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Lung Sound Pattern Analysis for Anesthesia Monitoring

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Abstract— **This paper introduces a set of characterizing parameters for identifying patterns in lung sounds. Stochastic analysis is performed to extract sound patterns and understand the impact of noise artifacts on sound pattern recognition and diagnosis.**

I. INTRODUCTION

Respiratory sounds are physiological vital signs designated by American Society of Anesthesiologists (ASA). They contain a rich reservoir of vital physiological and pathological information that is of critical importance for clinical diagnosis and management in operating rooms (OR). Continuous monitoring of lung sounds can provide a non-invasive and inexpensive means of diagnosing accurately and promptly for many clinical conditions or even life-threatening situations.

Assisted by standard engineering tools for signal processing, the fundamental characteristics of sound waveforms can be extracted, classified, and employed to detect specific adventitious sound patterns and analyze their pathological implications. These findings have led to many publications on computer-aided detection of asthma, fibrotic and obstructive lung diseases, asbestosis, and heart failure. Several research groups have investigated potential computer-assisted sound analysis and classifications, etc., see [13], [14], [15] and references therein.

To advance the frontier in this technology to real operating-room applications, it is necessary to develop individualized pattern recognition techniques. It is well understood in the pulmonary medicine that there are no universal sound patterns or parameter thresholds that indicate a disease or medical condition. Individualized pattern recognition that combines information from sounds and other measurements must be established that is capable of capturing pattern shifting in each patient. Along this direction, this team has constructed a system for continuous lung-sound monitoring. The system contains a multiple-sensor array consisting of several lung sound sensors on auscultation sites such as tracheal and bronchial, and one or more noise reference sensors. The signals from these sensors are fed into an analog/digital data acquisition module from the National Instruments, Inc. After signal conditioning, scaling, and synchronization, the lung-sound signals and noise references are inputted to a signal processing module for noise cancellation, pattern recognition, and diagnosis.

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In this paper, we introduce a new methodology of lung sound pattern recognition. The method starts with a set of characterizing variables that can be extracted from lung sound waveforms. Changes in these variables will provide information on lung sound pattern variations. The goals of lung-sound pattern recognition and diagnosis include: (1) to dynamically capture changes in these key parameters; and (2) to relate these changes to potential causes. This paper will concentrate on a development of pattern recognition methods. The key properties of pattern recognition accuracy, confidence levels, noise impact, noise reduction will be analyzed.

II. ESSENTIAL CHARACTERIZING VARIABLES OF LUNG SOUNDS

There have been many targeted studies of lung sound analysis in relation to specific diseases. The goal of this paper is to develop a general methodology that will facilitate sound pattern analysis. The main features derived in this paper can be specialized to different diagnosis requirements.

A. Typical Lung Sound Waveforms

Fig. 1 is a typical respiratory sound. For signal processing, a ventilation or breathing cycle is divided into three stages: Inhale (T_i), exhale (T_e), and transitional pause ($T - T_i - T_e$). They are identified by ventilator variables or by smoothed breathing wave profiles. For diagnosis, the inhale and exhale waveforms contain rich information. This information is usually perceived by an experienced physician to detect abnormal sound patterns such as wheeze, crackles, etc.

To facilitate computerized sound analysis, it is necessary to identify certain variables that are relevant to medical diagnosis. These will include both time-domain and frequency-domain characteristics. For frequency domain analysis, a stochastic process needs to be stationary. While the overall breathing sounds are not stationary processes, signals that are confined in each stage are approximately stationary. Mathematically, if one extracts all inhale segments of a breathing sound and concatenate them into a single waveform, then this waveform is approximately stationary. We shall denote such signal segments as y^i for inhale sounds, y^e for exhale sounds, and y^p for pausing sounds. For a stationary process, one can perform frequency-domain analysis. As shown in the bottom plot of Fig. 1.

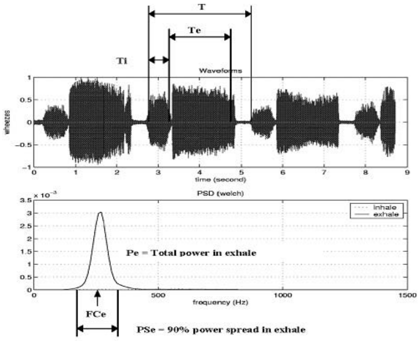

Fig. 1. Main Lung Sound Characteristics

B. Characterizing Variables

To understand what variables might be useful to capture pattern changes in lung sounds, we tested some typical normal and abnormal lung sound waveforms and their frequency spectra during inhale and exhale. For example, the wheeze can be clearly characterized by a substantial narrowing of spectrum, shifting of center frequency (towards low pitch in this example), and power imbalance between inspiration and expiration.

