An Adaptive Search Algorithm for Detecting Respiratory Artifacts Using a Wireless Passive Wearable Device

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***Abstract*—With the use of a wireless, wearable, passive knitted smart fabric device as a strain gauge sensor, the proposed algorithm can estimate biomedical feedback such as respiratory activity. Variations in physical properties of Radio Frequency Identification (RFID) signals can be used to wirelessly detect physiological processes and states. However, it is typical for ambient noise artifacts to appear in the RFID signal making it difficult to identify physiological processes. This paper introduces a new technique for finding these repetitive physiological signals and identifying them into two states, *active* and *inactive*, using k-means clustering. The algorithm detects these biomedical events without the need to completely remove the noise components using a semi-unsupervised approach, and with these results, predict the next biomedical event using these classification results. This approach enables real-time noninvasive monitoring for use with actuating medical devices for therapy. Using this approach, the algorithm predicts the onset of respiratory activity in a simulated environment within approximately one second.**

***Index Terms*—Adaptive Signal Processing, Biomedical Signal Processing, Prediction Methods**

I. Introduction

In the field of medicine, there are many different devices that can capture physiological data. The purpose of these pieces of equipment range from collecting a patient's heart rate, respiratory rate, blood pressure, or any other vital sign needed by medical professionals. Many of these devices are fastened to the patient to function [1].

Placing equipment on babies or preterm infants increases the risk of injuring a patient and decreases the amount of body surface area available [2] [3]. These devices are attached to patients in various ways (e.g. gel and velcro), but these methods can be accidentally removed due to human error when handling the patient. The sudden removal of these devices can cause injury or discomfort to the patient while simultaneously disrupting the collection of data. A passive wireless knitted textile strain gauge sensor device called the Bellyband [4]–[6] can be used to help limit the number of sensors that are placed on a patient, deal with the issue of accidentally removing sensors, and allow for more open body surface area on patients.

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A. Bellyband

Figure 1 illustrates the Bellyband wrapped around an infant's diaphragm. The Bellyband is a wearable smart fabric that requires no power source to operate and has no need for any wires to be attached at any time during operation [6]. Using this device, the algorithm performs statistical signal processing to capture respiration rate, urinary contraction in pregnant women, or a patient's heart rate [7] [8].

Fig. 1. A programmable mannequin Simbaby wearing the Bellyband about the abdomen. The Bellyband stretches and relaxes during respiratory activity, which is observed through changes in RF reflected from the knitted antenna on the Bellyband.

The components that make up the Bellyband are a conductive fiber antenna and a RFID chip knitted into the Bellyband [4]. The Bellyband uses an interrogator antenna that sends out an Ultra High Frequency (UHF) signal at a bandwidth of 902-928 MHz. Once this signal reaches the Bellyband, the Bellyband's RFID chip is powered, and a return signal is reflected to the interrogator antenna. The return signal's information is then polled by a database system on a server [9] that includes the following data: Received Signal Strength Indicator (RSSI), Doppler shift, Phase, and Arrival time. This information is then analyzed on a server to infer biological meaning from the collected data, such as respiratory rate [7],

[10], [11]. Figure 2 shows an illustration of the physical setup of the Bellyband.

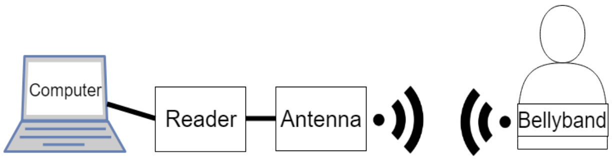

Fig. 2. The Bellyband infrastructure configuration includes an interrogator (reader) attached to an antenna which interrogates the Bellyband worn about the subject. Reflected energy from the interrogation is passively reflected back to the interrogator for processing by our algorithms running on a computer. The Bellyband contains an embedded passive MAGICSTRAP RFID LMXS31ACNA-011 chip or Monza X Dura chip, and the interrogator used is an Impinj R420 interrogator with an RFMAX S9028PCLJ antenna.

