# Respiration Estimation and Apnea Detection Using Fuzzy Logic

Akrit Mudvari, *Student Member, IEEE* and Taikang Ning, *Senior Member, IEEE*

***Abstract*— This paper presents a fuzzy logic-based respiration monitoring algorithm that is capable of providing accurate respiration rate and detecting apnea episodes. The proposed algorithm employs several signal processing techniques to extract useful features that signify different respiratory behaviors. We implement a fuzzy logic-based system that examines the extracted respiratory signal features and categorizes the respiratory signals into respiration, body motion, and apnea. The performance of the underlying algorithm is validated using both the MIT physiology database and in-house respiration measurements.**

## I. INTRODUCTION

Sleep apnea syndrome is a serious health threat problem that affects 5% of the world's total population. The percentage is even higher among certain demographics. For example, it rises up to 30% for males over the age of 70 [1]. Apnea is known to result in multiple problems including abnormal behavior during sleep such as body movements resulting in injuries, nocturnal enuresis, headache in the morning, and drowsiness during the day due to lack of proper sleep [2]. While sleep apnea is a prevalent disease, clinical diagnosis of sleep apnea still has a lot of room for improvement [3].

In this paper, four signal processing methods were used in our study to extract multiple respiration signal features. Adaptive approach was utilized to dynamically adjust the thresholding values to gain better accuracy in respiration rate estimation. For instance, adaptive threshold was used to account for loosening of the abdominal strain gauge, which is an impedance measurement device strapped to an elastic band [6]. This is a necessary measure because respiration rate varies by the health condition [6] and the patient's age.

Once the breathing activity is recognized using these methods, respiration rates measured using different methods and signal strength are used to detect the definite instances of apnea. Here, higher preference is allocated to eliminating false negatives because a real time detection would enable immediate medical attention. However, it is necessary to realize that with the onset of apnea, body struggles could result in some activity in strain gauge, which resembles but is not identical to body movements during normal breath [8]. Since it is more difficult to separate normal breathing activity from signals effected by the noises due to body movement, fuzzy logic-based approach is employed to process the signal and classify a period of respiration into normal breathing and body movement. Episodes with overlapping time periods are taken to minimize the chances of missing out on instances of apnea, and data obtained for different source are used to verify that the apnea is detected in each case.

A. Mudvari and T. Ning are with the Engineering Department of Trinity College, Hartford, CT 06106, USA (tel: 860-297-2517; fax: 860-297-2531; e-mail: akrit.mudvari@trincoll.edu)

## II. METHOD

To provide an accurate estimation of the respiration rate and to correctly detect the apnea episode, we have employed several signal processing methods to extract key features that score the respiration behavior.

### *A. Adaptive Thresholding*

In this method, breath information is extracted based on the waveform fluctuations across an adaptive threshold. This threshold is dynamically adjusted using most recently detected breathing features. Weighted average of previous breaths is calculated, where most recent breaths are assigned more weight. The main advantage of an adaptive threshold is that the breath waveform changes due to body movement or loosening of respiration transducer during sleep will have much less effect on accuracy of the respiration rate estimation. The threshold of adaptive thresholding is initialized and calibrated using several normal breaths from the human subject.

In case of respiration with body movement, the signal resembles amplitude variation of normal breathing but exhibits aperiodic and irregular waveform. Time period between consecutive signals of breath is taken into account and anomalous data is excluded. As such, the processed result enables us to know whether the recorded signal is caused by normal respiration or motion artifacts. Fig.1 exemplifies the classification of detected peaks into normal breathing and breathing with body motion artifacts.

### *B. Zero-crossing and Signal Energy*

In the second process, strength of the signal is acquired in real time, and a few seconds-long samples are processed to have zero average. In order to acquire a zero-average, weighted averages of the most recent data are taken and the weights are assigned to allocate more importance to the most

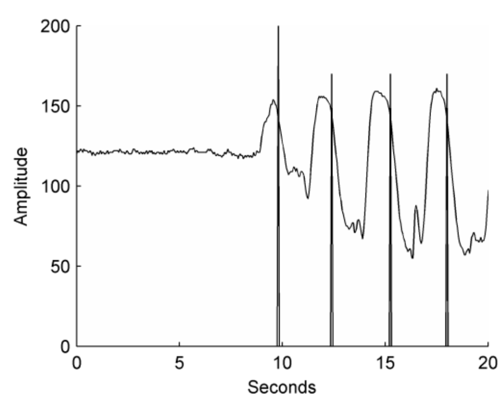


Figure 1: Adaptive thresholding detection: detected breaths are noted by as vertical lines where lines having amplitude near 200 represent body movement noise.

