pi x(t)/\lambda\right) \mathbf{s} + \mathbf{w}(t) \end{aligned}$$

At 2.4 GHz λ is 13 cm, while the maximum displacement $x(t)$ due to respiration is 12 mm [12], so $x(t)/\lambda$ is small and a within a good approximation $\exp\left(\jmath 2\pi x(t)/\lambda\right) \approx 1 + \jmath 2\pi x(t)/\lambda$, so that

$$\mathbf{r}(t) \approx \mathbf{M}(\mathbf{1} + \jmath 2\pi \mathbf{x}(t)/\lambda)\mathbf{s} + \mathbf{w}(t)$$

If there are now S subjects at different positions, they will likely have different vectors $\mathbf{s}$, and we can write the total received signal as

$$\mathbf{r}(t) = \jmath 2\pi \frac{\mathbf{x}(t)}{\lambda} \mathbf{M}\mathbf{s} + \mathbf{M}\mathbf{1} + \mathbf{b} + \mathbf{w}(t) \tag{2}$$

with $\mathbf{M} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_S]$, $\mathbf{x}(t) = [x_1(t), \ldots, x_S(t)]^T$, and $\mathbf{b}$ is background reflection. Because of this, the DC does not contain any information, and is removed prior to quantization.

The model (2) describes a linear mixing of the sources, and BSS methods therefore can be applied. Notice that this depends on the approximation of the complex exponential. At higher frequencies this is not satisfied, and the mixing is non-linear. Notice also that while the received IQ signal is complex, the sources $x_s(t)$ are real, and real BSS (such as RACMA) should be applied. Note that the main problem remains the low SNR.

3. SEMI-EXPERIMENTAL RESULTS

In order to demonstrate the usefulness of the ACMA, RACMA, and ICA algorithms to separate two different heartbeats, we first consider a semi-experimental setup. We use reference heartbeat signals that were recorded using finger pulse sensors and bandpass filtered. Two reference signals from different people are then assumed to pass through a typical wireless environment scenario characterized by a matrix $\mathbf{M}$ as in (2), and white Gaussian noise is added. Simulations were conducted for scenario mimicking our 2-element receiving antenna array radar system. We used different Signal Noise Ratio (SNR) in the semi-synthesized cases.

We used our database of heartbeat signals from finger pulse sensors, to mix them pairwise to assess the chosen algorithms. We have measured 10 subjects, so we were able to form 45 couples. Each measurement was 700 samples long at a frequency of 20 Hz, so 35 second (approximately 30 beats). For each couple, we repeated the experiment 5 times with different noise, so that we had 225 independent runs. The use of these "semi-experimental" mixed heartbeat signals allows us to carry out a general performance analysis of any algorithm on realistic signals.

To isolate the fundamental tone of the heartbeats, we filter the mixed data with a band-pass filter over the range $[0.75; 2]$ Hz in the experiment. Next, we apply ICA and RACMA directly on the mixed data, while for ACMA we pass the data though a Hilbert transform prior to application.

We investigate the influence of the Noise power over the algorithms, the SNR ranges in $[-20, , 20]$ dB. In this case the mixing matrix was chosen to be: $[1\ 1\ 1\ 1;\ 1\ \text{-}1\ 1\ \text{-}1]^T$, which has a conditioning number of 1. Once the separation algorithm has delivered output signals, they are used to estimate the heart rate. The separation is declared a success if both measured hearbeats are within 0.08 Hz of their true values, otherwise it is a failure.

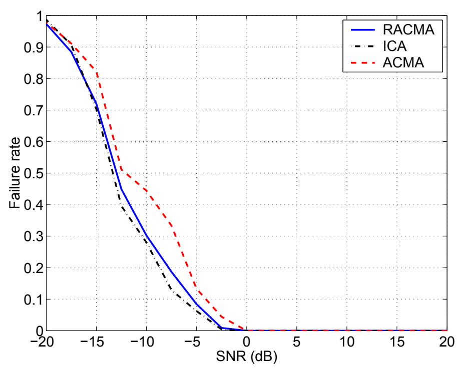

Fig. 4. Failure rate of the algorithms as a function of SNR.

Figure 4 presents the failure rate as a function of the SNR. All algorithms have about a similar performance. We note that ICA is slightly better than the CM based algorithm, and RACMA slightly better than ACMA, which we believe is due to the fact that the heartbeat signal is not exact CM.

4. EXPERIMENTAL RESULTS

In this section we consider fully experimental data, measured by the setup in Figure 1.

In the previous sections, we have concentrated on heartbeat. However, usually people also breathe, and the displacement due to breathing is much stronger than that due to heartbeat. This signal can therefore be expected to be easier to separate than the heartbeat. One approach to separating the heartbeat is therefore to first separate the respiration, and then use the same beamforming vector to separate out the heartbeat, assuming the mixing matrix for respiration and heartbeat are similar. On the other hand, people might not be breathing due to medical reasons or to hide; also, the respiration signal is more irregular, and therefore more difficult to distinguish from other movement. We therefore consider both separation of respiration, and separation of heartbeat.