This understanding leads to the following variables to represent essential sound characteristics: T_i (inhale length), S_i (inhale strength: RMS values), T_e (exhale length), S_e (exhale strength: RMS values), T (breath cycle length), FC_e (exhale center frequency), P_e (exhale total power), PS_e (exhale 90% frequency bandwidth, i.e., frequency band that contains 90% of total power, around FC_e); and similar inhale parameters FC_i, P_i, PS_i.

It follows that we can define an inhale vector $v^i = [T_i, S_i, FC_i, P_i, PS_i]$ and exhale vector $v^e = [T_e, S_e, FC_e, P_e, PS_e]$, or an overall vector $v = [v^i, v^e]$. Although the above variables are identified as representing key characteristics of lung sounds, the following theoretical development is generic and applicable if other variables are used in v^i, v^e, v.

III. Basic Approaches for Sound Patterns

The main issue for sound pattern classification is to dynamically capture the changes of the above key parameters. To detect sound pattern shifting (say, deviation from normal ventilated lung sounds towards wheezing), we treat these calculated parameters, over each breath cycle, as sequences of random variables.

Sound pattern changes have significant implication in their causes. Although from different motivations and background, this diagnosis problem is related to fault detection problems, see, e.g., [4], [10], [5], [22]. A medical cause carries certain distinctive features that are typically used by physicians to diagnose medical conditions. For example, a bronchial intubation is typically indicated by a combination of diminished sound from one lung, increased sound from another.

Diagnosis can be developed based on the following ideas of detection algorithms, that quantify the "degree of chance" of one specific cause. First, characteristic features of a medical cause are translated to a region in the parameter space, which will be called *a diagnostic region*. Sound patterns will form a sampled value v of observations. The distance between the sampled value and a given diagnostic region Ω (defined by a cause C) provides a measure of chance that the cause C may have occurred. The critical task here is to evaluate this chance rigorously and compute it efficiently.

By virtue of asymptotic normality, we can regard v_k as a sequence of normally distributed random variables. For concreteness, we shall use the following scenario as a typical case for derivations. There are two diagnosis sets, Ω_1 (normal breath) and Ω_2 (wheezing) with $\Omega_1 \cap \Omega_2 = \emptyset$. In what follows, we present a confidence-region method for pattern classification. The motivation comes from the work of [25], [23], which is inspired by [1]. For simplicity, we shall assume that v_k is normally distributed. The justification of it stems from a viewpoint of asymptotic normality. Assume that v_k has a distribution $N(\mu^1, S^1)$ if it is under normal breath and $N(\mu^2, S^2)$ if is a wheezing. Our task is to find a procedure to detect if a measured sequence is normal or wheezing.

A. Confidence Region Approach

For an r-dimensional normal vector $X \sim N(\mu, S)$, we can construct an ellipsoidal confidence region as follows. Let

$$U = (X-\mu)' S^{-1} (X-\mu).$$

Then, Ellip $= \{U; U \le c\}$ is an ellipsoidal confidence region for μ with specified confidence level α so that

$$P(U \in \text{Ellip}) = 1 - \alpha.$$

With Vol denoting the volume of Ellip. The following formula was derived in [2]

$$\text{Vol} = \frac{\pi^{\frac{r}{2}} c^{\frac{r}{2}} |S|^{\frac{1}{2}}}{\Gamma(\frac{r}{2}+1)},$$

where $\Gamma(\cdot)$ is the gamma function, and $|S|$ denotes the determinant of S.

If X is only asymptotically normal, then the ideas in [26] can be used to construct confidence regions. The volume of the ellipsoid enables us to construct the confidence region and is analytically useful. For the sound analysis we consider, computationally it appears to be much easier to use confidence rectangles, a natural extension to confidence intervals; see [27].