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recent data. This ensures that loosening or tightening of the strain gauge does not reduce accuracy of the algorithm. Zero crossing method allows the algorithm to detect and distinguish "normal breath" and "breath with movement" in real-time and calculate the respiration rate. A difference between this technique and the threshold crossing method is that here, the standard deviation of the data is used to measure the threshold, rather than the average.

Another used of the zero averaged data is calculation of the signals "energy" (root mean squared of the signal's zero-averaged amplitude for a particular sample collected in real time). This method is particularly useful in detecting apnea because the absence of adequate expansion and contraction of abdominal strain gauge means that there is neither normal breathing nor any signal generation due to body movements.

### *C. Respiration Waveform Slope*

This method uses the magnitude and the rate of change in respiration amplitude to categorize the signal into normal respiration, apnea, and body movement artifacts. Normal breathing signal is used to obtain the baseline data that characterize normal respiration. The "rise" and "fall" of a breath signal are noted by their associated "slopes." These waveform slope features are included in the proposed algorithm to classify respiration waveform signals.

### *D. Autoregressive (AR) modelling*

The respiration rate can be efficiently estimated using second order autoregressive (AR) model. While higher order AR models are also applicable, it is sufficient to use a second-order AR model (1) to capture the dominant frequency of a short data segment [9].

$$e_k = x(k) - a_1 x(k-1) - a_2 x(k-2) \tag{1}$$

AR model coefficients $\{a_1, a_2\}$ are estimated using a short data segment and the respiration rate is estimated by

$$freq = \frac{f_{samp}}{2\pi} \tan^{-1}\left(\frac{\sqrt{4a_2 - a_1^2}}{a_1}\right). \tag{2}$$

where $f_{samp}$ is the sampling frequency used during respiration measurement.

Since the normal breath signals were found to exhibit regular behavior similar to a sinusoidal signal while body movement artifacts displayed irregular fluctuations, the 2nd order AR model refection coefficient ($a_2$) can be used to signify the closeness to a sine wave, where the magnitude of $a_2$ closer to 1 indicates a regular waveform.

## III. Fuzzy Logic approach

A Fuzzy-logic [9] based approach is used in our study to analyze respiration signals. We developed membership functions that assign varying degrees of membership to the variables that are used in decision-making [9]. The first input variable used in the calculation is the relative magnitude of the dominant frequency obtained from autoregressive modelling. For the second input, average of healthy peaks detected using adaptive threshold method, zero crossing method and respiration waveform slope method are used.

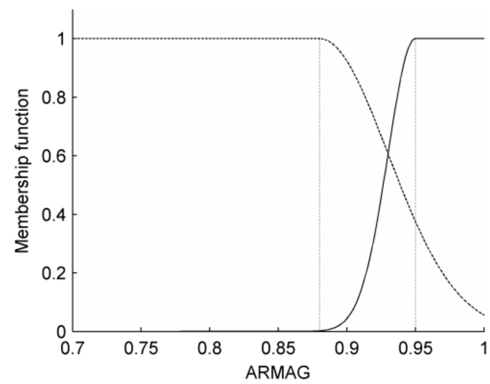


Figure 2: Membership function of the relative magnitude of dominant frequency for normal respiration (solid line) and body movement artifacts (dashed line)

### *A. Membership Function Using AR Coefficient Magnitude*

After obtaining data on episodes that are definitively normal (based on the observation of healthy breathing episodes), the average and the standard deviation of relative magnitude of the dominant frequency are obtained. Same process is repeated for episodes that were classified as a result of body movement. The membership functions as shown in Fig.2 are constructed using the obtained values. Input membership functions (IM) for normal breath is obtained using the following formula:

$$IM_{normal} = \begin{cases} e^{-\frac{(x-\mu_{normal})^2}{2*\sigma_{normal}^2}} \; for\ x \le \mu_{normal} \\ 1 \;\; for\ x > \mu \end{cases} \tag{3}$$

Similarly, $IM_{movement}$ is calculated with 1 for $x<\mu_{movement}$.

### *B. Membership Function Using Peak Average of 'normal' and 'movement artifact':*

Once the respiration rates for signals classified as 'normal' and as 'affected with movement' are obtained, membership functions are heuristically assigned (the assignment emulated decision-making of the experts and was later statistically verified). Table I. shows the example of assigned membership function values.

