Analysis on Diaphragm for the Identification of Asthma Pattern using Active Contour Technique
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Abstract:
Ultrasound imaging has been generally used in co-medical imaging diagnosis for a long history because of its benefits: no radiation, high penetration depth, and real-time imaging capability. In this process, we propose an ultrasound-based system that audits respiratory status of asthma subjects via detecting of diaphragm movement. This system implements Chan - Vese algorithm to exactly segment diaphragm area from ultrasound image sequences and exert 1D breathing waveform by computing mutual information (MI) between two consecutive ultrasound frames. In addition, four types of respiratory signals are described: normal breath, fast breath, apnoea, and cough, which are relevant to four symptoms of asthma attack and decide as the breathing templates used for early asthma detection. In experiments, the proposed system is calculated with a public dataset from “Ultrasound image gallery” which contains nine ultrasound videos and our dataset possessed by “Interson Suremore” probe which consists of five ultrasound videos in the diaphragm area. The results show that Chan - Vese segmentation method is preferable to the alternative three algorithms: adaptive thresholding, EM/MPM, and Fuzzy C Means (FCM), and MI is a feasible method to extract exact respiratory signal and clear information of the phase of respiratory cycle from 2D images.

Index Terms: asthma pattern, image segmentation, respiration signal extraction, Ultrasound

I. INTRODUCTION

Asthma is common and worldwide chronic inflammatory disease of the airway. It is characterized by variable and recurring symptoms, reversible airflow obstruction, and bronchospasm. Its common symptoms include recurring wheezing, coughing, chest tightness, fast breathing, and shortness of breath. The occurrence of asthma has increased significantly since the 1970s. In 2011, 235 million people have been diagnosed with asthma and asthma attack caused 250,000 deaths globally [1]. This number increased to 334 million in 2014[2]. Meanwhile, in the United States, asthma prevalence increased from 7.3 in 2001 to 8.4 percent in 2010. 25.7 million Persons had asthma in 2010 that means one of 12 people had asthma. Among these asthma patients, more than half of them have experienced an asthma attack. What are worse, asthma results in a high cost for individuals and the nation. In the United States, every person with asthma spent 3,300 dollars each year from 2002-2007 in medical expenses and the overall nation-wide expense is about 56billions for medical costs, lost school, work days, and early deaths in 2007[3].

However, many asthma attacks could be prevented. For example, if patients know how to identify and avoid asthma triggers, then they could try to be away from those triggers. Besides that, monitoring breath is also very important, which can recognize warning symptoms of an impending asthma attack, such as slight coughing, wheezing, and shortness of breath. Sometimes, lung function decreases before any symptoms are noticed. Those subjects who have airway obstruction for a long time are less likely to be aware of dyspnoea than subjects with acute onset of airway Obstruction. In another word, subjects are more likely to be aware of the poor function of lung with hypoxia during an acute exacerbation, predisposing to severe, and life threatening attacks. Therefore, monitoring lung function and condition are very important for looking after asthma patients, early detecting exacerbations, and controlling asthma day to day.

Currently, asthma patients have to take asthma examine with an interval of at least two to three months between visits. However, it is vulnerable for recalling bias as a result of retrospective assessment of symptoms when physicians evaluate asthma control during clinical visits. Wireless/ portable ultrasound becomes a desirable approach for asthma control because it can continuously monitor lung function and asthma symptoms in home environment. It is more efficient than taking asthma examine periodically[4]. Therefore, it is crucial to investigate a computational method for evaluating asthma in home environment. Nowadays, proposed methods for monitoring asthma are usually based on lung volume, gas sensing, and imaging. The first two types of technology cannot provide continuous and real-time information of user’s breathing.