Two challenges arise when using RFID in the Bellyband. The first issue was handling noise artifacts in the return radio frequency (RF) signal from the Bellyband. There are two main causes for the noise artifacts that appear in the return signal. First, RFID technology has some inherent issues like multi-pathing, reflection, and absorption that can cause RF signals to become heavily altered or lost after being sent out from an antenna. Second, the Bellyband can be used in a hospital setting that can see a constantly changing environment. Even small changes or subject movements can have a noticeable impact causing noise artifacts to appear in the return signal. To overcome the issue of noise artifacts the proposed algorithm uses a semi-unsupervised algorithm capable of distinguishing what is valid data from the patient [7], [10], [11], and what data points are noise components in the return signal.

The second issue is latency. The physical setup of the Bellyband will lead to a delay between the time a physiological event occurs (*e.g.*, breathing) and when it will be observed by the interrogator. This latency is caused by the antenna sending out an RF signal and waiting for a return RF signal from the Bellyband to reach the origin point. To compensate for this latency, our algorithm uses an unsupervised adaptive filter using the past twenty-second of data to predict the next physiological event. This predictive algorithm is adaptive, based upon recent classifications, and is the focus of this paper.

B. Paper Outline

This paper describes an algorithm to detect, in real time, the onset of strain activity such as respiration using changes in the RF passive signal backscatter properties. The goal for this algorithm is to classify when a patient is inhaling or exhaling. Using this information, predict the next respiratory activity in a passive, noninvasive manner, by observing the distribution of inter-breath intervals from the medical literature [12] [13].

The rest of the paper is outlined in the following Sections: related works are shown in Section II, the approach for the algorithm is shown in Section III, results are shown in Section IV were the proposed algorithm's classification capability is compared to the results from a medical device currently being used to capture respiratory activity.

II. Related Work

This paper covers three main subjects: wearable smart fabrics, clustering algorithms, and respiratory monitoring.

A. Wearable Smart Fabrics

In the past twenty years, there has been considerable interest in the research and development of wearable smart fabrics that provide constant monitoring of an individual's personal health. WiBreathe is one such device [14]. Like the Bellyband, WiBreathe is capable of capturing an individual's respiration rate using RF signals. WiBreathe operates in a 2.4 GHz range that is common for most wifi devices. This gives WiBreathe the ability to track an individual's respiration rate through multiple structures (e.g. walls) and removes the need to have a physical sensor on a patient. However, WiBreathe is limited because it is hard to distinguish between individuals if multiple people are in the same area. Thus, in a hospital setting, WiBreathe is not the optimal choice to capture multiple patients' respiration rates.

Another smart fabric that is capable of capturing respiration rates uses a Doppler radar system, harmonic tags, and operates in a 2.4 GHz range [15]. Like the approach above, this smart fabric is capable of capturing an individual's respiration rate. With the use of a wifi signal and a harmonic tag, this system is capable of tracking an individual's respiration rate through multiple structures and allows the unique identification of anyone wearing this device. The Bellyband and this approach achieve the same goal but operate in two different ways. The Bellyband operates on a higher frequency and uses different RF technology. This approach also provides a method of predicting when the next physiological event will occur.

B. Clustering Algorithms

The proposed algorithm clusters the data from the Bellyband into two essential states. In state 0, the patient is neither in the process of inhaling or exhaling. In state 1, the patient is in the process of respiratory activity. Due to the use of RFID technology and some of its drawbacks related to noise, these two states become confounded.

Our algorithm uses k-means clustering, and one of the issues with k-means is the need to select the number of centroids as a fixed parameter prior to processing any data. There has been research done on how to choose the number of centroids [16] with various levels of success and drawbacks. Most of the algorithms for determining the optimal amount of clusters for a particular data set attempt to break down the data into as many small clusters as possible. Although this would give us more information about our data, it would be difficult to decipher the significance of these clusters. Thus, the proposed algorithm identifies potential misclassifications made by a two centroid k-means algorithm, to avoid dividing the signal into smaller clusters. Instead, the temporal meaning of each data point and its proximity to a cluster will be resolved later in order to correct the coarse-grained classifications made into these two clusters.

C. Respiratory Monitoring

There are many ways of recording respiration rate [17] [18]. Each of these methods have advantages and disadvantages. For instance, electrocardiograms (ECG) are capable of finding a patient's heart rate, respiration rate, and even diseases related to the patient's heart or respiration system. However, ECGs must be fastened to the patient's body in order to operate. Non-invasive ventilators (NIV) also capture a patient's respiration rate. NIVs have the advantage of allowing patients to have full body motion, while still being able to capture both the respiration rate and certain medical conditions related to the respiration system. Due to the NIV design, however, these devices are subject to some potential errors related to their use in certain environments.

