Multiresolution Segmentation of Respiratory Electromyographic Signals

Haan-Go Choi, Jose C. Principe, Senior Member, IEEE, Alastair A. Hutchison, and John A. Wozniak

Abstract—Analysis of respiratory electromyographic (EMG) signals in the study of respiratory control requires the detection of burst activity from background (signal segmentation), and focuses upon the determination of onset and cessation points of the burst activity (boundary estimation). This paper describes a new automated multiresolution technique for signal segmentation and boundary estimation. During signal segmentation, a new transitional segment is defined which contains the boundary between background and burst activity. Boundary estimation is then performed within this transitional segment. Boundary candidates are selected and a probability is attributed to each candidate, using an artificial neural network. The final boundary for a given transitional segment is the boundary estimate with the maximum a posteriori probability. This new method has proved accurate when compared to boundaries chosen by two investigators.

I. INTRODUCTION

ELECTRICAL potentials measured from a respiratory muscle result from the summed resting membrane potentials and the action potentials which occur when its muscle fibers are stimulated. Respiratory muscle fiber action potentials are generated by the integrated neural motor output of the central nervous system. Each single motor nerve fiber stimulates several muscle fibers to produce muscle action potentials. The spatial and temporal summation of the potentials arising from the activity of a single motor nerve is referred to as a single motor unit action potential (MUAP). The superposition of all MUAP's within the vicinity of the electrode constitutes the electromyogram (EMG) signal. While the nature of the recorded EMG signal is affected by the geometry of the recording electrode and its position relative to the muscle fibers, the primary factor determining the nature of the EMG is the frequency of neural stimulation. In the case of respiratory muscles, the EMG activity can be divided into periods of high stimulation (burst activity) and periods of minimal or lesser stimulation (background).

Observation of a patient's respiratory pattern is a key initial step taken by the physician in assessing respiratory function. Respiratory pattern is characterized by the airflow signal, whose shape and timing are dependent upon the central nervous system stimulation of respiratory muscles and subsequent interaction of these activities with the mechanics of the respiratory system. Thus, the study of the control of respiratory pattern requires that both the air flow signal and a measure of central nervous system output be recorded. In the awake human and animal, respiratory muscle EMG's provide such information [1]–[3]. Specifically, information about muscle interactions and neuromechanical delays (lags between the onset and cessation of EMG activities, and airflow changes) can be derived from a study of the neural and mechanical timing information [1]–[3]. The timing intervals are affected by underlying system mechanics as well as central and reflex control mechanisms. Variations of only a few milliseconds may have important implications regarding respiratory pattern recognition [4]. Thus, a very accurate measurement of the timing of respiratory muscle EMG's is required to elucidate mechanisms of airflow control.

Reflex afferent input is an important component of the very rapid, within-breath changes in the timing of respiratory muscle activities, and is prominent in the human newborn [2], and the lamb [4]. In both species at birth, such within-breath changes are noted during a grunting pattern of respiration [4], [5]. Thus, representative segments of airflow and respiratory muscle EMG during grunting respiration after birth in lambs [4], were used to develop the proposed technique and automatically find the onset and cessation of respiratory activity. The respiratory muscle EMG's analyzed were: the posterior cricoarytenoid muscle (PCA), the sole muscle which opens the laryngeal valve, and the diaphragm (D), the main inspiratory pump muscle. Fig. 1 shows a typical pattern during grunting respiration. This pattern of respiration is characterized by a period of severe early-to-mid-expiratory airflow retardation, giving the expiratory airflow signal a biphasic pattern. This airflow retardation is effected by upper airway closure and is thought to function to maintain lung volume in conditions of low lung compliance, e.g., after birth and in hyaline membrane disease [6]. Focus was placed upon the onset and cessation of burst activity, as accurate timing of these boundary points is used to determine respiratory muscle interactions and neuromechanical delays in normal and abnormal breathing [1]–[3].

