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Automatic Identification and Accurate Temporal Detection of Inhalations in Asthma Inhaler Recordings

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Abstract— **Asthma is chronic airways disease characterized by recurrent attacks of breathlessness and wheezing. Adherence to medication regimes is a common failing for asthmatic patients and there exists a requirement to monitor such patients' adherence. The detection of inhalations from recordings of inhaler use can provide empirical evidence about patients' adherence to their asthma medication regime. Manually listening to recordings of inhaler use is a tedious and time consuming process and thus an algorithm which can automatically and accurately carry out this task would be of great value. This study employs a recording device attached to a commonly used dry powder inhaler to record the acoustic signals of patients taking their prescribed medication. An algorithm was developed to automatically detect and accurately demarcate inhalations from the acoustic signals. This algorithm was tested on a dataset of 255 separate recordings of inhaler use in real world environments. The dataset was obtained from 12 asthma outpatients who attended a respiratory clinic over a three month period. Evaluation of the algorithm on this dataset achieved sensitivity of 95%, specificity of 94% and an accuracy of 89% in detecting inhalations compared to manual inhalation detection.**

I. Introduction

Asthma is a chronic respiratory disease which causes the airways of the lungs to become narrow, constricted and inflamed. The most common symptoms of asthma include breathlessness, wheezing, tightness of the chest and coughing. According to the World Health Organization (WHO) some 235 million people currently suffer from asthma worldwide, while is it the most prevalent chronic disease amongst children [1]. Asthma prevalence is expected to increase in the coming years and subsequently lead to increases in morbidity and mortality rates [2].

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Medications such as corticosteroids are commonly prescribed to treat the symptoms of asthma. Medication for asthma is usually delivered directly to the lungs via inhalation of a drug using an inhaler device. Regular use of inhalers has been shown to improve patients' clinical outcomes [3]. However, in spite of this there is evidence to suggest that patients are consistently not taking their medication as directed [4]. Non-adherence to medication regimes refers to missing doses of medication, misuse of inhalers and over medication. Non-adherence is rooted in a lack of understanding about medication and misunderstanding of directions [5,6] The inability of patients to understand the advice given to them by clinicians and also the inability to learn the necessary self-management skills leads to frequent presentation at the emergency departments for asthma-related reasons [7].

An adherence monitoring device, which records an audio signal each time a common dry powder inhaler is used, was employed in this study. Each recording is individually saved with a time stamp that provides a log of inhaler use. The detection of an inhalation from an inhaler recording provides empirical evidence that medication was taken and allows clinicians to closely monitor patients' inhaler use. Manual classification of inhalations from inhaler signals is a tedious and time consuming process for clinicians and therefore an effective algorithm which can identify and demarcate inhalations would be of great advantage.

Automatic identification of breath sounds has had several signal processing applications. Several sleep studies have used breath identification to isolate snores from recordings of sleep [8]. Alshaer et al. automatically classified breathing cycles using knowledge about the different frequency spectrum of breath phases [9]. This study reported that 97% of breathing phases were identified correctly by the automated system. Rapcan et al. identified and extracted breath sounds from recordings of older adults reading in order to accurately measure utterance and pause durations [10]. A study by Ruinskiy & Lavner set out to identify and extract breath sounds from speech and song recordings in order to improve the quality of audio signals [11]. This study achieved a correct identification rate of 98% and a specificity of 96%.

The main aim of this study was to design an automatic detection algorithm which is able to identify inhalations from acoustic recordings of inhaler use. Employing a device which can record pertinent acoustic information surrounding inhaler use provides valuable information regarding patients' adherence to their medication.

II. Methods

A. Background

20 asthma patients (11 female & 9 male) who attend an outpatient's respiratory clinic were recruited for this study. The age range was 20 – 68 (mean 43.5 ± standard deviation 14.2). Subjects had all previously been prescribed Seretide inhalers and were very familiar with the mechanics of using such inhalers. Subjects were each given a Seretide Accuhaler/'Diskus' type inhaler [12] with the adherence monitoring device attached and instructed to use the dry powder inhaler as one normally would in a clinical visit. The addition of the adherence monitoring device did not impact on the normal functioning of the inhaler. Each time the inhaler is opened the adherence device switches on and records the acoustic signal until the inhaler is subsequently closed. The subject's inhaler use was recorded for a period of three months, with each subject returning to the clinic at monthly intervals to have their inhaler recordings uploaded to a database.