The Bellyband is capable of finding a patient's heart rate, respiration rate, and certain diseases-related to a patient's respiration systems. The Bellyband offers a third option for monitoring a patient's vital signs. Instead of placing a sensor on a patient's body or in the general area around the patient, the Bellyband can be knitted into a patient's garments. This allows the patient to move freely around a room and limit the amount of sensors on the patient's body.

III. Approach

To predict respiratory activity, preliminary processing is needed to verify that the return signal contains valid information about the patient. These pre-processing steps include removing the effects of frequency hopping III-B, checking for a valid return signal in Section III-A2, applying noise reduction techniques in Section III-A3, and pulling information from other parts of the Bellyband's framework in Section III-A4.

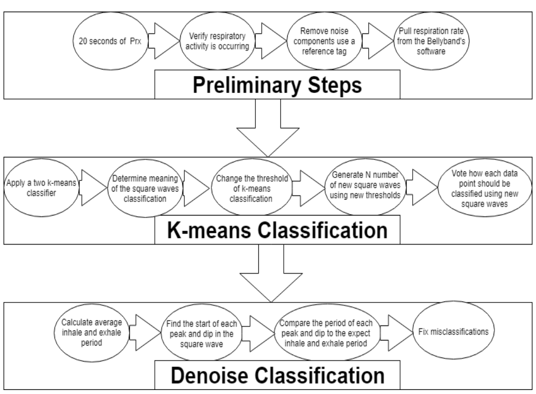

Fig. 3. High level overview of proposed algorithm

A. Algorithm

1) Handling Frequency Hopping: The first step in these checks is caused by the United States Federal Communications Commission (FCC) regarding the use of single receiving antennas in the US. The FCC regulations dictate that any radio signal operating in a high-frequency range should change its frequency every 0.2 seconds, also known as frequency hopping. As a result of frequency hopping, the RSSI value from the Bellyband's return signal comes with a certain level of uncertainty. The algorithm's calculations use a modification of RSSI, which is called P_{rx} defined in Equation 1 [19] [7].

$$P_{Rx,reader} = P_{Tx,reader} \times G^2_{reader} \times G^2_{tag} \left(\frac{\lambda}{4\pi r}\right)^4 \times R \quad (1)$$

where G represents the gain of the tag or antenna, P denotes the power, r the distance between interrogator and tag, and R the return path loss.

2) Validating Return Signal: To confirm that respiratory activity is taking place, the algorithm implements an unsupervised algorithm to filter P_{rx} with a Kalman filter which then feeds the results to a Support Vector Machine (SVM) [10] [20]. This algorithm is capable of alerting symptoms of apnea, which can be defined as a period of 10 seconds of a reduction in respiratory activity by 95% [21]. Since this algorithm can detect periods of sleep apnea, any data that is collected is considered to contain valid respiratory activity as long as no alarms are triggered.

3) Noise Reduction: Since the Bellyband is a wearable smart fabric that utilizes RFID technology, it is expected that some unknown quantity of noise artifacts will appear in the return signal. To limit the amount of noise in the return signal, the Bellyband uses a reference tag to help identify and remove noise artifacts. This reference tag is placed somewhere on the patient's body where the physical movements of respiratory activity will not affect the reference tag in any way. Using this reference tag, data can be distinguished as valid increases in P_{rx} compared to increases in P_{rx} due to noise components [22].

4) Estimating respiratory rate: To estimate the respiration rate of a subject wearing the Bellyband, this algorithm uses data fusion techniques involving a Gaussian Mixture Model [7]. This estimation yields a noisy average respiratory period, which informs the voting classifier in a later step, in order to resolve misclassifications during k-means clustering (see section III-C). Because this estimate of respiratory rate is computed before the algorithm, we allow a short time (5 seconds) before starting the proposed algorithm in this paper.