Detection of an abrupt signal change (or boundary) is not a simple procedure, even when the signals are of good quality with high signal-to-noise ratios. A boundary can appear "fuzzy" when the time scale is expanded. Current techniques, which employ the averaged EMG signal, have difficulty separating weak burst activity from background. In addition, due to the averaging process, the resolution obtained using such
Fig. 1. Relationship between airflow and EMG (PCA and D) signals for grunting respiration. A: Onset of respiration. B: Cessation of respiration. C: Background activity marker. F1–F6: Landmarks on airflow used as markers for the segmentation algorithm. S1–S5: Search segments for algorithm (see text).

response of the muscle. Thus, the averaged signal allows better discrimination between burst activity and background. Signal segmentation, per se, begins by dividing the averaged EMG signal into regions of definite burst activity and background, using as initial landmarks the zero-crossings of the airflow signal. Thereafter, a coarse transitional segment is determined, being the region which contains the boundary samples between the definite regions of burst and background activities. Within this coarse transitional segment, a fine transitional segment is further derived.

**Boundary Estimation:** Although the averaged signal is useful in the signal segmentation process, giving a robust estimate of where the boundaries might be, it introduces delays and smoothing, thereby distorting the fine timing information contained in the input signal. In our proposed method precise onset and cessation points will be estimated from the unprocessed EMG signal to increase the resolution of boundary detection. Boundary estimation simply provides “pointers” to half-waves where a boundary might lie.

Short-time energy functions are derived to obtain pointers to half waves (boundary candidates) within the coarse transitional segment. The pointers are determined from thresholds in the short-time energy which correspond to sharp changes in signal energy. Features from half-waves in the unprocessed EMG signal, occurring at these points, are utilized as inputs to a multilayer perceptron. The neural network estimates the *a posteriori* probability of each boundary candidate, and the largest output is chosen as the half-wave that contains the final boundary. A simple algorithm determines the final boundary point within this half-wave.

The segmentation model is based on a multiresolution analysis: EMG signal → transitional segment → half-wave → boundary point. The multiresolution analysis narrows the duration of the signal segment targeted for in-depth analysis, keeping the robustness and improving the accuracy of boundary detection.

**III. DESCRIPTION OF THE SEGMENTATION METHOD**

**A. Preprocessing**

There are two principal noise sources in the collected respiratory EMG signal. Firstly, low-frequency noise is produced by subject movement and/or weak activity generated by motor units distant from the electrode. Secondly, 60 Hz electrical interference and its harmonics are picked up from poor contact (high resistance) between the recording electrode
and the muscle, and from inadequate grounding. The spectrum of the respiratory muscle signal has over 90% of its energy in the 60–450 Hz bandwidth [10]. A 63rd-order finite impulse response (FIR) bandpass filter was designed to reduce the low- and high-frequency noise, using the optimal design technique of Parks and McClellan [7]. The characteristics of the bandpass filter are: transition bands at 58 ~ 128 Hz and at 450 ~ 550 Hz, in-band ripple of 0.01 and maximal gain of 2.1 in the passband, and 50 dB out-of-band attenuation. After bandpass filtering, rejection of electrical interference is performed if necessary. The 60 Hz interference is a common problem in biological signals and can often be eliminated using a notch filter. Spectral analysis of the sampled EMG signal was used to verify that not only 60 Hz, but also its odd harmonics (180, 300, and 420 Hz) are normally present. An adaptive noise canceller (ANC) is selected here, since it can track changes and preserves the correct phase relationships for canceling, and thus produces a sharper and narrower transition band at the notch frequencies of interest [8], [9]. The parameters used in the ANC algorithm were a sampling frequency of 2000 Hz and an adaptation step of 0.011. A detailed description of the algorithm has been published [10]. We want to stress that not only the fundamental frequency (60 Hz) but also its harmonics should be notched for good results. We have not implemented any filters for ECG elimination due to the fact that with needle electrodes this contamination is normally reduced.