TABLE I: ASSIGNED MEMBERSHIP FUNCTIONS OF NORMAL RESPIRATION AND MOTION ARTIFACTS

| **Motion Peaks** | **Normal Respiration Peaks** | | | | |
|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 |
| 0 | 0 | 0.1 | 0.6 | 0.9 | 1 |
| 1 | 0 | 0.1 | 0.5 | 0.85 | 0.96 |
| 2 | 0 | 0.1 | 0.45 | 0.85 | 0.93 |
| 3 | 0 | 0.07 | 0.45 | 0.83 | 0.88 |
| >=4 | 0 | 0.05 | 0.35 | 0.8 | 0.85 |

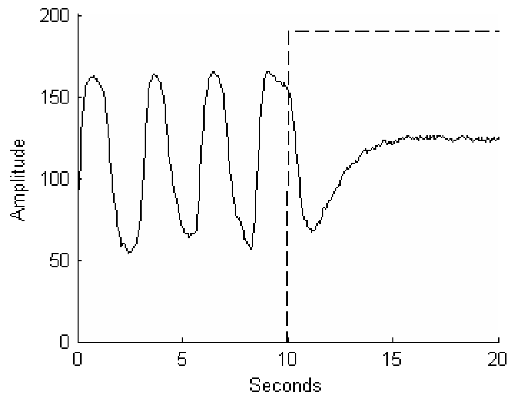

Figure 3: Detection of apnea (apnea is signified by a lack of signal strength). The program increases the amplitude (of dashed line in the figure) to about 180 when apnea episode is detected.

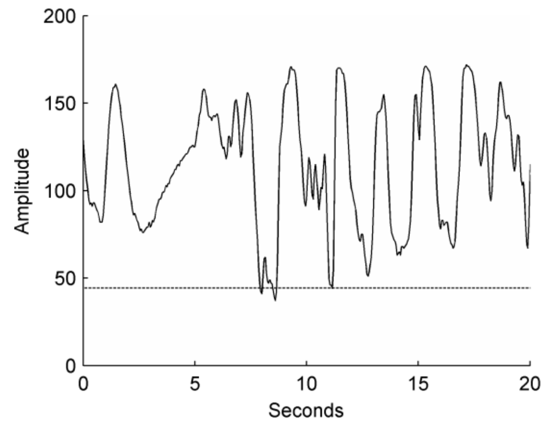

Fig 4: Detection of episodes of body movement (noisy signal). Detection of such episodes is shown by horizontal line with non-zero amplitude (~50).

### C. Fuzzy Inference and Classification

Based on the aforementioned membership functions, output memberships are calculated using fuzzy inference engine [11]. An algorithm is used where the following equation gives output membership function for normal breath

$$OM_{normal} = a * (IM_{ARMAG})_{normal} + b * (IM_{PD})_{normal} \quad (4)$$

Where, OM refers to output membership function, ARMAG refers to relative magnitude of the dominant frequency and PD refers to detected peaks. *a* and *b* are the weights assigned to each membership function (*a*+b=1). The values of a and b were obtained after statistical analysis of the acquired set of data, and these values can be further strengthened with further study and use of more data. The following equation is used to calculate the output membership function (OMF) for movement:

$$OM_{move} = a * (IM_{ARMAG})_{move} + b * (IM_{PD})_{move} \quad (5)$$

Each output membership function is compared to decide whether the episode should be categorized as normal breath episode or episode with body movements.

## IV. Results and Discussion

To examine the performance of the proposed algorithm, respiration signals measured by an abdominal strain gauge were used [4] with a sampling rate of 20 Hz. Respiratory measurements were classified as ‘breathing with instances of apnea’, ‘normal breathing’ and ‘breathing with body movement’. The algorithm was designed to process respiratory data in short segments of duration of 10 seconds or 15 seconds. Each short segment will be categorized according to the extracted respiration features.

Apnea is characterized by a lack of breathing for a period of 10 seconds or longer; an average of 25 seconds was noted in the literature [3]. In our algorithm, we used an interval of 20 seconds as a time frame for a respiration segment for analyzing the data and classifying the episodes into apnea, normal breath or body movements. The algorithm is also run by overlapping 50% of the episode with adjacent segments. For instance, the first 20 seconds are considered to compose first episode while the second episode covers 10-30 seconds. The 50% overlapping increases the detection of short apnea episodes. Two key parameters were used to ensure that every instance of apnea is detected. They are strength of the signals (i.e., root mean square of energy) and the average respiration rate (detected using threshold crossing method, zero-crossing method and waveform slope measurement method). If either technique detects an instance of apnea, it would be safe to assume that the analyzed episode represents apnea.

For data containing mostly respiration activities and apnea episodes in between, our algorithm successfully detected all apnea instances. The more complicated situations were when either possible apnea episodes were distorted with significant body movement artifacts, or when the data segment under examination was the combination of apnea and respiration. The former was categorized as “body struggle” by the algorithm. When we changed the disjoint 20-second data segments into 50% overlapped data segments, the precision of detecting the onset of apnea was improved. Fig.3 shows that our algorithm can accurately detect the onset of apnea.