B. Applying k-means

The first step in the classification process is to partition the data into a rolling window of twenty seconds. In each window, twenty seconds of P_{rx} values are observe that were calculated in Section . This sliding temporal window is classified by a k-means clustering algorithm that partitions the data into two clusters, representing applying strain to the Bellyband (*i.e.*, during respiratory movement), or stationary Bellyband (*i.e.*, non-breathing). These two clusters are represented by the "non-breathing" class, and the "breathing class" (classes 0 and 1). The result of this two k-means algorithm is a square wave representing the nearest k-means centroid to each data point seen in Figure 4. As Figure 4 shows, there is a considerable amount of fluctuation in the square wave. Low-frequency elements in P_{rx} rolling window represent respiratory activity.

High-frequency elements represent noise components in the P_{rx} rolling window. In the next section, information from the square wave will be extracted to successfully amend errors in k-mean's classification caused by noise components.

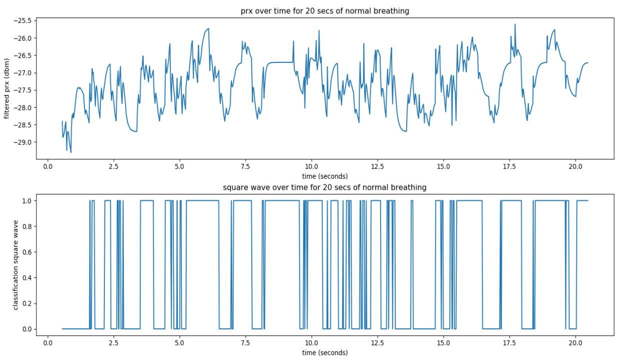

Fig. 4. k-means classification of 20 seconds of P_{rx}

To do this, we find the maximum P_{rx} value and its position in the twenty second P_{rx} rolling window. Then, using this location, find the corresponding value in the square wave. Whatever the value may be (0 or 1), this value will be considered what represents respiratory activity in the square wave. To understand why this is the case, consider how the Bellyband functions. As an individual inhales while wearing the Bellyband, the knitted antenna in the Bellyband stretches and is capable of returning a stronger P_{rx} value due to the antenna's change in structure and subsequent change in impedance and resonant frequency. $p = argmax(P_{rx})$ in the rolling window indicates the corresponding temporal location of the peak in the square wave, and the square wave is adjusted such that this "active" cluster is always represented as state $cluster(p) = 1$.

C. Removing noise artifacts from the square wave

In this section, possible noise artifacts are found and removed. For this approach, only data points that k-means has classified as state 0, representing the inactive will be handled.

To identify noise components, a list of acceptable percentages (LAP) are defined. LAP is a set of thresholds of the normalized distance between each data point and each of the two centroids defined by k-means. LAP can also be viewed as the accepted distance required for a data point to be classified as state 0, the inactive state. The range of percentages in LAP goes from 0% to 200%. A percent difference of 0% indicates that this data point is located exactly in the middle of the two centroids generated by k-means. Such a data point is a likely candidate for potential misclassification under k-means. If a data point is classified with a percent difference of 200%, then this data point is located exactly on one of the centroids locations. If this is the case, then there are no doubts that this data point was correctly classified by k-means. The second thing that should be noted when picking LAP percentages is that there should always be an odd number of percentages in LAP. An odd number of percentages in LAP will guarantee a tie-breaker if one should arise. Finally, keep the size of LAP relatively small. In an upcoming step, multiple different square waves will be generated based on the values in LAP, and the more values that exist in LAP, the longer the time it will take to process and edit these unique square waves. In using LAP, the goal is to determine the optimal frequency that data will be marked as state 0. The method proposed will find this threshold in a semi-unsupervised way. In the final step of this approach, these thresholds are used and compared to the estimated respiration rate pulled in Section III-A4.

Next, generate $N = |LAP|$ new square waves using the original k-means square wave, according to each threshold of the LAP. Following this, every percentage that exists in LAP is assigned to one of the N copies of the original square wave. At this point, every value in LAP has been assigned to their very own square wave that has been generated from the original k-means classifications square wave. From here, these unique percentages are assigned to each square wave and used to evaluate only the $state = 0$ data points in the square wave. To evaluate the $state = 0$ data points using LAP, calculate the percent difference for all inactive data points in the square wave using their distances from both centroids as inputs to the percent difference equation. Once these percent differences have been calculated for each data point, compare them to the assigned percent difference to the square wave. If the result are found to be less than the assigned percent difference, then, assume the state of the data point is misclassified and update the data points classification to $state = 1$ (the active state). Else, this confirms that the data point is correctly classified and should remain marked as state 0, see Figure 5 as an example. Then, repeat this process for all the generated square waves until every value that was in the LAP has been used to create a new unique square wave.