B. Burst Activity Identification and Signal Segmentation

1) Signal Averager: The original EMG signal is first smoothed into a moving-time average (MTA) signal. The MTA signal attenuates rapid variations from point to point through local averaging, but retains slow variations (i.e., lowpass filtering). The smoothed value \( y(n) \) is an average of the input signal \( x(n) \) in the vicinity of sample \( n \). One can consider averaging over \( N + M + 1 \) neighboring points, using a difference equation of the form

\[
y(n) = \frac{1}{N + M + 1} \sum_{k=-N}^{M} x(n-k).
\]

This equation states that the filter impulse response is a rectangular pulse of finite duration (FIR). A delay of \( N \) points makes this filter causal. The frequency response is given by

\[
H(w) = \frac{1}{N + M + 1} e^{-jw(N+M)/2} \frac{\sin((N+M+1)w/2)}{\sin(w/2)}.
\]

The cutoff frequency of the MTA filter is controlled by the window length \( N + M + 1 \) and corresponds approximately to \( (2 \pi)/(N+M+1) \), which can be put in terms of the input sampling frequency \( f_s \), yielding \( f_s/(N + M + 1) \) [11].

The selection of the window type does not affect the smoothing of the burst activity envelope significantly. In this study, a Hann window is used because it provides slightly better smoothing. More important than window type is the choice of a window length which prevents false detection of burst activity in the background. Empirically, a window length of 81 samples (MTA81) was shown to provide a conservative smoother for burst activity identification [10]. In addition, a smaller sampling window of 21 samples (MTA21) is employed to determine the transitional segment. The cutoff frequencies of MTA21 and MTA81 are 95.2 Hz and 24.75 Hz, respectively, for a sampling rate of 2000 Hz.

2) Signal Segmentation:

a) Determination of Initial Landmarks: Burst activity detection using the EMG signal alone is difficult because of the variability of the signal amplitude between breaths. We utilized the airflow to give a coarse, robust initial estimate of the burst activity. We cannot rely on this signal for accurate neuromuscular timing, since this signal varies slowly and timing differences do occur between the onset of EMG activity and airflow. For airflow to occur the glottis must be open, i.e., PCA burst activity must be present. During inspiration, but not during expiration, this is accompanied by diaphragmatic burst activity. Thus, during grunting respiration, an initial airflow search point for burst activity was chosen in the middle of the cycle of PCA and D muscle burst activity. Similarly, the initial search point for baseline activity was chosen in the middle of a baseline period for the PCA and D muscle activity in grunting respiration. Timing landmarks, defined by the zero-crossing points of the airflow signal, are used as initial reference points to guide the selection of burst activity and background segments in the MTA81 signal.

The normal relationship between airflow, PCA and D activities, are shown in Fig. 1. Points \( F1'–F3' \) in the airflow signal are zero-crossing points which are used as landmarks in a breath cycle. The airflow interval between \( F2 \) and \( F3 \) corresponds to inspiration, and the interval from \( F3 \) to \( F5 \) (\( F2 \) of the next breath cycle) is expiration. Total breath duration is the sum of inspiration and expiration. The time interval during onset of the respiratory muscle activity (PCA or D) is shown by \( A \), while \( B \) depicts the interval of cessation of activity. The searching periods for the onset and cessation are determined as follows [10]:

- The zero-crossing points \( F1, F2, \) and \( F3 \) are detected.
- A point \( mid.x \) related to the end of the burst activity is calculated as \( (F3 + F2)/2 \). The interval between \( mid.x \) and \( F3 \) is defined as \( S1 \). This interval \( S1 \) is used to search for the point of cessation of burst activity in both PCA and D signals.
- A point \( C = (F4 + F3)/2 \) is identified, which always lies in the background segment. The interval \( S2 \) between \( C \) and \( F5 \) is used to search for the onset of D activity.
- The PCA signal used for analysis consists of two components. The onset of PCA activity is taken to be the onset of the initial component. Within this initial burst activity, an algorithm detects a maximum-value point \( P \) between \( C \) and a point \( K \), where the point \( K \) is determined as the minimum-value point between \( (F4 + (F5 - F4))/4 \) and \( F5 \). The onset in PCA activity is then detected within the interval \( S3 \), between \( C \) and \( P \).

