Utilizing Convolution Neural Networks for the Acoustic Detection of Inhaler Actuations

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***Abstract*—Asthma is a chronic respiratory disease and a significant burden for patients, their families and the healthcare system as a whole. Unfortunately, the management of the disease is far from optimal mainly due to the reduced adherence of patients to their medication plan. In order to solve this problem, a number of novel inhalers have been proposed over the past that monitor and support the proper use of inhaled medication. Aiming in this direction, the current study investigates the use of acoustic signals for the detection of inhaler actuations during activities of daily living and outside the controlled environment of the laboratory. The proposed algorithm is based on Convolution Neural Networks. The results of the current approach, have led to high levels of accuracy (98%), demonstrating the potential of this method for the development of novel inhalers and medical devices in the area of respiratory medicine.**

***Keywords*— asthma; metered dose inhaler; inhaler actuation; biosignal processing;convolution neural networks.**

Introduction

Asthma is a major chronic disease of the airways that affects more than 235 million people worldwide [1]. More specifically and for the region of Europe, 30 million adults suffer from asthma [2], while the number of children suffering from the disease is continuously rising in eastern countries towards the high levels of prevalence observed in the western part of Europe [3]. This diversity of asthma prevalence is a global rather than a European phenomenon [4] and reveals the inability of even developed countries to effectively support asthma patients [5, 6]. All the above, together with the wide spectrum of socioeconomic consequences of asthma disease that reduce the quality of life of patients and the efficiency of the healthcare system [7], underline the need for novel healthcare approaches and innovative devices in support of patients and healthcare professionals.

One of the most important aspects for the effective management of asthma is medication adherence which is defined as the extent to which patients follow their prescribed action plan and use their inhaler correctly. Reduced adherence has been identified as particularly problematic for asthma patients, both adults [8, 9] and children [10, 11], and has been associated with increased asthma attack incidents and patient hospitalizations [12, 13].

It is therefore more than evident that the accurate monitoring of adherence can be an important step towards the effective management of asthma disease. Firstly, doctors and healthcare professionals will be able to use this information in order to understand the progression of the disease in relation to the actual dosage of inhaled medication received by each patient, rather than the assumption that the patient followed the prescription accurately and consistently over time. Furthermore, patients could be supported by their doctor when they neglect their medication regimen and receive personalized reminders that do not rely on the patient's input but objectively detect whether and when the patient used the inhaler.

In this direction, the current study proposes an algorithmic methodology for the assessment of adherence of patients that use Metered Dose Inhalers (MDIs) on the basis of acoustic measurements. A recent publication by Taylor et al. [14] has provided the starting point in this area of research by introducing a fundamental and robust approach for the acoustic detection of MDI actuations in the laboratory environment. As an alternative approach, the current study utilizes Convolutional Neural Networks aiming to produce more accurate results for real life environments, as opposed to controlled laboratory conditions with reduced levels of noise.

Inhaler Based Monitoring Devices

A number of devices have been proposed over the past for the accurate monitoring of medication adherence which mainly based on the detection of inhaler actuations. Even though, these devices have been initially introduced as tools of academic research, due to their increased price and complexity, modern technological advances have made possible the development and commercialization of such devices at a low cost and in combination with intuitive smartphone applications for their intuitive control. A number of review studies have focused on the comparison of such devices and have led to useful results regarding their technical characteristics and their great potential for the improvement of asthma treatment [15-17]. The majority of devices presented in these studies are based on electromechanical sensing capabilities ranging from plain push buttons attached on the top of the inhaler's canister, to force sensing elements attached in the back of the inhaler's plastic casing. The second most prevalent sensing approach adopted by electronic inhaler devices is the use of microphones, the measurements of which are locally processed and used to indicate inhaler actuations.

Despite the fact that the use of electromechanical elements has been proven to produce reliable results without any risks to the privacy of patients, acoustic sensors are considered less invasive to the actuation process and hold the promise to allow the assessment of the entire inhaler technique as opposed to the plain detection of actuation events. The technique that a patient follows when using inhaled medication devices is another important factor that significantly affects the amount of medication reaching the patient's lungs. It is therefore, very useful and important to produce significant indicators for this process that will help doctors understand if their patients are using their inhaler properly and also allow patients to optimize their technique by using the provided indicator as feedback.

MATERIALS AND METHODS

A. Data Acquisition Setup

In order to allow the acoustic recording of inhaler actuations outside the confined laboratory environment, a miniaturized and portable recording setup was implemented based on the capabilities of modern smartphones (Fig. 1). In detail, an electret condenser microphone (Manufacturer Part Number: MD9745APZ-F) was fixed in the front side of MDIs facing the inhaler's mouthpiece. The microphone was then connected with the smartphone, which was used for the collection of sound measurements with a sampling rate of 16kHz at 16 bits/sample. As it will be described in the following sections the sampling frequency used for the analysis is 4kHz which was selected in order to balance the tradeoff between the accuracy of the produced solution and the computational complexity of the final algorithm.