Suppose that v_k has a normal distribution under normal breath. Since the jth component of v_k also follows a normal distribution, $v_k \sim (\mu_j^1, \sigma_{j,1}^2)$ with $\sigma_{j,1}^2 = e_j' S^1 e_j$, if $c_{\alpha^{j,1}}$ is the $100(1-\frac{\alpha^{j,1}}{2})$th percentile of a standard normal random variable, then

$$P\Big(\Big|\frac{\sqrt{k}(v_{k,j}-\mu_j^1)}{\sigma_{j,1}}\Big| \le c_{\alpha^{j,1}}\Big) = 1-\alpha^{j,1}.$$

A $100(1-\frac{\alpha^{j,1}}{2})\%$ confidence interval for μ_j^1 is given by

$$I_k^j = (v_{k,j} - c_{\alpha^{j,1}}\sigma_{j,1}, v_{k,j} + c_{\alpha^{j,1}}\sigma_{j,1}).$$

Consider the n-dimensional rectangle

$$I_k = \{\mu^1; \mu_j^1 \in I_{k,j},\ j \le n\}$$

with I_k^j given above. Then the well-known Bonferroni's inequality yields that

$$P(\mu^1 \in I_k) \ge 1 - \sum_{i=1}^{n} P(\mu_i^1 \notin I_k^i).$$

The procedure outlined above can also be used for construction of confidence rectangles for μ^2.

B. Classification via Optimization

The method developed in this section is inspired by [25], [23]. Consider a sample of sound observation from patients having 2 possible (normal and wheezing) patterns. We wish to design a decision rule so as to classify an observed sample. With two patterns in the system, there are two types of errors. That is, an observation actually from Ω_1 being classified as from Ω_2 or vice versa. To design a decision rule, we use the probabilities of these errors weighted by the 'undesirability' of them. Then our detection procedure is to minimize the above expected cost.

Let $f_i(v)$ be the probability density of v_k having pattern i. If the region Ω_i is classified as from f_i by using a decision u, the probability of correct classification of an observation coming from Ω_1 is

$$P(1|1,u) = \int_{\Omega_1} f_1(v)dv,$$

and the probability of misclassification of an observation in fact coming from Ω_1 as from Ω_2 is

$$P(2|1,u) = \int_{\Omega_2} f_1(v)dv.$$

Denote the cost of the misclassification by $C(2|1)$. Then the cost associated with the above misclassification is

$$L(1,u) = C(2|1)P(2|1,u).$$

Assuming the probabilities of the occurrence of Ω_2 are known *a priori* as q_1 and q_2, respectively, the expected cost of misclassification of an observation that belongs to Ω_1 as from Ω_2 is

$$L_1(1,u) = q_1C(2|1)P(2|1,u),$$

and the total expected loss from costs of misclassification is

$$L_T(u) = q_1C(2|1)P(2|1,u) + q_2C(1|2)P(1|2,u).$$

We aim to design a decision rule to minimize of the expected cost $L_T(u)$ from misclassification.

With known q_i and $f_i(v)$, a decision rule can be devised. Observe that

$$\begin{aligned} &q_1C(2|1)\int_{\Omega_2} f_1(v)dv + q_2C(1|2)\int_{\Omega_1} f_2(v)dv \\ &\quad = \int_{\Omega_2}\Big[q_1C(2|1)f_1(v) - q_2C(1|2)f_2(v)\Big]dv \\ &\quad +q_2C(1|2)\int_{\Omega_1} f_2(v)dv. \end{aligned}$$

The second term on the last line is a given number, and $q_1C(2|1)$ and $q_2C(1|2)$ are nonnegative constants. Thus the first term is minimized if Ω_2 includes those points of v that make the integrand negative and excludes those v that make the integrand positive. Since Ω_1 is the complement of Ω_2, the regions of classification should be chosen according to

$$\begin{aligned} \Omega_1:\ \frac{f_1(v)}{f_2(v)} &\ge \frac{C(1|2)q_2}{C(2|1)q_1} \\ \Omega_2:\ \frac{f_1(v)}{f_2(v)} &< \frac{C(1|2)q_2}{C(2|1)q_1}. \end{aligned}$$

If the first inequality holds, we conclude that it is in Ω_1. Otherwise, we infer that it is in Ω_2.