b) Initial Determination of Burst Activity Segments: The method to detect burst activity involves the determination of a
threshold value which separates the high-amplitude signal and the background level. However, background activity varies between breaths, and thus, determination of what represents the reference background level is critical. The method employed here is similar to some described previously [1]–[3].

The duration of S4 for PCA (S5 for D) in Fig. 1 is divided into segments of 100 ms and mean values for each segment of the MTA81 signal are computed. The segment with the minimum mean amplitude [min\_seg in Fig. 3(a)] is chosen as representative of the background. The burst activity period is defined as the time segment where the MTA81 signal amplitude exceeds a threshold above background. The threshold is defined as a constant $k^*$ mean value of min\_seg, where the value of the constant $k$, determined experimentally, is between 2 and 4.

The threshold value is also used to detect the initial onset and cessation of diaphragm burst activity [points $P_{io}$ and $P_{lc}$ in Fig. 3(a)], by searching the MTA81 signal between $S1$ and $S2$. The interval $P_{lc}$ to $P_{io}$ constitutes the initial background segment, while $P_{(i-1)c}$ to $P_{io}$ is the initial burst activity segment. Although this method provides only a rough estimate of the boundary between burst activity and background, it explicitly locates the burst and background activities. The same method is applied to the PCA signal.
c) Determination of Translational Segments: Signal segmentation is performed on a breath-by-breath basis and signal variation must be taken into account. This is especially true for boundary detection where the transition between background and burst activity can be sharp or more gradual, depending upon the rate of change of the signal amplitude. Thus, having determined the above initial estimates of the burst activity segment, the next step is to localize the boundary region more precisely by determining a new segment, which we call the translational segment.

Coarse and fine translational segments are defined using the initial boundary of the EMG burst activity. Fig. 3(b) illustrates the determination of the onset translational segment for the D signal. The first trace in the figure is the original D signal followed by its MTA21. The third is the MTA81 output and the fourth is its derivative, calculated using the central finite difference

\[ y_n = \frac{(y_{n+5} - y_{n-5})}{10}. \]

**Coarse Translational Segment:** Zero-crossing points \( Z_1 \) and \( Z_2 \) in the derivative of MTA81 are found by searching forward and backward from \( P_{ao} \). These zero-crossings correspond to the local extremes of the MTA81 in the neighborhood of \( P_{ao} \). The point \( T \) in the MTA81 between \( Z_1 \) and \( Z_2 \) that corresponds to the background level is also found. The coarse translational segment is defined as the interval between \( T \) and \( Z_1 \). The step of finding \( T \) can be omitted, but in some cases it decreased the length of the coarse traditional segment appreciably.

**Fine Translational Segment:** Having used MTA81 to obtain global information of the burst activity pattern, a finer translational segment is determined using the MTA21 signal. The inner and outer limits of this fine translational segment are set by detecting the minimum level of EMG activity prior to the onset of burst activity and an early point in the burst activity which is significantly different from background. The outer limit of the fine translational segment is defined as the first local minimum point \( M \) in the MTA21 within \( Z_1 \) and \( Z_2 \) (search starting from \( Z_2 \)). A new background reference value is then calculated in the 5.5 ms period (seg1) prior to the instant \( M \). The other limit of the fine translational segment \( Q \) is the first peak on the MTA21 signal whose amplitude is greater than \( 10^3 \text{ mean(seg1)} \). When no early peak \( Q \) is detected, the time of the outer limit of the fine translational signal is set equal to \( Z_1 \).