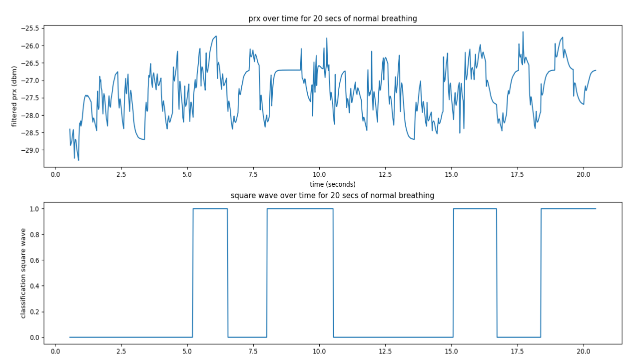

Fig. 5. k-means classification with a 175% LAP value

After these square waves have been generated, a unified denoised square wave is constructed via a vote. This voting system analyzes each individual data point in the square waves. A running tally for each individual data point in the square wave determines whether or not a data point should be classified as inactive or active. The voting parameters are as follows. If a data point is classified as $state = 0$, then, this data point will cast a negative vote towards its own tally. Else, if a data point is classified as $state = 1$, then, this data point will cast a positive vote towards its own tally. Once all the data points in all the square waves have been analyzed, check the running tally to see if it is either less than zero, or greater than or equal to 0 to determine the data points classification. If the tally is 0, then the data point will be classified as $state = 1$. If the running tally is 0, then the data point will be classified as an $state = 0$. These running tallies are used to build a new square wave (see Figure 6).

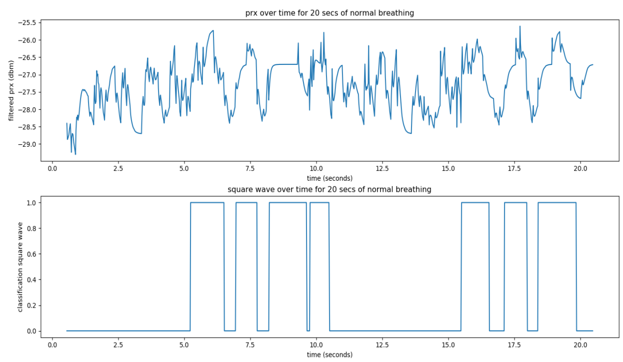

Fig. 6. Square wave after LAP vote

Using this new square wave, we classify noise components that still exist in the square wave. The first noise artifacts that will be removed are from the data points that have been marked as active. To do this, compare the inactive data points to the active data points in order to apply a noise reduction process. For this step, locate the maximum P_{rx} value for all the data points that are classified as inactive. Once the max P_{rx} value is found for the inactive data points, we will compare the P_{rx} value of every point classified as active. If the max P_{rx} value from the inactive data points is larger than any data point classified as active, change the classification from active to inactive to remove the noise artifact. See Figure 7 to see the results of this step.

