Statistical Analytics of Wearable Passive RFID-based Biomedical Textile Monitors for Real-Time State Classification[1]

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Wearable smart devices have become ubiquitous, with powered devices capable of collecting real-time biometric information from its users. Typically, these devices require a powered component to be worn and maintained, such as a battery-powered sensor, Bluetooth communications device, or glasses. Pregnancy and infant monitoring devices may be uncomfortable to the mother or baby and are subject to signal loss if the patient changes position or becomes mobile because the device must remain tethered to the patient by a belt and plugged into a wall for power. Our wearable, wireless, smart garment devices are knitted into the fabric using conductive thread to which a Radio Frequency Identification (RFID) chip within the fabric is inductively coupled. Our work utilizes the Received Signal Strength Indication (RSSI), which changes as the knitted antenna is deformed due to stretching of the garment, to determine different types of motion in the inductively-coupled chip and knit antenna structure as it is moved by the wearer.

The workflow includes interrogating the medical device, parsing the result to obtain the timestamp and values, grouping and sorting by device and timestamp, filtering, plotting, and performing statistical analytics to classify the motion state of the subject and compare against the control data being simultaneously collected from a comparable medical device. Each step of this process was developed into a software module with web-service endpoints to enable loosely-coupled communication between the components. We simulate and detect respiration on a Laerdal SimBaby programmable infant mannequin, using signal processing, filtering, and data classification algorithms on statistical aggregations of this data, to determine when events (such as sleep apnea) occur. Filtering modules were created to reduce noise and quantization issues within the data, in order to determine when a certain amount of stretching has occurred on the band.

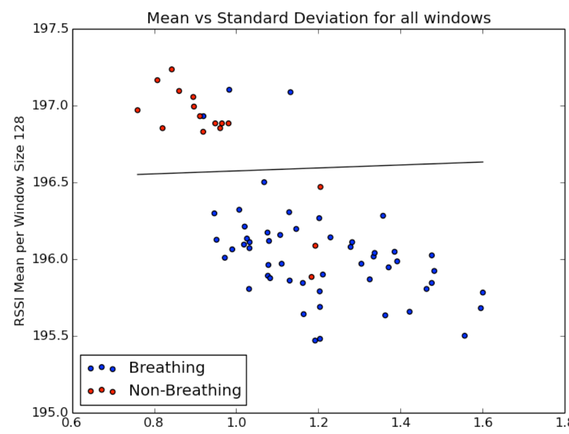

Fig.1: the mean and standard deviation of each time horizon of data is plotted and separated via an SVM

The SimBaby was deployed and programmed to breathe for one minute at a rate of 28 per minute, then to cease respiration for one minute, before repeating. The data collected (at between 30-55 Hz) was filtered via a Kalman Filter, aggregated into time horizons ("windows"), with the mean and standard deviation of each window used as features. Window sizes of 30-600 in increments of 30 were taken. The Support Vector Machine (SVM), Elliptic Envelope, hypothesis testing, and other approaches were studied for inferring subject state using RFID interrogation. The statistical features to collect for these state classifiers were chosen by computing the Fisher Linear Discriminant Ratio (FDR) metric, which resulted in the selection of the mean and standard deviation of the data windows, as well as the p-value of the hypothesis test. An example SVM classification of the mean and standard deviation of windows of data is shown in Fig. 1. In addition, the rate of stretching is computed by taking the Fast Fourier Transform (FFT) of the collected data, seeking the frequency with the highest magnitude to determine the observed rate. The FFT has been used to accurately determine the inflation rate of the air bladder, after applying a Gaussian filter to the collected data. The Support Vector Machine performed better with larger windows, likely due to the sensitivity of the standard deviation to classification as predicted by the FDR. Although classification also improves with a larger training set size, even smaller training sets yield reasonable classification with window sizes larger than 300 (approximately 5-10 seconds of data), with an average ROC AUC of 0.71. Comparing against other learning approaches, we found that, although the Elliptic Envelope underperformed the SVM, it classified well with sufficient training data even when smaller windows were used. This is useful to detect potential anomalies after a short period of time and inform more accurate classifiers that rely on longer windows of data via an ensemble approach.

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STATISTICAL ANALYTICS OF WEARABLE PASSIVE RFID-BASED BIOMEDICAL TEXTILE MONITORS FOR REAL-TIME STATE CLASSIFICATION

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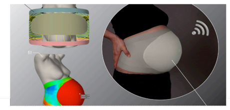

Introduction

- RFID is traditionally used for inventory management, but can be inductively coupled to a stretchable fabric antenna.
- When this knitted antenna is stretched, the corresponding Received Signal Strength Indicator (RSSI) returned to the RFID interrogator changes, enabling wireless, passive measurement of smart garment deformations.
- We can utilize these changes in RSSI as a biomedical feedback signal and correlate them with subject activity state, such as a uterine contraction, respiration, or other motion artifacts.
- We developed software to perform filtering and signal processing on these signals from our RFID smart garments and from proprietary state-of-the-art medical devices already in use for comparison.
- Several statistical modeling and learning approaches were compared for classifying this data, which yielded varying training set and time horizons enabling an ensemble learning approach.