To minimize the effect of signal variation on the length of the fine translational segment, refined inner and outer limit points are computed. If a point \( N \) with an amplitude less than the mean of seg1 can be detected between \( M \) and \( Q \), then it replaces \( M \) [Fig. 3(b)]. Similarly, if the time interval from the start of the fine translational segment \( M \) or \( N \) to the peak of the derivative signal \( (P_K) \) is less than the interval \( M \) or \( N \) to \( Q \), then the outer limit is redefined as: \( P_K + (Q - P_K)^*3/4 \).

The above decision rules were determined empirically [10]. The same methodology is applied to the PCA signal and to the determination of the translational segments for the cessation of burst activity. The length of the translational segment varies depending upon the slope of the averaged signal. Sharper signal changes result in a shorter length of the translational segment and vice versa. The time intervals of coarse \((C1 \text{ and } C2)\) and fine \((B1 \text{ and } B2)\) translational segments in the raw EMG signal are then used for boundary estimation. The mean of these segments can be utilized as a first definition of the onset and cessation of burst activity as will be described in the results section. In the next section we highlight our proposed methodology to define with high resolution the sample that corresponds to the boundary point.

IV. DESCRIPTION OF BOUNDARY ESTIMATION

A. Detection of Boundary Candidates

The amplitude of the raw translational signal varies appreciably with time. The use of a short-time energy function provides a means of enhancing signal amplitude differences between background and burst activity. Here we define the short-time energy (STE) as

\[ E_n = \frac{1}{2N+1} \sum_{m=-N}^{N} (x(m) \cdot w(n-m))^2 \]

\[ = \frac{1}{2N+1} \sum_{m=-N}^{N} x^2(m) \cdot h(n-m) \]

where \( h(n) = w^2(n) \). The signal \( x^2(n) \) can be interpreted as being filtered by a linear filter with impulse response \( h(n) \), which corresponds to the window. The choice of the window length determines the nature of the STE representation. A short window energy function is preferred for separating burst activity from background with high resolution. However, it carries the disadvantage of being too sensitive to local amplitude variability hence, the STE function is computed following the moving time average filters discussed in the previous section. Assuming a rectangular window, the signal processing function of the combined MTA and STE can be expressed mathematically as

\[ z(n) = \text{MTA} \cdot y(n) \cdot \text{STE} \cdot x(n) \]

\[ y(m) = \frac{1}{2l+1} \sum_{j=m-l}^{m+l} x(j) \]

\[ z(n) = \frac{1}{2k+1} \sum_{k=n-i}^{n+i} y^2(k) \]

\[ = \frac{1}{K} \sum_{k=n-i}^{n+i} \left( \sum_{j=k-l}^{k+l} x(j) \right)^2 \]

\[ = \frac{1}{K} \sum_{k=n-i}^{n+i} \left( \sum_{j=k-l}^{k+l} x(j) \right) \left( \sum_{j=k-l}^{k+l} x(j) \right) \]

where \((2i+1)\) is the number of samples of the MTA filter, \((2l+1)\) the length of the STE filter, and \( K \) is \((2i+1)(2l+1)^2\).

In this work, the cascade of two STE processing blocks with different windows followed by a MTA block comprise a boundary candidate channel. Detecting amplitude changes
at the output of these channels becomes very sensitive to the values of \( i \) and \( l \), the window lengths (we experimentally found that the MTA is dominant). Instead of trying to determine experimentally the best compromise of window lengths for the STE and MTA, several parallel channels with different window lengths are used to determine a representative sample of probable boundary candidates [10]. Five boundary candidate channels are implemented with the following window lengths: 1-1-1, 2-2-2, 31-7-9, 51-9-11, and 71-2-2. The moment the output of the last STE in the cascade passes a threshold is used as a pointer to a half-wave of the unprocessed EMG signal, which we call a boundary candidate. This threshold is not crucial for the performance since the channel output changes abruptly near the waves corresponding to probable boundaries (we set it at three times the background level). The first two boundary candidate pointers detect relatively small-scale variations in the signal, while the remainder provide information about large-scale variations. Most of the boundary candidates are detected from the first two combinations. The above mentioned arrangement of pointers produce an ensemble of boundary candidates which, in our training data sets, represent all boundary points detected by expert investigators. The problem is to choose the best candidate. This is achieved using an artificial neural network. Increasing the number of these fiducial candidates reduce the probability of boundary detection failure, but increases the computational load.