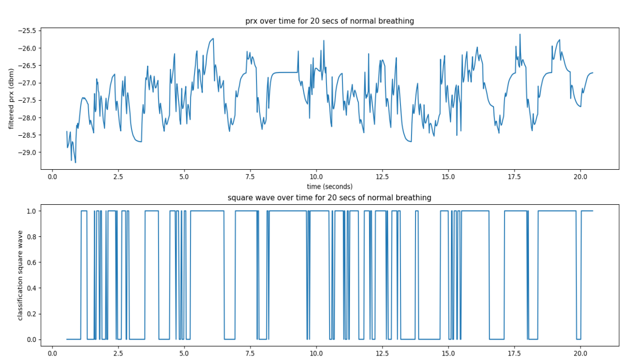

Fig. 7. Square Wave after comparing inactive and active data points

The next step in the adaptive noise reduction utility is using the respiration rate of an individual wearing the Bellyband. Using the estimated respiration rate gives an additional piece of data that indicates the expected length of each inhale and exhale. This information can then be translated to our square wave by locating the start and end times of each active and inactive period in the square wave. This can be done simply by looping through the square wave and identifying the times that the states change from active to inactive and vice versa. Then, take each start and end time of each active and inactive period and subtract the start and end time to get the duration of the state. Then using the duration of each state, compare the states duration to the respiration that we pulled in section III-A4 to see the likelihood a certain period has been misclassified. If a state of active or inactive is less than the estimated time for an inhale or exhale, this state is considered to be misclassified and record its location in the rolling window. Else, consider the period to be correctly classified and will do no further analysis on this particular period.

Assuming that the square wave has at least one misclassified period, this method of noise reduction will replace some of the noise artifacts. To do this, view all misclassified periods between two valid periods. Once this is found, start the final noise reduction process, by calculating the width of both the inactive and activer for the misclassified periods. Then calculate the the sum of both the misclassified active and inactive periods separately by adding up the total widths of both active and inactive periods. After this, take the mean of both the active and inactive periods and compare the two to see which one is greater. Depending on the results, the entire width of the misclassified periods may be considered active or inactive, and the square wave will update accordingly. After this step is complete, the square wave has been classified, and noise components should be completely or partially removed. See Figure 8 to see the results of this step.

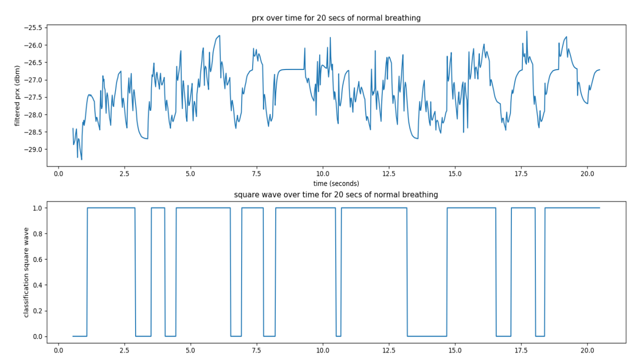

Fig. 8. Final square wave after all noise reduction and classification

IV. RESULTS

The Laerdal SimBaby is a programmable mannequin that can be configured to simulate respiratory movements according to a defined rate and schedule, without external movements aside from the chest cavity motion of respiratory activity. We used the SimBaby programmable mannequin to breathe at a

Breaths	Medical device	Bellyband
1	1.35s	1.08s
2	3.36s	3.52s
3	5.36s	4.44s
4	6.92s	6.90s
5	8.93s	8.23s
6	10.94s	10.71s
7	12.94s	Miss
8	14.94s	14.70s
9	16.82s	17.11s
10	18.95s	18.39s

TABLE I
RESULTS OF THE BELLYBAND'S CLASSIFICATION OF RESPIRATORY ACTIVITY COMPARED TO A MODERN DAY MEDICAL DEVICE CLASSIFICATION

rate of 30 breaths per minute. The SimBaby was then hooked up to the medical device capable of capturing respiration rate. The Bellyband was then placed on the upper abdomen, and the antenna was placed roughly 30 cm away from the SimBaby.

The efficiency of our classification algorithm can best be seen when compared to a modern-day medical device that can be used in hospitals to capture respiratory activity. When doing this comparison, we place both the medical device and the Bellyband on a SimBaby to record respiratory activity. Using this method of comparison, we generate Table I that shows the Bellyband's results compare to the medical device.

V. Conclusion and Future Work

In conclusion, we our noise classification algorithm performs well when classifying respiratory artifacts in the return signal from a device that uses the power of RFID technology, and when using those classifications to adaptively inform a prediction of upcoming respiratory behavior. To summarize our approach, we first perform preprocessing steps that involve checking to ensure that we have a valid signal, noise reductions process, and pulling data from other parts of the Bellyband framework. Second, we applied k-means to a rolling window that contained P_{rx} values, then, optimized k-means by using LAP. The final step is a noise reduction that involves classifying invalid structures/periods of data and classifying them to the correct state. As a result of this method, we have achieved a classification that is within an average of $\approx 0.5s$ of ground truth.

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