B. Adherence Monitoring Device

This study uses the Seretide Accuhaler/'Diskus' inhaler in conjunction with an attached adherence monitoring device (Manufactured by Vitalograph) [13]. The adherence device consists of a microphone, a microcontroller, a battery and a micro SD card. The microphone is a medium quality Knowles Acoustics SPM0204HE5 microphone. The adherence device was bonded securely to one side of the Diskus inhaler, as can be seen in Fig. 1, allowing patient use of the inhaler to be seamlessly recorded.

The adherence device is activated, i.e. begins recording, the first time the diskus inhaler is opened. Each time the inhaler is used by a patient an audio file of the event is recorded and saved as a mono wav file, sampled at 7913 samples/second with a bit depth of 8 bits/sample, on the memory card. The adherence device goes into sleep mode, to conserve power, when the inhaler is closed.

The acoustic signal of a typical patient recording is shown in Fig. 2. The correct procedure for using the Seretide Diskus inhaler involves firstly sliding the device open to reveal the mouthpiece (t=0s), sliding a lever that releases a dose of medication into the mouthpiece (t=1s), taking an inhalation (t=3.5-5.5s), holding ones breath for about 10 seconds (t=5.5-15s) and finally sliding the device closed.

C. Signal Processing

The algorithm employed to identify and detect the temporal onset/offset of inhalations can be broken up into two distinct sections. The first section involves identifying and demarcating inhalation type events in the recordings, while the second stage involves removing false positives i.e. false inhalation classifications.

Figure 1: (Left) The adherence monitoring device (Right) The adherence monitoring device bonded onto the side of a Seretide Accuhaler/Diskus inhaler

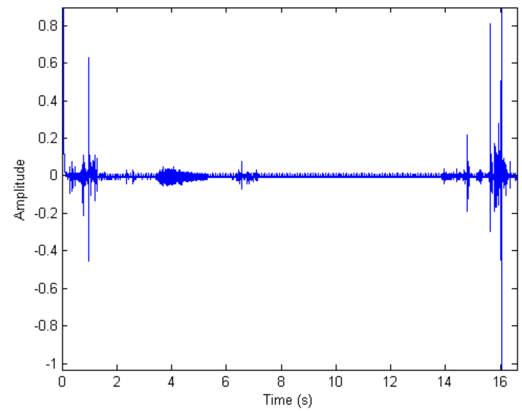

Figure 2: Acoustic signal from a typical inhaler recording with an inhaltion present between time 3.5 to 5.5s

Extracting mel frequency cepstral coefficients (MFCCs) is a common parameterization method for vocalization, due to the fact that MFCCs model the known variation of the human ears critical bandwidth with frequency. It is known that breath sounds have a characteristic pattern which allows them to be distinguished from other sounds [11]. Based on this observation an algorithm was designed to detect this pattern.

The algorithm firstly went through a training procedure on a set of 20 randomly selected inhaler recordings. Each signal was separated into frames of length 700ms which overlapped every 20ms. 12 MFCCs were calculated for each frame in the signal, forming a short-time cepstrogram of the signal. Using Singular Value Decomposition (SVD), a normalized singular vector was computed from the cepstrogram of the signal. Singular vectors can be used to capture the most important characteristics of breath sounds obtained from MFCC calculations. An adaptive threshold is automatically set that is 14% higher than the lowest singular vector in the inhaler recording. Singular vectors above the adaptive threshold were marked as potential inhalation events, while those below it were discarded. This adaptive threshold was found empirically to produce the most accurate detection of events, and subsequently inhalations in the training set.