B. Boundary Classification Using a Neural Network

1) Quantification of Boundary Candidates for Neural Network Input: As explained above, the boundary candidates are utilized as pointers to half-waves in the unprocessed EMG signal where the boundary might lie. We returned to the original EMG signal to provide good resolution. Twenty half-waves from the original EMG signal (Fig. 5), ten before and ten after each boundary candidate point are selected, and their features are used as the input to a neural network. A piecewise linear approximation of the EMG signal, using a peak detection algorithm [12], is computed for each half-wave, and it is multiplied by the corresponding local slope to give a measure of the “duration-slope” (Fig. 5).

The duration-slopes have a large dynamic range, which makes the training time of the neural network very long (see next section). Thus, they are normalized with respect to an average duration-slope in the background segment, and are transformed into discrete input levels which result in more stable and faster training of the neural network [10]. Based on experimental results, four quantization levels (0.0, 0.5, 1.0, and 1.5) were selected. This gives the minimum training error with the minimum number of iterations until convergence. The input level of 0-0.5 was further divided into four equal discrete levels, because most of the boundaries are in this range and smaller quantization can improve the accuracy of boundary detection.

2) Boundary Estimation Using Neural Networks: A discriminant function is required to rate the boundary candidates consistently. Artificial neural networks (ANN’s) have been applied to solve pattern recognition problems [13]. The ANN learns the classification problem through the presentation of sufficient and meaningful examples. The implementation of the ANN is conceptually simple because, after fixing the ANN structure, the network discovers the discriminant function for the boundary classification through training. The main disadvantages of the ANN lie in the long period required for initial training and poorly understood discriminant properties, which make incremental solutions difficult.

Under certain conditions, the ANN output can be interpreted as an \textit{a posteriori} probability that the boundary estimate belongs to the correct class, i.e., that it represents the “true” boundary. This is a potentially useful property for biomedical signal classification that was explored in this research [10].

a) Factors in Implementing Neural Networks: Implementation of the neural network requires selection of the network architecture, collection of training data sets and learning. All these conditions are addressed in this design [10].

ANN Architecture: To solve the boundary problem non-linear discriminant functions are anticipated. Thus, the ANN must have at least one hidden layer [13]. Two hidden layers provide arbitrary discriminant functions, but they increase the number of weights, which leads to the requirement of more training patterns and also slows training. The output of the network consists of a single processing element. The number of processing elements in the hidden layer is related to the number of required partitions in the pattern space and their required resolution, and is experimentally set to 18 (Fig. 6). The number of input elements is selected to be 20, because of pattern diversity. Twenty half-wave segments, which correspond to roughly 40 ms, are considered adequate to represent the variability of the input pattern space.

Collection of Training Sets and Learning: The success of the network implementation relies on good training. The training sets are collected from EMG signals, chosen by experts and encompassing a wide spectrum of signal conditions. During neural network training, the desired output is set to
V. IMPLEMENTATION AND PRELIMINARY RESULTS

The multiresolution methodology has been implemented on a NeXT workstation, using an object-oriented paradigm (objective-C language). The NeXT computer is well suited to implement this system, since it provides a graphical user interface, PostScript, and other sophisticated hardware resources such as a digital signal processor. Another useful tool is the Interface Builder which helps significantly the programmer in the design of the graphical user interface and, during analysis, in obtaining the clinical investigator's input.

