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Preliminary Feasibility Analysis of Remote Subject Identification during Hemodynamic Monitoring by Radio Frequency Impedance

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Abstract— **Non-contact, non-invasive monitoring of hemodynamic parameters would be ideal for medical monitoring in a variety of environments. Radio Frequency Impedance Interrogation (RFII) measures hemodynamic function via resonance frequency coupling to a hydrophilic protein molecule. While the application of this technology to hemodynamic monitoring has demonstrated initial success, this preliminary study examined the use of RFII for subject identification by waveform signal analysis, which would allow confirmation of the identity of a subject in an operational setting prior to rescue efforts. Preliminary results demonstrate an excellent recognition rate using the RFII signature and pattern classification. Each individual has a consistent pattern during the initial waveform identification period that is visually distinct from the other individuals in the data set. These results suggest that RFII may be of great utility in the pre-hospital triage setting for patient monitoring and for the rapid identification of subjects in the operational setting.**

I. Introduction

Monitoring of hemodynamic function without invasive techniques or skin contact has applications in domestic and operational medicine. Potential applications of such technologies include rapid assessment of hemodynamic status, improvement of early medical intervention, and continuous monitoring of subjects without risks associated with invasive techniques. Initial investigations have successfully demonstrated the use of a non-invasive radio frequency device for the non-invasive monitoring of heart rate (HR) and heart rate variability (HRV). However, such technology may also prove to be effective in the rapid identification of subjects by triage forces prior to triage and extraction efforts. Such identification could improve the ability in an operational scenario to verify the subject as friendly, injured, and/or requiring expedited evacuation. This paper proposes the use of a non-invasive radio frequency device applied for monitoring of HR and HRV to be further utilized for subject identification by waveform signal analysis, allowing triage forces to first confirm the identity of a subject prior to rescue efforts.

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RFII Background and Development

Radio frequency impedance interrogation (RFII) measures the resonance of a radio frequency signal with anatomical structures in motion then processes that signal's return loss via advanced algorithms to generate instantaneous as well as trending measurements of HR and HRV. The RFII device transmits a single frequency RF tone set between 905 to 925 MHz, with no transmitter modulation. The Transducer Antenna Probe (TAP) is a specially modified microstrip antenna that is designed to direct the RFII transmitter tone to the blood and tissue of the cardiac mass below the sternum. Biological materials are electrically heterogeneous with different tissue types having significantly different complex dielectric constants. Blood and blood-filled muscle are tissue entities with the highest dielectric constants, a magnitude higher than the lowest dielectric constant tissues such as bone and fat. The TAP has been specifically designed to match the frequency range for dipole resonance with water-bound hemoglobin molecules [1]-[2].

This resonant signal is received by the bidirectional TAP. A high isolation duplexer prevents any unwanted RFII transmitter energy from reaching the receiver. A cardiosynchronous waveform is generated by cardiac motion, dependent on blood volume and hemoglobin concentration. This waveform provides significant information at very low frequencies from less than 100 MHz to a few hundred Hz allowing the RFII to detect cardiac activity with temporal correlation to the ECG waveform (Figure 1).

The TAP is tuned for high return loss, detecting minimal changes in reflected energy from human tissue interfaces, enabling detection of the radiowave resonance as modulated by mechanical heart activity. At or near resonant frequencies, changes in blood volume and cardiac motion

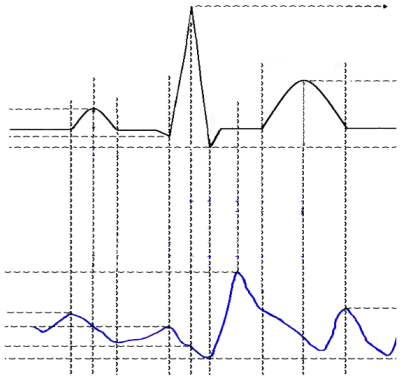

Figure 1: Temporal correlation of ECG (top) and RFII first derivative (dZ/dt) waveform (bottom).

will create small deviations in the radiowave resonant coupling frequency, thus modulating the RFII transmitter frequency tone. This modulation of the RFII transmitter tone is at a maximum level at or near the resonant coupling frequency since a small deviation in resonant frequency creates a significant phase change [3]. As opposed to pure Doppler, which would produce very small phase changes from detecting slight motion of the chest wall, the RFII system produces a larger modulated phase change, enhanced by dipole resonance, making RFII specific to blood and cardiac tissue and capable of detecting subtle changes [4].