It was observed from data that respiratory measurement caused by body movements was characterized by a lack of signal regularity, inconsistency in frequency and amplitude recording, and a sudden change of the waveform. To classify such waveforms, fuzzy logic-based decision making was used. Fig. 4 shows a set of signals resulting from body movements, and our algorithm was able to correctly categorize these instances as body movements. In case of the body movements, our fuzzy-logic based heuristic classification algorithm achieved more than 90% agreement with human experts. In case of episodes where the human judgment and the fuzzy logic based algorithm differed, the input membership functions for “normal breathing” and “instances of body movement” were found to be very close to each other. Here, expert opinion and the use of more data for statistical treatment could make the decision making process even more robust.

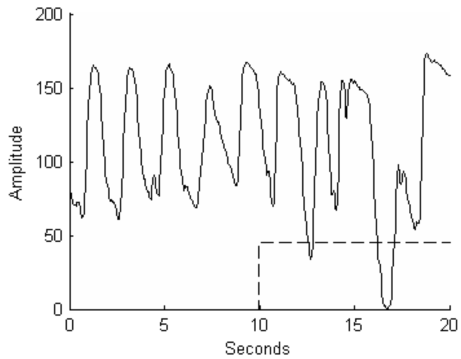

Figure 5. Detection of the onset of body movements (after around 10 seconds). Detection of the episodes with body movements is signified by horizontal dashed line with non-zero amplitude.

As Fig. 5 illustrates, the proposed algorithm is capable of separating episodes of healthy breathing from episodes with significant disturbances of body movement. The results were agreeable with human experts. In Fig. 6, we can see that the algorithm is capable of detecting apnea and body movement.

The performance of our approach was also validated using the PhysioBank MIT database [10]. We used both healthy breathing and apnea episodes. The algorithm was successful in detecting all apnea episodes as shown in Fig.7.

## V. CONCLUSION

This paper demonstrates the performance of a new respiration monitoring system. In absence of the apnea episodes, our algorithm was able to accurately estimate the respiration rate. Our results have shown that respiratory signal features extracted from multiple signal processing methods can be effectively analyzed in real time using a fuzzy logic-based expert system to correctly categorize respiratory signals into normal breathing, breathing with motion artifacts, and apnea.

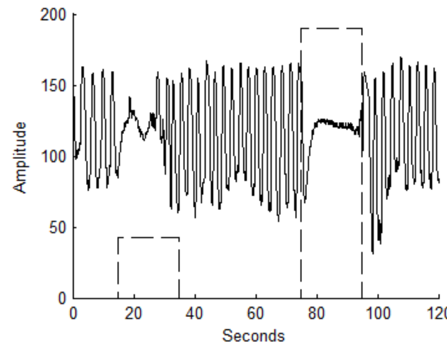

Figure 6. Real-time detection of i) body movement artifacts (shown by low-amplitude (~50) horizontal dashed line for a duration of 15-35 seconds, and ii) apnea (shown by high amplitude (~200) horizontal dashed line for a duration of 75-95 seconds).

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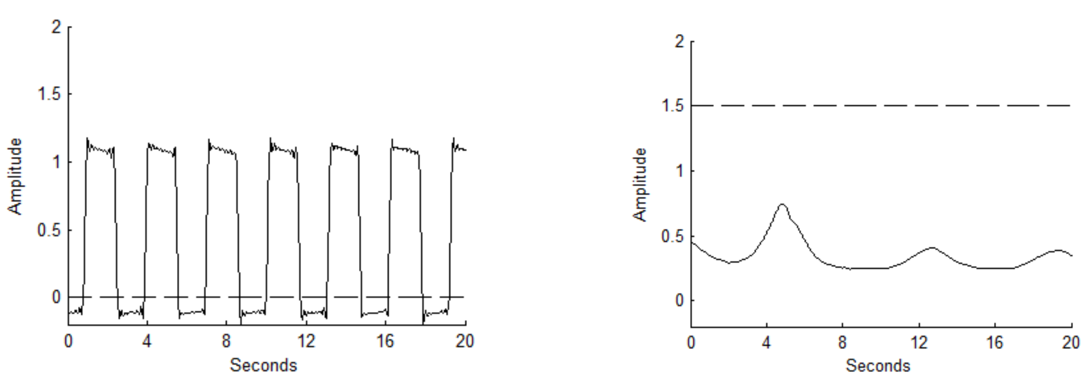

Figure 7. Detection of normal breathing (left) and detection of apnea (right) for signal collected from MIT online database [10]. Discussed algorithm shifts the horizontal dashed line from amplitude of 0 to 1.5 when it detects apnea, as shown above.