![Figure.1. Concept Diagram for Asthma Formation][15]

However, ultrasound devices instead can be used in portable forms[5],[6],[7] and have the ability to collect real-time images of the organs and their movement information[8],
ultrasound could be applied to detect respiratory signal via diaphragm movement monitoring[10],[11]. There are still some difficulties in implementing ultrasound images of diaphragm movement. First, ultrasound images have some properties: gray-scale, attenuation, speckle, blurred boundaries, and low contrast between region of interest and background, which makes proper segmentation difficult. In addition, many areas have the same gray value as the detected diaphragm area, which make the segmentation task of crescent diaphragm area complicated. Therefore, an appropriate segmentation method needs to deal with these problems. Simple threshold-based segmentation algorithms, but they cannot ensure the accuracy of segmentation in low-quality ultrasound images. To solve the problems mentioned above, we propose a system to extract respiratory signals from ultrasound videos collected by a portable ultrasound device. Implemented Chan-Vese algorithm of the developed system is robust for locating diaphragm areas in low-quality ultrasound image sequences.

Another contribution of this paper is defining four typical templates of asthma respiratory patterns. Respiratory symptoms accompanying with asthma attack occurrence include frequent cough, breathing faster than normal, shortness of breath, decreasing in a peak expiratory flow, and upper respiratory infection [12],[13],[14]. They are discussed four respiratory patterns of asthma subject detected by or nasal airflow. However, they did not build a relation between respiratory patterns of irregular symptoms and the occurrence of asthma attack. In this paper, we identify one normal breathing pattern and three irregular patterns related to three symptoms of asthma attack: frequent cough, breathing faster than normal, and shortness of breath. These patterns are extracted from ultrasound image sequences and defined as breathing templates. By splitting respiratory signals and comparing them with the stored templates, symptoms of asthma attack can be detected. The benefit of breathing signal extraction from 2D ultrasound is that when irregular breathing signal is detected, doctors/researchers can retrieve ultrasound images back to figure out how organ moves at that period, thus they will obtain more information for asthmatic analysis.

II. RELATED WORK

Scientists proposed many methods based on lung volume, gas sensing, and imaging[16]. In terms of lung volume methods, peak expiratory flow (PEF) is the most commonly used parameter for monitoring lung function of asthma patients. It is very popular in primary care because it can be measured easily by simple, cheap and portable devices. Forced Expiratory Volume in 1 Second (FEV 1) is also a widely used standard for measuring airflow caliber. However, methods measuring these two parameters have some common limitations: lack of compliance, possible falsification of results, and long recording periods [17]. Gas sensing method is another sensing modality to detect asthma by monitoring Nitric oxide (NO) and CO2. NO gas level will increase when asthma attack occurs [18]. The CO2 output patterns between healthy and asthma-suffering patients are different [16].

Furthermore, with the development of sophisticated imaging techniques, image of lung in asthma patients has evolved dramatically over decades, such as positron emission tomography (PET), magnetic resonance imaging (MRI), single photon emission computed tomography (SPECT), and ultrasound (US). These techniques provide different approaches to visualize gross anatomic abnormalities, regional lung mechanics, and airway anatomy. They are also very useful for understanding the different functions between the lungs of healthy subjects versus asthma patients[20]. Compared with these one shot images methods, ultrasound method can capture image sequences of moving organs and tissues, which enables users perform real-time analysis of respiration via ultrasound imaging technology. Better portability and no radiation are another two advantages of ultrasound sensing modality. There are many proposed approaches to detect respiratory motions based on ultrasound devices. Bruin et al.[21] found that asthma patients had thicker D T_relax, diaphragm thickness during relaxation. So they measured D T_relax from B-mode ultrasound images to detect asthma patterns. Researchers also could infer respiration pattern by quantifying the movements of a kidney, because kidney moves along with breathing[22].

According to research of the neighborhood relationship of organs is related with breathing cycle. They measured respiration by investigating 2D ultrasound images of liver and kidney. This method has the advantage that it is fully automatic and does not require a training phase or prior information about underlying anatomy, nor the interaction of user[23]. Proposed a 2D normalized cross correlation (NCC) based algorithm to estimate movement of a liver in 2D ultrasound images. But, due to the blur boundaries of kidney and liver in low contrast ultrasound image, the performance of monitoring still requires further improvement. In 2006, proposed a novel respiratory detection method based on diaphragm motion using a 2D ultrasound unit. Because white diaphragm region in ultrasound image is outstanding among dark regions of organs, their method could easily extract respiratory signal from an automated analysis of the internal diaphragm movement during breathing. They selected the region of interest (ROI) and computed the mutual information (MI) and correlation coefficient (CC) between reference ultrasound frame and all other frames. From their experiments, they discovered that MI and CC values produced a 1D signal corresponding to the respiratory cycle in both phase and magnitude.