The RFII waveform is clearly associated with the ECG waveform (Figure 2). RFII waves (and derivatives) appear to match ECG intervals, yet RFII peaks lag slightly behind the QRS peaks. This lag appears to be a relatively constant interval by approximately 50 msec. It is theorized that the RFII signal is responding to changes in velocity identified during contraction phase of the cardiac cycle, which would follow the electrical conduction identified by the ECG. In other words, the ECG identifies the electric signal as it passes through the heart, resulting in cardiac contraction; the change in velocity of the blood during contraction alters the return loss of the RFII signal, resulting in RFII waveform changes. Similarly, as blood velocity decreases during diastole, the RFII waveform would return to baseline.

The correlation of the RFII signal to ECG and cardiac impedance (dZ/dt, the first derivative of the RFII signal, where Z is impedance) is demonstrated in Figure 2. The second derivative of the RFII signal provides interesting results when compared to ECG and impedance. One example noted here in the systolic portion of the cardiac cycle is the timing of the peak amplitude of the waveform d^2Z/dt^2, which coincides with the end of the QRS complex of the ECG and the beginning of the peak rise slope of the dZ/dt waveform. These points match the timing of the opening of the aortic valve, the peak ejection time. This is intuitive since the d^2Z/dt^2 waveform (a second order time derivative of the RFII waveform) represents acceleration; in this case, the acceleration of blood as it is ejected from the left ventricle.

While much of this work is preliminary and requires further investigation, this correlation suggests that the RFII waveform can be utilized as a monitor of cardiovascular activity, specifically to identify heart rate and heart rate variability, without the limitations imposed by current wired and contact/invasive technologic standards such as ECG.

RFII for Subject Identification

In addition to successful cardiac monitoring of patients by RFII, one of the novel signatures unique to RFII technology is the initial impedance/phase response as the device achieves resonant coupling with the person's heart. It does this by finding the optimal tuning frequency resonance for each subject's cardiosynchronous waveform. The discriminatory capability of this impedance response function during the initial frequency tuning stage was investigated in a small subject pool to determine the feasibility of RFII as a subject-identifying biometric tool during hemodynamic monitoring in a triage scenario.

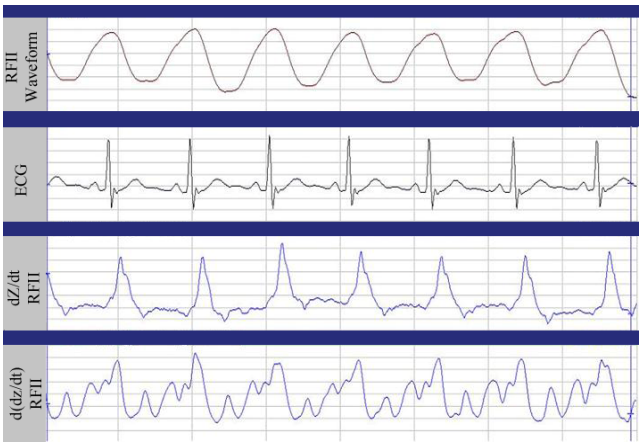

Figure 2: RFII I waveform correlated against ECG & ICG waveforms. The channels, top to bottom, are as follows: RFII waveform, ECG, dZ/dt (first derivative), RFII d(dZ/dt) (second derivative).

II. Methods

In this preliminary investigation, the initiation sequence utilized to identify the subject's optimal resonant frequency was investigated in four subjects. Four consenting, volunteer individuals were instrumented with the RFII device for monitoring. Each of these four individuals was recorded for 30 data sets. Each recording consists of 20 measurements of the waveform generated by the initiation sequence, taken at sampling intervals of 10 ms, approximately 0.2 seconds per recording. The recordings were made when the device first initiates and before the signal reaches the steady-state, during which time the initiation sequence normally examines the frequency tuning spectrum with a stepwise signal analysis of frequency ranges from 905-925 MHz. However in this experiment, all data were recorded at 910 MHz to minimize variation inherent at each frequency. The system was re-initialized 30 times for each subject, and 20 waveform measurements were taken from each dataset for analysis.

As a basic examination, the raw data was visualized to identify any possibility of using each individual's initiation sequence as a biometric signature. Figure 3 plots the RFII signals of the initial impedance response for each of 30 recordings of the subjects, with each subject represented by a different color. As shown, the raw data already demonstrate a discernable, unique pattern per subject.