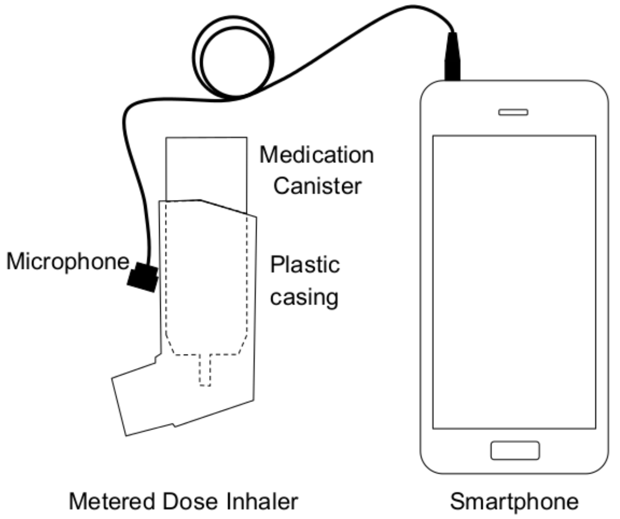

Fig. 1. Audio recording setup showing the microphone placement on the plastic casing of the Metered Dose Inhaler

B. Data Collection and Construction of Datasets

The above described setup was used for the recording of inhaler actuations in the real life environment (indoors and outdoors) and during the most common activities of daily living. Five subjects were asked to use the device for one day and record both environment sounds and inhaler actuations. It is important to underline that the inhalers where not used for their intended purpose but instead they were triggered in the open air and away from the subjects and any other people in the vicinity. Despite this inconsistency, the actuation measurements agree to a large extend with the acoustic signals of MDIs during their actual use by patients, as they are presented in the study by Taylor et al.[14] . Fig. 2 presents an indicative example from the collected actuation instances.

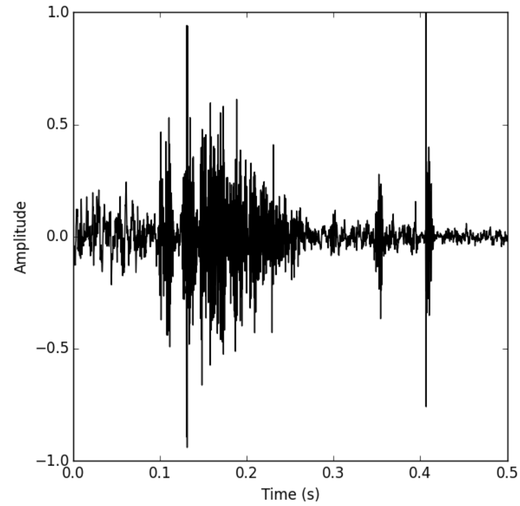

Fig. 2. Example of the acoustic signal during MDI actuation in open air.

After data collection, all files were manually annotated by identifying the starting points of all inhaler actuations. Using this information the full length of sound measurements was separated into segments of 0.5 seconds that were labeled based on whether they contained inhaler actuation events. This process produced 200 actuation recordings and the same number of non-actuation sound files. 142 of these files were separated for the training process of the algorithm, whereas the remaining files were separated into two equal groups for the validation and testing processes.

In order to increase the size of the training data and also test the accuracy of the proposed algorithm for measurements with increased levels of noise, the above 400 segments were randomly combined with 35000 segments of indoor and outdoor recordings as collected from freesound.org [18] producing a dataset of 70000 records segmented into non overlapping groups for training, validation and testing (50000, 10000 and 10000 samples respectively). All files were subsampled to 4kHz so as to create a homogenous dataset the can be used in the following signal processing steps and also reduce the computational complexity of the overall algorithmic process.

C. Signal Processing

Neural Networks (NNs) have been employed in the past for a variety of classification problems and have shown significantly accurate results in medical applications [19, 20] and general audio classification problems [21, 22]. Convolution Neural Networks (CNNs) are a specific type of NNs which are comprised of a series of convolution layers, often paired with subsampling layers, which are stacked before the fully connected multilayer perceptron that leads to the output layer. This architecture allows the CNNs to adapt to the characteristics of the training dataset and create a hierarchy of increasingly complex features [23] while at the same time they illustrate relatively fast and consistent convergence in the training process.

For the purpose of this study a CNN was implemented and trained in Python[24] using the Lasagne Library [25] and the Theano math expression compiler [26, 27]. The selected architecture consisted of two convolution layers of 16 1D kernels of size 100, followed by subsampling layers of size 2. Two fully connected layers of size 256 and 16, each of which was subjected to 50% dropout in the training process, lead to the output of two distinct states. For all layers of the CNN, rectifier was selected as the activation function in order to reduce the computational complexity of the algorithm. Furthermore, the initialization of the networks parameters was performed using a random generator of uniform distribution. Finally the training of the CNN utilized Stochastic Gradient Descent and was based on the categorical cross-entropy between the predictions and target values.