EMG signals were recorded with stainless steel wire electrodes inserted into the respiratory muscles (PCA and D) of five newborn lambs. The signals were amplified with Gould preamplifiers using conventional clinical specifications, and digitized at 2 kHz with a 12-bit A/D converter. Segments containing the grunting pattern, as shown in Fig. 1, were selected for analysis. The test set, comprising 552 boundaries in 138 breaths, is different from the data used to train the neural network. There are four different boundaries for each breath: onset and cessation boundaries of both PCA and D signals.

System-detected boundaries were compared with the boundaries selected by eye by two experts (A and B). Each test data set, consisting of two channels of signals (PCA and D), were printed and given to the two experts who detected the boundaries and entered them into the computer. Typical transitional segments, system-detected boundaries showing the a posteriori probabilities, final boundaries, and expert-detected boundaries are illustrated in Fig. 8 for two representative cases. The numbers in the figures denote the system-detected boundary probabilities. A and B indicate the boundaries detected by the two experts. The interval between C1 and C2 indicates the coarse transitional segment, and the interval between B1 and B2 indicates the fine transitional segment. F indicates the system-detected final boundary. Clear boundary conditions are shown in Fig. 8(a). The system- and manually-detected boundaries are in close proximity. A transitional segment with less clear burst activity boundaries is shown in Fig. 8(b). Although the expert-detected boundaries are relatively far apart, the system has assigned high probabilities to both boundaries.

Fig. 8 shows that the manually-detected boundaries, A and B, lie within the system-detected transitional segments. An important evaluation is to check the practical use of the newly defined transitional segment. We assessed its usefulness statistically, by counting how many of the expert-detected boundaries are located within the transitional segment. The duration of the coarse and fine transitional segments (mean ± standard deviation) and the fractions of how many expert-detected boundaries lie within the transitional segments are shown in Table I. The table shows the data divided by each lamb (subject) and confirms that all expert-detected boundaries lie within the corresponding coarse transitional segments. Indeed, only 1.27% (7 out of 552) are outside the fine transitional segments. The average row shows that the length of the coarse transitional segment is 47.1 ms, and the length of the fine transitional segment is significantly
smaller at 22.7 ms. The standard deviations of these values are small (1.23 and 0.75 ms). Taking the midpoints of these segments as the final boundary point, the system detects boundary points with an accuracy (with respect to the expertdetected boundaries) of at least 23.55 ms with 100% correct detection rate, and approximately 11.35 ms with a 98.7% correct detection rate. There is no significant difference in the duration of the transitional segment lengths among the five subjects. We are presently evaluating the timing accuracy of the neural network-defined boundaries.

VI. CONCLUSIONS

The major strength of the new method lies in its multistage approach, which uses both new and established techniques to overcome problems intrinsic to the EMG signal and to improve on the resolution of current boundary detection methods. In addition, the analysis is novel in that an artificial neural network is used to produce a probability for a possible boundary point, that can be interpreted as the probability of the true boundary. In this paper we presented the full algorithmic
methodology, but we only validated the timing error produced by assigning the boundary point to the middle of the transitional segment. Even at this "coarse" resolution the maximum timing error is less than 11.35 ms in 98.7% of cases (one half the length of the fine transitional segment as depicted in Table I). This timing error is appropriate for airflow studies, but must be decreased for the quantification of the timing of onset and cessation of respiratory muscles (airflow control) where resolutions of a few milliseconds are in order [4]. The timing error produced by the artificial neural network output should yield the appropriate resolution, but only preliminary evidence is available at this time. The development of an algorithm that automatically detects the transitional segment will help researchers by focusing their attention on the key area where the boundary is situated. If the system is developed further to run in real-time, only the transitional segments would need to be saved for later boundary detection analysis, thereby minimizing data storage.