Note that the above discussion is free of specific distribution. When the random sequence is normally distributed, we obtain a nicer result. In this case

$$f_i(v) = \frac{1}{(2\pi)^{n/2}|S|^{n/2}}\exp\Big[-\frac{1}{2}(v-\mu^i)'S^{-1}(v-\mu^i)\Big].$$

The ratio of densities of the two normal densities is

$$\frac{f_1(v)}{f_2(v)} = \exp\{-\frac{1}{2}[(v-\mu_1)'S^{-1}(v-\mu^1)-(v-\mu^2)'S^{-1}(v-\mu^2)]\}.$$

Denoting

$$\widetilde{K} = \frac{C(1|2)q_2}{C(2|1)q_1},$$

then classification rule is

$$-\frac{1}{2}\Big[(v-\mu^1)'S^{-1}(v-\mu^1) - (v-\mu^2)'S^{-1}(v-\mu^2)\Big] \ge \ln\widetilde{K},$$

or equivalently

$$v'S^{-1}(\mu^1-\mu^2) - \frac{1}{2}(\mu^1+\mu^2)'S^{-1}(\mu^1-\mu^2) \ge \ln\widetilde{K}.$$

IV. Applications to Lung Sound Pattern Analysis: Asthma Detection

This section presents some illustrated examples that demonstrate the utility of the method introduced in this paper. To provide flexibility in evaluating our method, extensive simulation has been performed.

A. Basic Sound Patterns

To evaluate the approaches described in the previous section, patient data were collected. The data were collected through a sophisticated Human Patient Simulator (HPS), manufactured by METI, Inc. Three electronic stethoscopes are used simultaneously to measure lung sounds and reference noise. Noises are generated by conversations, music, and instrumentation. Noise levels are controlled by music volumes and conversation loudness. To further evaluate noise impact, a variety of noises with different characteristics (such as waveforms, frequency centers, and bandwidths) are added to measured signals before signal processing. These noises are either collected from operating rooms or generated by computer.

We shall start with basic sound patterns. Under relatively quiet conditions (limited conversation and music turned off), breath sounds are collected under the following four scenarios: (1) A 20-year old healthy soldier with good body weight; (2) A 20-year old soldier with pre-existing asthma; (3) A 40-year old obese truck driver who is a smoker but has no pre-existing respiratory disease; (4) A 40-year old obese truck driver who is a smoker and has pre-existing asthma. Breath sounds are recorded and then we extract its parameters for each cycle: inhale length, inhale RMS, exhale length, exhale RMS, frequency center, frequency bandwidth, etc. An initial observation from the sound waveforms and spectra reveal that wheeze is reflected in the time-domain by a shortened inhale length and power (RMS times length), and in the frequency-domain by a shifted center and narrowed frequency spread. Fig. 2 shows these parameter data points.

It is noted from the data points that a difference between the patterns of normal and wheeze sounds exists. We performed basic statistical analysis by calculating the means (μ) and standard deviations (σ) of the data points. The rectangles in Fig. 2 shows 2σ confidence rectangles for the normal breath and wheeze. These regions will be used as the baseline regions for pattern recognition.

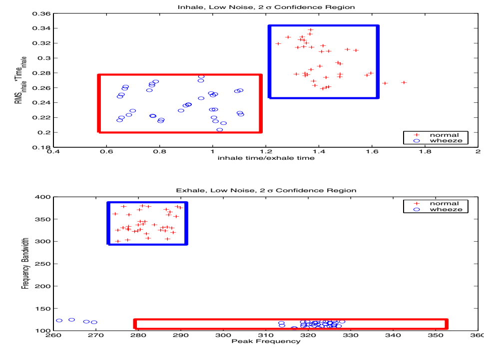

Fig. 2. 2 σ Confidence Regions for Pattern Recognition

B. Noise Impact on Sound Characteristics

The system includes several noise sources with different characterizations. There are two types of noises that influence sound pattern recognitions.

1) Inherent Noises: These include a diversified noise sourses that affect lung sounds. Noise sources pass through several different transmission channels to influence the lung-sound sensor and reference sensor. The structure and parameter values of these channels are not known to the identification algorithms. Since the noise reference sensor is placed in vicinity to the lung sensor, sound coupling may occur during data acquisition. These noises may have bias, resulting in drifts in parameter mean values.
2) Sensor Noise: These noises do not affect actual lung sounds. They are random noises from sensor measurements. They are usually zero mean, and often gaussian distributed.

We shall start with an illustration of noise impact on lung sound patterns. Fig. 3 illustrates data points under low noise, moderate noise and high noise levels. Under a low noise level, data points are clustered for both normal breath and wheeze, indicating a potential in achieving a high level of confidence in distinguishing wheeze from normal patterns. When noise levels increase, parameter patterns become intervened, leading to a more difficult pattern recognition problem.