In 2012, Hwang proposed a system that placed feature windows on ROI of each ultrasound image and calculated organ’s displacement through feature windows. Their proposed method can robustly extract respiratory motion signal with regardless of reference frame, because this method computed actual organ’s displacement instead of similarity measurement like MI or CC. This method could provide clear information of the phase of respiratory cycle such as inspiration and expiration. The drawback of Hwang’s approach is that adaptive thresholding algorithm implemented in his paper cannot detect diaphragm region robustly.

III. PROPOSED SOLUTION

In this project, we propose a system to perform analysis of respiration, which implements Chan-Vese algorithm to segment the diaphragm area from ultrasound image sequence accurately and identifies respiratory signals corresponding to diaphragm activities. To reduce the interference of cardiac motion, this system performs low-pass filter to purify time-series signals. Furthermore, in order to detect asthma attack by monitoring irregular breathing symptoms, we identify one normal breathing template and three irregular templates...
related to the three symptoms of asthma attack: frequent cough, breathing faster than normal, and shortness of breath. By comparing with these four templates, the proposed system can detect irregular respiratory patterns and notify asthma attack occurrence. The system design of asthma pattern identification is discussed. It consists of six parts: a USB ultrasound imaging probe, ROI Identification, 2D Image Sequence to 1D Time Series, heartbeat removal, respiratory pattern recognition for asthma, and visualization. First of all, ultrasound probe collects ultrasound image sequences around liver and diaphragm locations. Then these images are transmitted via USB to a computer.

In this paper, the goal is to monitor the movement of diaphragm to extract respiratory signal, so system identifies and segments the diaphragm area in the image sequence, and then computes 1D time-series signal drawn by mutual information which reflects relation among consecutive ultrasound image sequence. The original 1D waveform contains respiratory signal and unwanted interference, such as cardiac signal. Therefore, a low-pass filter is used to get rid of interference and preserve low respiratory frequency. Next, the computed 1D signal is compared to four templates: normal breath, fast breath, apnoea, and coughing. In the end, ultrasound video, original signal, purified signal, and respiration rate are displayed on a designed Matlab user interface.

Proposed methods for monitoring asthma are usually based on lung volume, gas sensing, and imaging. The first two types of technology cannot provide continuous and real-time information of user’s breathing. However, ultrasound devices instead can be used in portable forms and have the ability to collect real-time images of the organs and their movement information. Therefore, ultrasound could be applied to detect respiratory signal via diaphragm movement monitoring. There are still some difficulties in implementing ultrasound images of diaphragm movement. First, ultrasound images have some properties: gray-scale, attenuation, speckle, blurred boundaries, and low contrast between region of interest and background, which makes proper segmentation.

### CHAN VESE ACTIVE CONTOUR ALGORITHM

This system implements the Chan-Vese active contour algorithm [23] to find ROI. The basic idea of this model is that starting with a curve around the objects, the curve extends or shrinks toward its interior normal, and stops when touch the boundary of the objects. Given an image \( u_0 \), the goal is to look for the best approximation \( u \) of \( u_0 \) by minimizing an energy function \( F(c_1,c_2,C) \) which is the segmented result and it takes two values:

\[
u=\begin{cases} 
\text{average}(u_0), & \text{inside } C \\
\text{average}(u_2), & \text{outside } C.
\end{cases}
\]

The energy functions \( F(c_1,c_2,C) \) is defined by

\[
F(c_1,c_2,C)=\mu_1\int_{\Omega} \delta(\varphi(x,y)) \mid \nabla \varphi(x,y) \mid dx \, dy + \nu \int_{\Omega} H(\varphi(x,y)) dx \, dy + \lambda_1 \int_{\Omega} (u_0(x,y) - c_1)^2 dx \, dy + \lambda_2 \int_{\Omega} (u_0(x,y) - c_2)^2 dx \, dy + (1-H(\varphi(x,y))) dx \, dy,
\]