This multiresolution method was developed to quantify EMG burst activities in respiratory muscles. This infers the presence, in the unprocessed signal, of periods of background activity just prior to the onset of burst activities. The importance of signal preprocessing to reduce noise during the background segments should be stressed. However, despite filtering, the method cannot be applied to EMG signals without a sufficiently quiet background period. In such situations, signal segmentation and boundary detection can be performed using the averaged signal.

The proposed methodology is dependent upon a set of amplitude thresholds, but all other algorithmic parameters are preset for all cases. We plan to improve the technique by making it independent of adjustable amplitude thresholds. A good example of the effort to substitute thresholds is the use of the neural network to pick the half-wave that contains the final boundary point. The neural network solution to select the boundary point appears to be a robust method for improving the resolution of boundary detection. Due to the variability of the EMG signal in the region of the boundary, it would be very difficult and time consuming to create an accurate algorithmic or a parametric approach to find the boundary point. The advantage of using the ANN is that the boundary can be learned from examples, assuming that experts consistently determine the best boundary in a training set. Our preliminary results (an example is depicted in Fig. 8), show that ANN boundary detection can be as precise as expert-detected boundaries. However, testing of the method in terms of accuracy and reliability will be left to a follow-up paper.

The system presently does not run in real-time, but all the algorithms have been designed to operate on a sample-by-sample basis, which means that if sufficient computational speed is available, they can be easily extended for real-time implementation. Our preliminary analysis of the algorithms shows that a digital signal processing (DSP) chip, such as the Motorola DSP 56001 (the DSP chip available in the NeXT computer), is a viable candidate for real-time implementation of the multiresolution segmentation procedure proposed in this paper. In addition, the artificial neural network presents a very good compromise for real-time implementation, since in order to classify the data only the sum-of-products followed by a nonlinearity calculation are needed. The training of the neural network, which is the most time consuming step in the method, can thus be deferred to off-line processing.

REFERENCES

Han-Go Choi received the B.E. degree from the Kyungpook National University, Korea, and the M.S. and Ph.D. degrees in electrical engineering from the University of Florida, Gainesville, in 1988 and 1992, respectively. In 1993, he joined the faculty of the Department of Control Engineering at the Kum-Oh National University of Technology, Korea. His research interests are signal processing, pattern recognition, and neural networks.

Alastair A. Hutchison was born in Kirkcaldy, Scotland, in 1947. He received the medical degree (MBChB) from the University of Aberdeen in 1971 and postgraduate degrees in pediatrics from the Royal Australasian College of Physicians (FRACP) in 1981 and from the American Academy of Pediatrics (FAAP) in 1983. He has been a faculty member of the Department of Pediatrics at the University of Florida, Gainesville, since 1983, where he is an Associate Professor of Pediatrics in the Division of Neonatology. His principal research interests are respiratory control and respiratory mechanics in the newborn, neonatal neurology, and hydrops fetalis. Dr. Hutchison received his subboard in Perinatal-Neonatal Medicine in 1983.

Jose C. Principe (M’83–SM’88) was born in Porto, Portugal, in 1950. He received the B.S. degree in electrical engineering from the University of Porto in 1972 and the M.Sc. and Ph.D. degrees from the University of Florida, Gainesville, in 1975 and 1979, respectively. From 1980 to 1987 he was a Professor in the Department of Electrical Engineering at the University of Aveiro Portugal. He joined the University of Florida in 1987 where he is a Professor of Electrical Engineering. His research interests are biological signal processing and modeling, in particular the electroencephalogram. He is currently interested in the analysis and applications of neural networks for time varying signal processing.

John A. Wozniak received the B.S.E.E. degree from Massachusetts Institute of Technology in 1979, the M.S.E.E. degree from the University of Florida in 1986, and the Ph.D. degree in physiology from the University of Florida.

He is an Assistant Research Scientist in the Division of Pediatric Pulmonology. His research interests include signal processing of electrophysiological data, applying systems theory to biomedical applications, and developing novel approaches to determine pulmonary function in infants.