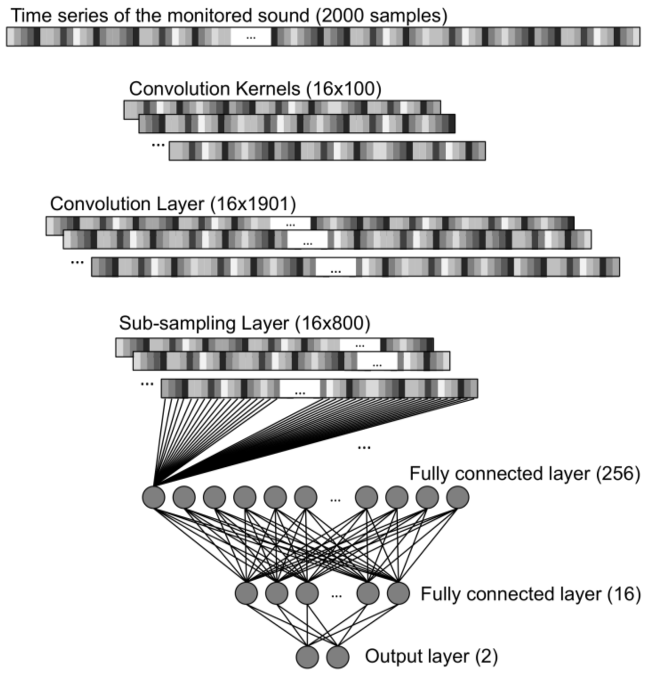

Fig. 3. Structure of the Convolution Neural Network for the classification of sound segments.

RESULTS

The algorithm proposed in this study is aiming to detect the actuation of MDI actuations in the daily living environment of patients by using acoustic measurements. The studied solution is based on a CNN, the training and testing of which was based on measurements of inhaler actuations in open air, in contrast to the actual use of the inhaler by patients. The experiments of the above described process has consistently lead to testing accuracies above 98%, despite the added noise and the diverse indoors and outdoors acoustic environment, leading to the conclusion that CNNs can form a reliable solution for related applications and the design of adherence monitoring devices. Fig. 4 presents the evolution of validation error as a function of training epochs for the conducted experiments. The best testing results among all trials indicated an accuracy of 99.5%.

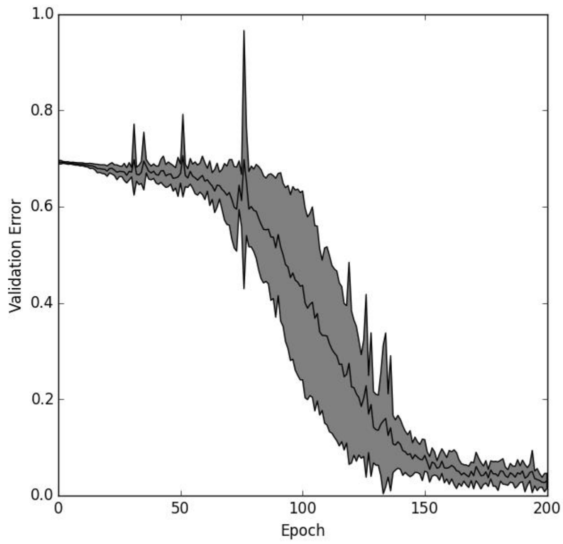

Fig. 4. Mean±Std of validation error .in the course of the training processes.

CONCLUSIONS AND FUTURE STEPS

The current study validates a new algorithmic approach for the detection of inhaler actuations in the real life of patients and outside the controlled laboratory environment. The proposed use of CNNs has been shown to hold great promise in this direction, as it produced highly accurate results despite the increased noise levels in the used dataset, especially when compared with previous approaches. Furthermore, the reduced monitoring sampling rate of the current solution (4kHz), can elevate some privacy concerns since it filters out a significant percentage of the human voice frequency spectrum.

As future steps the current study should be extended and supported with acoustic measurements of actual inhaler uses by patients in their environment and during common activities of daily living. Furthermore, the accuracy of the algorithm for different signal to noise ratios can be conducted in order to better characterize the performance of the algorithm in a variety of environments and types of acoustic noises. Finally, the current CNN approach should be carefully compared with algorithmic alternatives on the basis of a same dataset.

Finally, it should be underlined that the proposed solution is aiming to be integrated with a miniaturized smart device that could be attached to traditional inhalers and extend their function with adherence monitoring capabilities. Therefore, efforts should be made in the future so as to reach the optimum tradeoff between accuracy and computational complexity, and solutions such as the reduction of sampling rate, should be studied in order to minimize any possible concerns regarding the preservation of the users privacy.

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