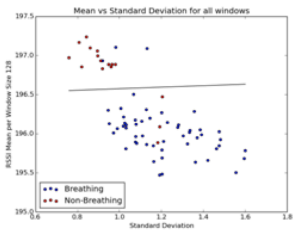

Fig. 1 - Plotting the mean vs the standard deviation of time horizons of data yields largely separable data points as predicted by the FDR

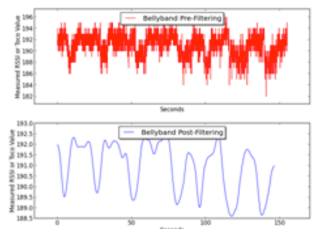

Fig. 2 - Bellyband RFID data is noisy and quantized, which is mitigated via the application of a Gaussian filter (bottom)

Background

- Typical biomedical monitoring devices require a powered component that is worn or tethered to a wall, which may be cumbersome or uncomfortable.
- Knitted antennas enable smart-garment devices embedded in clothing or unobtrusive wearable garments and passive monitoring.
- RSSI is quantized and the passive signal response is noisy, requiring filtering for smoothing.
- Statistical features are extracted from time-horizons of data, such as the mean and standard deviation of the previous 5 seconds of data.
- Changes in RSSI must be correlated to motion artifacts such as respiration rate, presence of a uterine contraction, *etc.*
- Each person may wear the garment device differently and under different environmental settings such as distance from the interrogator, so a baseline must be established for each user that forms the basis for statistical analysis.
- Classification output must be compared to traditional state-of-the-art medical devices for accuracy and as part of the FDA approval process.
- Some classification techniques perform better with fewer baseline training data, but not as well as other approaches which typically require more baseline training data; we investigate this relationship to form an ensemble learning approach.
- Some classification applications (such as respiration) require single-class baseline training because the subjects cannot be asked to "hold their breath."
- A modular software framework is needed for all of these considerations so that additional interrogator devices can be integrated easily.

Approach

- Developed software to collect data from a variety of interrogators, including mobile Bluetooth devices
- Used the Fisher Linear Discriminant Ratio (FDR) to determine the most separable statistical features of the data (mean vs standard deviation shown in Fig. 1), and separated for classification via a Support Vector Machines (SVM)
- Applied a Gaussian and a Kalman filter to the data for smoothing (Gaussian filter shown in Fig. 2)
- SVM, least square anomaly detector, elliptic envelope classifier, and a hypothesis test were used to classify the data using various time-horizons ("window sizes") and baseline training set sizes.
  - These classifiers classify subject state into "stretching" or "non-stretching" states.
- To determine rate of stretching, an FFT is taken on the data, and peak frequencies (by magnitude) are used to reconstruct a curve using an IFFT, from which the peak-to-peak rate is computed (Fig. 5).

Results

- A programmable mannequin was set to actuate the bellyband for 1-2 minutes at a time before resting for 1-2 minutes, and repeating.
- Accuracy trends are noted for each of the classification approaches; an example is given in Fig. 3, in which a one-class Least Square Anomaly classifier improves classification accuracy as the window size increases, and as the baseline training set size is increased.
- Some approaches, such as the moving average classifier, perform worse overall but outperform when the window size or training set are smaller, enabling early warnings via an ensemble approach.
- Filtered Bellyband data closely correlates with that of a traditional medical device (Fig. 4).
- Rate of motion is accurately computed (Fig. 5).

Sample Data

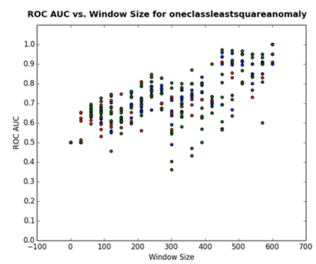

Fig. 3 - Plotting the ROC area-under-the-curve vs various window sizes and training sets (larger training sets are green, successively smaller training sets are blue and red) showing better classification for large time horizons

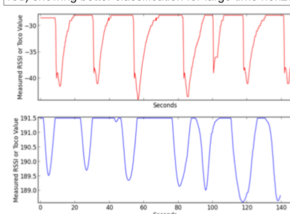

Fig. 4 - Comparing motion data collected from a tethered tocodynamometer transducer (top) to the filtered RSSI data collected from the Bellyband (bottom)

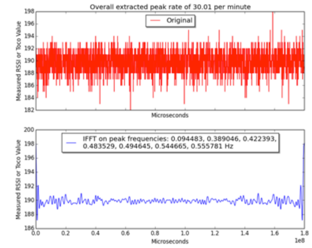

Fig. 5 - Applying an FFT to filtered RSSI readings, taking the top 1% of frequency magnitudes and reconstructing with an IFFT yields the peak-to-peak rate of subject motion

Future Work

- Integration of each of these approaches into an ensemble learning classifier
- Detection of "ambient motion artifacts" in which the subject moves while breathing
- Enabling the use of two-class learning approaches even when only a single class of training data is feasible
- Formalization of optimal baseline training set size and time-horizon
- Investigation of nonstandard features such as hypothesis test p-values and inter-window variance
- Clinical trial and FDA approval

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