Although classification on this raw data would have a reasonable performance, this approach would not be feasible as the number of subjects increase and data differences between subjects become more subtle. Thus, Principal Component Analysis (PCA) was applied to the initiation sequence RFII waveforms generated by each subject to obtain features [10]. The Nearest Neighbor algorithm was used as a classifier with a Euclidean distance metric. The

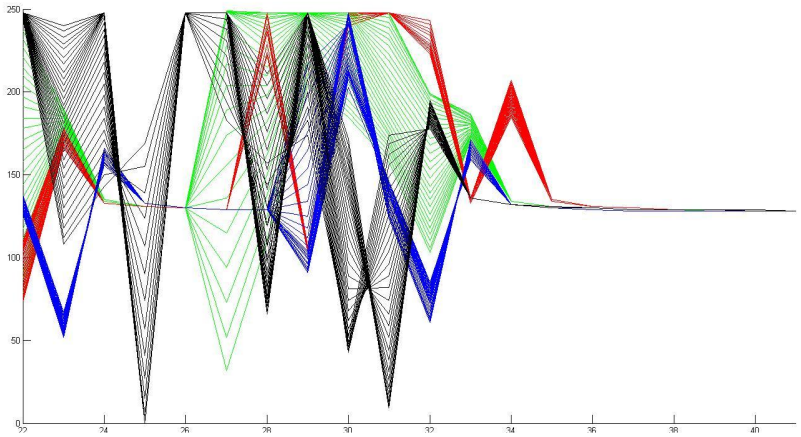

Figure 3: Plot of the RFII waveform initializing impedance response for each of the 30 recordings from the subjects. The plots are colored by subject. These patterns demonstrated exclusivity of the signal pattern for each subject.

training set was formed from ten randomly selected data points from each of the four subjects, comprising forty data points in all. The remaining twenty data points from each subject (80 in total) were withheld for testing as a validation set.

PCA extracts features in the signals based on analyzing the directions of maximum variation, which improves subject identification despite very subtle differences. The motivation is to find a projection space that will encode any variance in data while maintaining a small reconstruction error to conserve information. This results in an optimization problem to maximize the variance (assuming zero mean centered data):

$$\underset{\|\omega\| = 1}{arg\ \max}\ E\left[(\omega^T x - \omega^T \mu)^2\right] = \underset{\|\omega\| = 1}{arg\ \max}\ \omega^T \Sigma\, \omega$$

Each signal of the training set is placed into the data matrix χ vectorizing each sample, where μ is the global mean and Σ corresponds to the sample covariance matrix.

The optimization problem under the unit norm constraint for the projection vectors can be solved using the following Lagrangian optimization:

$$L(\omega, \lambda) = \omega^T \Sigma\, \omega - \lambda\,(\omega^T \omega - 1)$$
$$\nabla L(\omega, \lambda) = 2\,\Sigma\, \omega - 2\,\lambda\, \omega = 0$$
$$\Sigma\, \omega = \lambda\, \omega$$

This optimization results in computing the eigen-decomposition of the covariance matrix, where the eigenvectors of largest eigenvalue represent directions with maximum variance. These eigenvectors form an orthogonal basis that can represent the input data. More interestingly, it allows us to reduce the dimensionality of the feature space by retaining the most dominant eigenvectors. Each sample can now be represented in a minimum squared error reconstruction sense in relation to the corresponding eigenvalues. The eigenvalues represent the variance captured along the direction of the corresponding eigenvectors. We can choose how many of the PCA feature vectors to use depending upon the percentage of variation in the data captured by those eigenvectors.

We employed a k=1 Nearest Neighbor classification with a Euclidean-distance metric used to determine to which subject each signal belongs. Since the training and testing sets were randomly partitioned, the classification experiment was run twenty times to account for any variability. Individual PCA (IPCA) was also attempted using the thirty segments from each of the four subjects to build individual subspaces. Ten segments from each subject were randomly chosen for the training set, and the remaining twenty segments were used for the testing set. IPCA builds an individual subspace for placement of each subject's waveform data. The same process for PCA was used separately for each subject, giving us four feature spaces. For classification, the testing set was projected onto each feature space. The Euclidean-distance metric was used to determine the error between the test signal and the closest training signal of each subject. Each test point was ascribed to the class whose feature space had the minimum error.