In the second stage of the algorithm, the zero crossing rate (ZCR) (1) and median amplitude were computed to reduce the number of false positives detected by the algorithm, i.e. artifacts classified as inhalations. Inhalations were empirically found to have a characteristically high ZCR compared to that of non-inhalations in the training set. A fixed threshold constant of 0.17 was therefore introduced to reflect this fact. In the training set, inhalations consistently had a ZCR above this threshold value, while false positives were successfully removed.

$$ZCR = \frac{1}{N}\sum_{n=N_0+1}^{N_0+N-1}\frac{1}{2}|sign(x[n]) - sign(x[n-1])| \qquad (1)$$

The median amplitude of the proposed inhalation event was also calculated. Similar to the ZCR threshold, a fixed threshold was introduced to remove false positives based on empirical observations from the training set. Inhalations were found to have a median amplitude threshold value higher than 0.012, while any artifact lower than this threshold was discarded. This combination of threshold values was empirically found to produce the most accurate detection of inhalations in the training set, and was thus applied to a new validation set of 255 separate files.

III. RESULTS

The algorithm was applied to acoustic signals obtained from asthmatic outpatients who attended a respiratory clinic. Fig. 3 shows the identification and temporal onset/offset detection of an inhalation in a typical inhaler recording. The algorithm was designed so that various artifacts such as speech, fumbling of the inhaler and background noise are not detected as events. Both the onset and offset time of the inhalation are calculated by the algorithm.

In order to validate the algorithm, 255 audio files were selected at random to be analyzed from the inhaler recordings database. The audio files were randomly selected from 12 out of 20 subjects who were part of the study and the files were also selected at random from the three months of recordings from each subject. Two human raters, trained by an experienced Respiratory Clinician on how to identify inhalations, independently classified each of the 255 audio files by visual and aural inspection. The human raters firstly identified if an inhalation was present and secondly demarcated the onset and offset time of the inhalation. The human raters agreed on the presence of inhalations in 100% of the audio files. The average difference between raters in the detection of the inhalations onset time was ±19ms, while the average difference in the offset times was ±15ms.

Table I shows the performance of the algorithm in detecting inhalations, compared to that of the human raters. Results were classified as True Positive (TP), False Positive (FP) and False Negative (FN), according to the classification

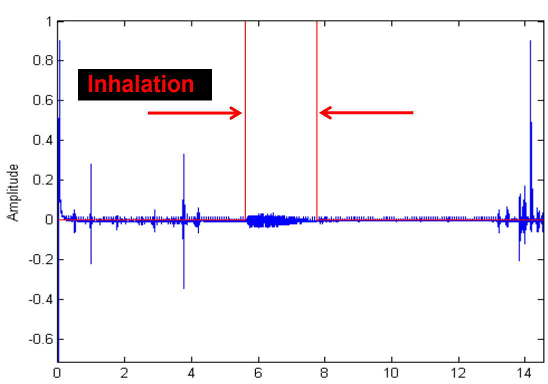

Figure 3: Identification and temporal onset/offset detection of an inhalation (indicated by the red arrows) in a typical inhaler recording by the algorithm

TABLE I
PERFORMANCE TABLE OF THE ALGORITHM

Inhaler Recordings	Total # Inhalations	TP	FP	FN	Sen	Spe	Acc
255	255	242	16	13	95%	94%	89%

of the human raters. It was found that the algorithm had sensitivity (Sen) of 95%, specificity (Spe) of 94% and accuracy (Acc) of 89% in detecting inhalations.

The result of the algorithm in accurately identifying the onset and offset of the inhalations is shown in Table II and Table II respectively. For this analysis only the true positive inhalations were considered. For inhalation onset time, the average difference between the human raters was ±57ms and ±61ms respectively. For inhalation offset time, the average difference was ±104ms and ±107ms. Taking into consideration that an average inhalation was found to be 1.8s in duration, the algorithms inhalation onset time classification varied by ±3.16-3.38%, compared to that of the human raters classification. Furthermore the algorithms inhalation offset time was found to vary by ±5.77-5.94%, compared to that of the human raters' classification.