A more quantitative analysis on parameter vector distributions is shown in Fig. 4. It is noted that when noise level increases sound patterns have larger deviations and have a pattern shifting as well. As discussed before, inherent noises result in pattern shifting which cannot be eliminated by stochastic averaging. Reduction of impact from inherent noises must be done by noise cancellation techniques, which will be discussed later. On the other hand, increased sensor noises result in larger deviations. Averaging can be used when the size of data samples becomes larger.

Fig. 5 presents the results of a simple sequential algorithm of stochastic averaging. The algorithm computes the average values of the available parameter data points. The algorithm is recursified to reduce computational burden. It can be seen that although stochastic averaging is effective in reducing the impact of zero-mean noises, pattern shifting due to inherent noises cannot be effectively reduced. Consequently, sound patterns move away from the baseline diagnostic regions, represented by the rectangles in the plots.

C. Noise Reduction by Time-Shared Adaptive Noise Cancellation

To reduce the impact of inherent noises on accuracy of sound pattern recognition, we apply the method of time-shared adaptive noise cancellation introduced in [19], [28].

Location proximity between the lung and reference sensors allows us to represent noises from many sources approximately by a lumped noise near the reference sensor, such as d in Fig. 6.

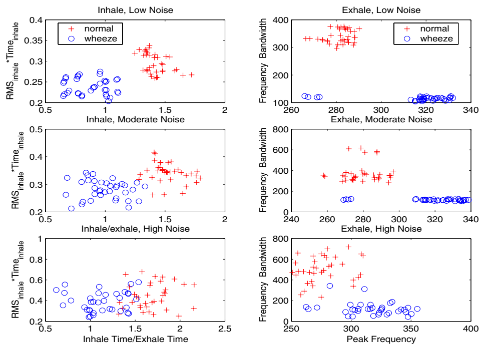

Fig. 3. Noise Impact on Normal Sound and Wheeze

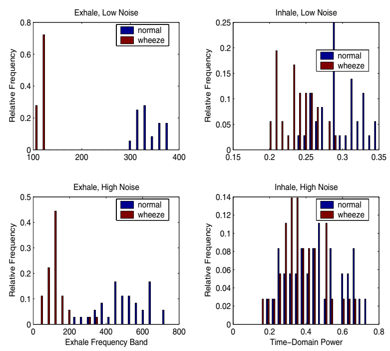

Fig. 4. Histograms of Sample Points of Sound Parameters

If we view the measurement y_2 from the reference sensor as a virtual noise source, we basically replace distributed noise sources d (which are impossible to describe accurately and separately) in a lumped noise source y_2, as shown in Fig. 7. The problem of noise cancellation is now reduced to identification of the virtual noise channel G (in terms of the system in Fig. 6, G is the inverse of C_3 followed by C_2). Indeed, if we can estimate the noise channel G, then the noise-free lung sound y can be approximately extracted as

$$\widehat{y} = y_1 - \widehat{G} y_2$$

During the time from the end of exhale and the beginning of inhale, there is a pause interval in which lung sounds are

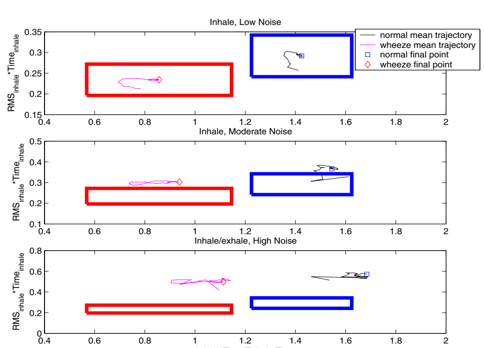

Fig. 5. Mean Trajectories of Parameters

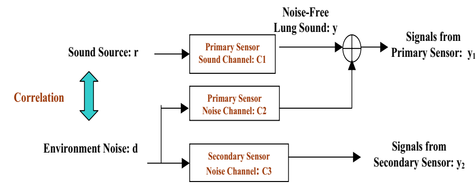

Fig. 6. Sound Channels

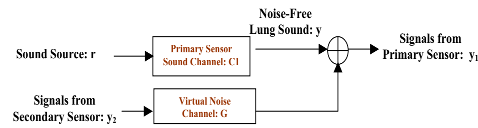

Fig. 7. Virtual Noise Formulation

very small. In other words, in that interval the lung sound, denoted by y, is nearly zero. While the overall breathing sounds are not stationary processes, signals that are confined in each stage are approximately stationary. It is shown in [28] that to reduce estimation errors on channel dynamics, it is highly desirable to reduce correlations between lung sound and noise. It is observed that due to diminishing lung sounds during the pause interval, the correlation between the sound, denoted by y^p, and noise in the pause interval is much smaller than that for inhale and exhale processes, leading to our time-shared adaptive noise cancellation algorithm.