III. Results

While only a small number of subjects were analyzed during this preliminary study, a high classification rate was achieved using the RFII signature and pattern classification. Each individual has a consistent pattern during the start-up period that is visually distinct from the other individuals in the data set. The system was re-initialized 30 times per person, yet the patterns are quite consistent and discriminative. The results of the waveform analysis of this start-up period are presented in Figure 3.

Principal Component RFII Transient Analysis

The minimum data retention in the first two eigenvectors across all the twenty runs was 92%. We chose to retain the first three eigenvectors to provide more than sufficient capture of variability and discrimination. The projection of these data onto three-dimensional space spanned by the three dominant eigenvectors shows good separation among the four classes (projection results from one random run are shown in Figure 4). Each subject in the dataset is represented by only 3 numbers, the first three principle eigenvalues.

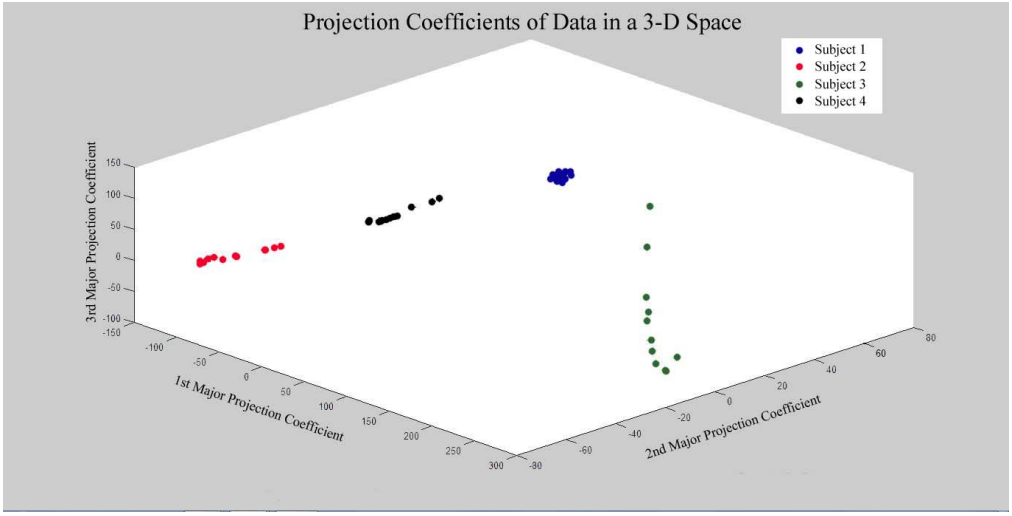

Figure 4: Projection coefficients of the training data in a three-dimensional space for one demonstration run.

This low overhead provides a feasible algorithm to embed on a hardware platform, and a rapid search of the database, ideal for rapid subject identification in an operational setting.

Using a nearest-neighbor classifier, we obtained 20/20 accurate subject identification for each of 4 runs. A 100% recognition rate is achieved through the use of only two eigenvectors out of the total of twenty eigenvectors.

Individual Principal Component Analysis

An IPCA individual subspace was built for each subject then nearest-subspace classification was performed [11]. Specifically, the ID corresponding to the subspace that yielded the smallest reconstruction error of each test sample was chosen. A 100% recognition rate, with 20/20 accurate subject identification, was achieved through the IPCA with a Nearest-Subspace classification.

IV. Conclusions

Clearly, the results are highly encouraging even with such a small initial dataset. Comparing to state-of-the-art published literature on ECG biometric analysis, which included pools of only 9-20 subjects with a range of 83%-100% recognition rates, these initial data have yielded similar or superior performance on a small dataset with a less computationally intensive classification schemes [5]-[9]. It is noted that this RFII signature is unlike ECG data and unique to RFII technology, providing a technological edge in non-invasive biometric identification using the RFII.

Further analysis needs to be performed utilizing a significantly larger human subject dataset. In addition, waveform analysis of all the frequency sweep transient signals should be examined. It is expected that this will provide a larger set of rich features to generalize and allow scaling to a much larger population for robust biometric identification. It is anticipated that future development of different pattern classification methods, evaluation of computational complexity, and integration of methods onto compact hardware platforms will allow for rapid subject identification while monitoring hemodynamic parameters, which could provide great value when applied to operational medical triage efforts.

Acknowledgments

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