Where \( C \) is an arbitrary variable curve, and constants \( c_1,c_2, \) depending on \( C \), are averages of \( u_0 \) inside \( C \) and respectively outside \( C \). \( \mu \geq 0, \nu \geq 0, \lambda_1, \lambda_2 > 0 \) are fixed parameters and function \( H \) is the Heavyside function, defined by:

\[
H(z)=\begin{cases} 
1, & \text{if } z \geq 0 \\
0, & \text{if } z < 0
\end{cases}
\]

In this equation, the first item is the length of curve and the second item is the area of the region inside. They is the regularizing items. Primary steps of the algorithm are shown in the Algorithm.

#### Algorithm:
/* Initialization */
Step 1: \( \varphi^0 \leftarrow \varphi_0, n<0 */ Iteration */
Step 2: Compute \( C_1(\varphi^n) \) and \( C_2(\varphi^n) \).
Step 3: Solve the PDE in \( \varphi \) to obtain \( \varphi^{n+1} \).
Step 4: Reinitialize \( \varphi \) locally to the signed distance function to the curve (this step is optional).
Step 5: If the solution is stationary, stop, otherwise go to Step 2.

### IV. SYSTEM ARCHITECTURE

It describes the process of monitoring the asthma. Ultrasound device have the ability to collect real-time images of the organs. It identifies the respiratory signals through ultrasound image sequence. It can identify one normal breathing and three irregular breathing based on asthma. The input image is taken from the dataset. In segmentation process, Chan-Vese Active Contour Techniques will be used. The signal extraction process is used to convert the signal from 1D to 2D using the Peak Detection Method.

#### Figure 2 System Architecture

Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features (also named a "features vector"). This process is called feature extraction. The accuracy represents the efficiency of the process. Finally, to identify the one normal breathing and three irregular breathing in the classification process.

### V. EXPERIMENTAL DESIGN AND RESULTS

#### 1. PREPROCESSING

In this process preprocessing is carried out by the two major methods like, Noise removal & Image Enhancement. Image enhancement is the process of adjusting digital images so that the results are more suitable for display or more image analysis. For example, you can remove noise, sharpen, or brighten an image, making it easier to identify key features. Digital images are flat to a variety of types of noise. Noise is
the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be proposed into an image, depending on how the image is created.

**Gaussian Filter:**
The input skin images were pre-processing we are applying Gaussian filtering to our input image. Gaussian filtering is often used to remove the noise from the image. Gaussian filter process is employed to filter the image in order to remove unwanted image pixels in the image. Gaussian filter uses a different kernel that represents the shape of a Gaussian. Discrete approximation to the Gaussian function is generated before convolution is performed. The degree of filtering is determined by the standard deviation of the Gaussian. The Gaussian outputs a 'weighted average' of each pixel's neighborhood, with the average weighted more close to the value of the central pixels. Discrete Gaussian filtering is an important space for the weighted mean filter. It is based on the shape of the Gaussian function to privilege the right value of linear smoothing filter. It usually uses the Gaussian function of discrete two-dimensional by zero-mean to be smoothing filter.

**Median Filter:**
In image or signal processing, it is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to extract noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very generally used in digital image processing because, under certain conditions, it preserves edges while removing noise. Typically, by far the majority of the computational effort and time is used on calculating the median of each window. Because the filter must process every entry in the signal, for large signals such as images, the efficiency of this median calculation is a critical factor in determining how fast the algorithm can run.

**Edge Preservation Properties (Median Filter):**
Median filtering is one kind of smoothing technique, as is linear Gaussian filtering. All smoothing techniques are effective at removing noise in smooth patches or smooth regions of a signal, but negatively affect edges. Often though, at the same time as reducing the noise in a signal, it is important to preserve the edges. Edges are of critical importance to the visual presence of images, for example. For small to moderate levels of (Gaussian) noise, the median filter is demonstrably better than Gaussian blur at removing noise whilst preserving edges for a given, rigid window size. However, its performance is not that much better than Gaussian blur for high levels of noise, whereas, for speckle noise and salt and pepper noise (impulsive noise), it is specially effective. Because of this, median filtering is very widely used in digital image processing.