TABLE II
INHALATION ONSET TIME ACCURACY

	Inhalation Onset Time	
	Rater 1 V. Algorithm	*Rater 2 V. Algorithm*
Average Difference (+/-)	57ms	61ms

TABLE III
INHALATION OFFSET TIME ACCURACY

	Inhalation Offset Time	
	Rater 1 V. Algorithm	*Rater 2 V. Algorithm*
Average Difference (+/-)	104ms	107ms

IV. DISCUSSION

An algorithm has been designed to automatically detect and demarcate inhalations from recordings of inhaler use in real world environments. Validation of the algorithm was completed by running it on 255 audio files obtained from asthma patients' actual inhaler recordings and comparing it to results from manual classification. Results have indicated that the algorithm was able to detect, on average, inhalations in 95% of audio recordings that contained inhalations according to the human raters. The algorithm had a specificity of 94%, while accurate identification of inhalations took place, on average, in 89% of audio files. This high level of accuracy is a promising result if this approach is to be included in a fully automated system for identifying inhalations from audio recordings.

Of the inhalations that the algorithm detected, it was observed that it was able to identify the onset/offset times of inhalations with a high degree of accuracy. In comparison to the human raters, the algorithm differed in inhalation onset time by ±57ms and ±61ms and in inhalation offset time by ±104ms and ±107ms. A possible explanation as to why the algorithm was not as accurate in detecting the inhalation offset time, compared to that of the onset time can be found in the mechanics of inhaler use.

Inhalation of asthma medications using inhalers involves a deep and steady inhalation from the user, in order to inhale the drug successfully into the small airways of the lungs. Such inhalations have a characteristic pattern, in both the time and frequency domains, when the correct inhalation technique is followed by the users. The onset of an inhalation is commonly accompanied by a period of silence in the period before the inhalation takes place. Although artifacts can occasionally interfere with the accuracy of the inhalation onset time identification, the algorithm achieved quite good correlation compared to that of the human raters.

The accurate identification of the offset time of inhalations from inhaler recordings represents a more challenging task. As patients inhale the drug from their inhalers there is a tendency to gradually reduce inhalation flow rate in the last few hundred milliseconds of the inhalation. At the end of the inhalation the patient will remove their lips from the mouthpiece of the inhaler device before clasping their mouth shut and holding their breath. The reduction in the flow rate of the inhalation towards its completion, the sound artifacts produced by the removal of the lips from the mouthpiece, in addition to artifacts associated with the fumbling of the inhaler as it is removed from the area of the mouth, are a number of factors which contribute to making the accurate identification of inhalation offset times challenging.

As the inhalations analyzed by the algorithm in this study were from asthma patients in real world environments, the accurate detection of inhalations onset and offset time was always going to be challenging. The accuracy and specificity results are slightly lower than those achieved by Ruinskiy & Lavner [11]; however the recording environments were very different for these two studies. Ruinskiy & Lavner employed recordings of speech and song signals in a controlled environment while the recordings for this study were recorded in the real world and thus much less controlled. Possible future methods to improve the temporal onset/offset detection of inhalations may lie in changing the audio sampling rate in the adherence monitoring device used from 7913bits/sec to a higher rate.

An algorithm that can accurately detect and demarcate inhaler recordings has a wide range of implications for both clinicians and asthma sufferers. Incorporating this algorithm into devices that can record audio signals of patients taking their asthma medication opens the door to a completely new approach to adherence monitoring. The algorithm provides a fast and easy method to analyze patients' inhaler use and thus can provide clinicians with strong empirical evidence of patients' adherence to their medication. This information can be used to give active feedback to patients. Such feedback may encourage patients to take better control over their asthma and lead to an overall improvement in their adherence to their medication. This in turn may improve the efficacy of the drug treatment regime, reduce the occurrence of asthma attacks and decrease hospitalizations.

V. Conclusions

In conclusion, an algorithm has been designed that can detect and demarcate inhaler inhalations to a high degree of accuracy. This algorithm may prove useful to both clinicians and asthma sufferers in improving adherence to asthma medication. Following on from this algorithm future versions may extend the algorithm to investigate if the correct technique for using inhalers is followed by patients. Possible future applications of this algorithm include extracting pertinent features from inhalations which may be used to provide real time information on patients' lung conditions in a remote monitoring scenario.

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