The measured lung sound y_1 during the pause stage is essentially the output of the noise channel in that interval. As a result, we can use input/output pair (y_2 and y_1) to identify G in this interval. This will not require any assumption on independence of y and y_2. This idea leads to the following lung sound/noise separation algorithms.

- **Initial Channel Identification:**
  During a pause stage, the measured y_2 (virtual input) and y_1 (output) are used to identify the noise channel $G(\theta)$, using a recursive algorithm. The estimated model will be denoted by $G(\widehat{\theta}_0)$.
- **Step 1: Inhale and Exhale Stages**
  At the k-th breathing cycle ($k = 0, 1, 2, \ldots$), during the T_i (inhale) and T_e (exhale) stages, the estimated noise channel model $G(\widehat{\theta}_k)$ is used to extract the original lung sound via $y = y_1 - G(\widehat{\theta}_k) y_2$.
- **Step 2: Transitional Pause Stage**
  During the pause stage of the k-th breathing cycle, the estimated noise channel model is updated by using the new data from measured y_2 (virtual input) and y_1 (output). The channel model $G(\widehat{\theta}_k)$ is used as the initial condition and the model is updated by a recursive algorithm (the RLS estimation in this paper), leading to an updated model $G(\widehat{\theta}_{k+1})$.
- **Recursive Steps:**
  In the $(k+1)$-th breathing cycle, go to Step 1 with the newly updated channel model $G(\widehat{\theta}_{k+1})$. These steps

are then repeated from cycle to cycle.

This cycle-to-cycle recursion will be computationally very efficient since models are updated by using only new measurements and no past data need to be remembered. Also, by gradually discarding old data via, say, exponential discarding data windows, one can in fact track time-varying channel characteristics, that can be used in continuous monitoring and diagnosis of breath sounds.

We identify the noise-transmission channels with the time-shared identification method. We use a 30-th order moving average regression model structure to identify the channel. While the lung sound is significantly corrupted by the noise, its envelope profile still retains an indication of its inhale, exhale, and pause stages. This profile information is used to divide each breathing cycle into the phases for identification or noise cancellation. During the identification phase (pause stage), a recursive least-squares identification algorithm is used to update the parameters in the regression model. During the noise-cancellation phase (inhale or exhale stages), the estimated regression model is used to derive noise estimates, which are then subtracted from the signal measured by the lung sensor. The process is then repeated in the next breathing cycle. We now show the effectiveness of noise cancellation on sound patterns. Due to reduction by the above noise cancellation techniques, the level of inherent noises is greatly reduced. Combined with stochastic averaging, sound patterns are more coherent for diagnosis. This is illustrated in Fig. 8.

V. Concluding Remarks

Sound pattern recognition in respiratory medicine can be viewed as a stochastic decision process in which parameter sequences that characterize sound features are to be analyzed for medical diagnosis. This paper introduces a method that combines noise cancellation and stochastic pattern recognition to enhance accuracy of diagnosis. Wheeze is used as an example to illustrate the utility of this method. Applications of this method to detect other respiratory diseases require further detailed analysis that incorporate medical knowledge into this process. This direction is currently under investigation.

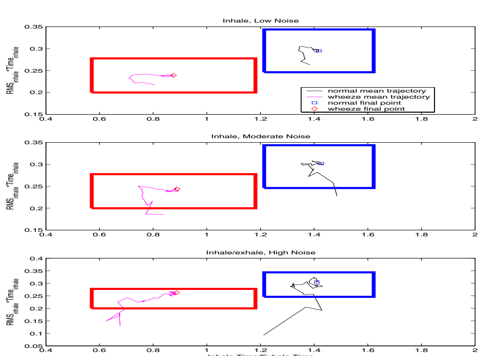

Fig. 8. Pattern Recognition after Noise Reduction by Time-Shared Adaptive Noise Cancellation

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