**2. Segmentation**
This segmentation process is implemented using the Chan-Vese Active Contour method. The Active Contours without Edges method by Chan and Vese ignores edges absolutely. Instead, the method optimally fits a two-phase piecewise constant model to the given image. The segmentation boundary is represented implicitly with a level set function, which allows the segmentation to knob topological changes more easily than explicit snake methods. This process describes the level set formulation of the Chan-Vese model and its numerical solution using a semi-implicit gradient plunge.

**3. Signal Conversion:**
Convert the Segment Image into signal. Then, find R Peaks values, Q Peaks values, S Peaks values, T Peaks values from the output of signal.
FEATURE EXTRACTION

Features are extracted using wavelet transform and statistical features. In numerical analysis and functional analysis, a discrete wavelet transform (dwt) is any wavelet transform for which the wavelets are discretely sampled. A discrete wavelet transform (dwt) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over fourier transforms is sensual resolution: it captures both frequency and location information (location in time). Here we extract multiscale energy and eigen space. The statistical features are kurtosis, skewness, mean, variance, median, entropy, standard deviation, maximum amplitude, minimum amplitude, central moments, mode, magnitude, phase, frequency, and energy.

CLASSIFICATION

In machine learning and statistics, classification is the problem of determining to which of a set of categories (sub-populations) a new observation belongs, on the basis of a training set of data containing experience (or instances) whose category membership is known. An example would be assigning a given email into "spam" or "non-spam" classes or assigning a diagnosis to a given patient as expressed by observed characteristics of the patient (gender, blood pressure, presence or absence of certain symptoms, etc.). In the terminology of machine learning, classification is considered an instance of supervised learning, i.e. learning where an instruction set of correctly identified observations is available. The corresponding unsupervised procedure is known as clustering, and concerns grouping data into categories based on some measure of inherent similarity or distance.

PERFORMANCE MEASURES

1. The accuracy, sensitivity and specificity of the classifier is measured.
2. The accuracy represents the efficiency of the process.
3. The sensitivity shows how the algorithm gives correct classification.
4. The specificity shows how the algorithm rejects the wrongly classification results.

\[
\text{Accuracy} = \frac{TP}{TP+FN} \\
\text{Recall} = \frac{TP}{TP+FN} \\
\text{Precision} = \frac{TP}{TP+FP}
\]
VII. CONCLUSION

Thus we concluded the process is well efficient by using the Gaussian filtering and Median filtering, hence the white noise removal is done by this filtering method. Gaussian filter process is employed to filter the image inorder to remove unwanted image pixels in the image. Median filter process is used to remove a salt & pepper noise in the image. Hence the process was implemented by Chan-Vese Active Contour for Asthma Pattern Identification.

VIII. FUTURE WORK

In the future, these templates can be used to predict asthma attack. For example, if some patterns occur in specific orders, then the subject is likely to undergo an asthma attack. Because of ultrasound’s portability, we can design a portable device for home health monitoring which can extract respiratory signal. Therefore, patients will not need to take asthma exams in hospital periodically.

VIII. REFERENCES


[8]. Y. Hwang, J.-B. Kim, W.-C. Bang, J. Kim, C.-Y. Kim, and H. Lee, “Robust Real-time respiratory motion tracking using ultrasound image sequences,” in Proc. IEEE Int. Ultrasonics Symp., 2012, pp. 1666–1669. Fig. 12. Respiratory signal computed by MI method and the corresponding frames. Frames 21 and 72 are captured in the end of inspiration. Frame 46 is captured in the end of expiration. Fig. 13. Four breathing templates.LIU AND HUANG: ASTHMA PATTERN IDENTIFICATION VIA CONTINUOUS DIAPHRAGM MOTION MONITORING 83