One measurement we made consisted of two subjects breathing (and of course with their hearts beating!). Unto their chests were strapped by resistive respiration transducers, which give a direct reference for chest displacement (respiration+heartbeat). The received signal was low-pass filtered (cut off at 0.75 Hz), and we then applied RACMA. With the chest information, we were able to derive a non-blind solution, the mixing matrix was obtained by the use of the Moore-Penrose pseudo-inverse of the reference signals on the received signals:

$$\widehat{\mathbf{M}} = \mathbf{X}\mathbf{S}^T(\mathbf{S}\mathbf{S}^T)^{-1}$$

Figure 5 presents the reference sources and the separated versions by the non-blind scheme and the RACMA. One can note that the separation is almost perfect in both cases. It is also possible to note the small presence of the heart rate on the breathing reference. This example (and a few other) indicates that it is possible to separate respiration using RACMA, although the constant modulus assumption is perhaps less reasonable for respiration.

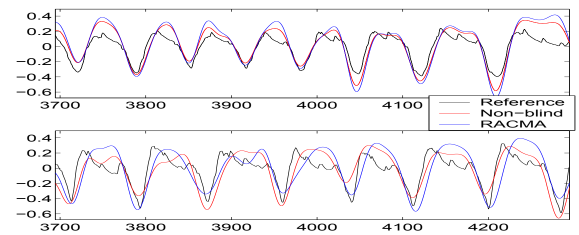

Fig. 5. Breath signal: References, estimates from non-blind separation, and estimates from RACMA.

We next consider direct separation of heartbeat. As explained previously, this is most relevant in the case when there is not respiration. We therefore had two subjects holding their breath for 36 s, with a sampling rate of 20 Hz, giving 720 samples. We also took as reference their finger pulses. In this case, separation turned out to be much harder than the semi-experiments seem to indicate. We were not able to separate the signals using RACMA (RACMA gave the one of the heartbeats twice instead of two different heartbeats), but by using ICA with four components, separation succeeded. To our surprise, one of the heartbeats shows up as two sources, while the other shows up as a single source.

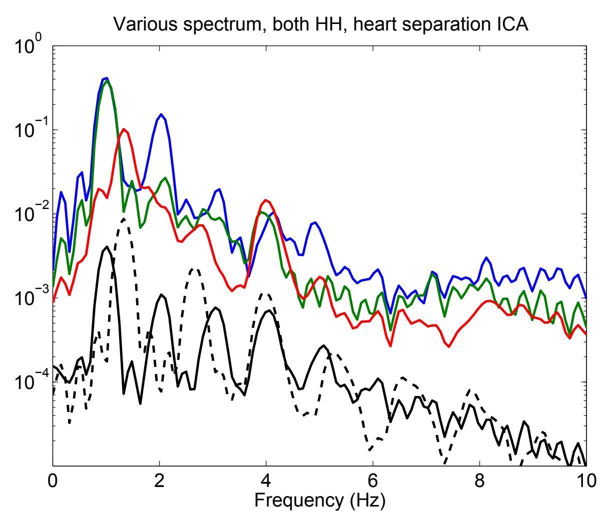

Fig. 6. Average peridogram of heart signal: References (black), estimates from blind separation (blue, green, red).

This can be seen in the frequency domain in Figure 6 and in the time-domain in Figure 7(a-b). It can be seen that the two sources from a single person have the same fundamental frequency, but different harmonics; in the time domain, both synchronize with the reference, but the shape is different. While this is just one measurement, it is consistent with phenomena observed in a larger set of measurements (e.g., the number of significant eigenvalues is sometimes larger than the number of subjects).

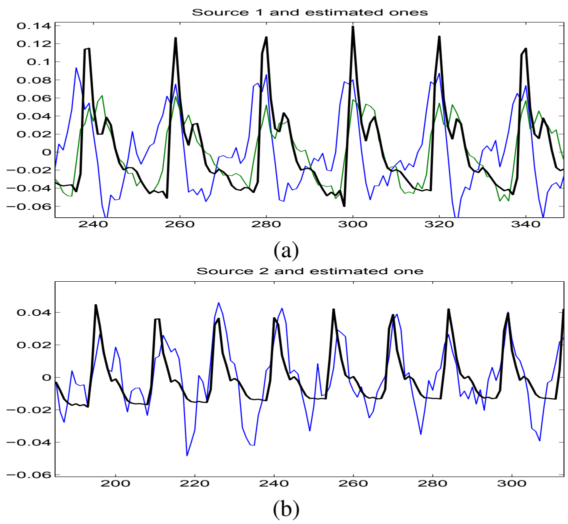

Fig. 7. ((a) First and second reconstructed signal versus first reference zoomed (b) third reconstructed signal versus second reference zoomed.

Our hypothesis as to why this happens is that the radar picks up the heartbeat signal from the whole body, as well as possibly internally in the body. At 2.4 GHz, the penetration into the body should be small, but perhaps not insignificant. The heartbeat (i.e., pulse) in different parts of the body could be delayed and have different shape. If we assume that there is a linear relationship between these different heartbeat signals, it appears that space-time BSS [13, 14] is needed to isolate individual heartbeats. However, we are conducting more experiments to understand the phenomenon better.

5. CONCLUSIONS

In this paper, we have investigated the feasibility of the separation of the breathing and heartbeat of two persons. The concept has been demonstrated in the semi-experimental case, and full experimental examples have shown promising results for a generalized separation. The fact that a single person can show up as multiple sources indicates that space-based separation is not sufficient, and space-time methods should be employed. However, we are conducting more experiments to investigate more closely the chest movements. We plan on doing laser scanning [12] to map the chest movements more accurately than the chest strap can do.

While the experiments have shown ICA to work at least as well as RACMA, we still consider CM based algorithms (or even algorithms using more advanced signal modeling) to be more promising due to presence of many sources of interference in real applications outside the lab. Furthermore, ACMA and RACMA for a low number of samples is superior to HOS-based algorithms.

6. REFERENCES

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