A Mobile Percussograph for Medical Examination of the Torso

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Abstract - Medical percussion is a free, low-risk procedure used by physicians during physical examination of patients. Although it is a very useful procedure, a downside to manual percussion is that its results are subjective, with typically low inter-observer agreement. Not much work has been done, however, to create automated and reliable percussion devices or percussograph. This paper reports the development of a mobile percussograph. A spring-loaded solenoid was used as the plessor generating mechanical impact for application to a subject's skin. Generated signals were amplified and digitized at a rate of 22.1 kHz. Thereafter, Frequency B-Spline (FBSP) base wavelet transform at 512 scales was used for feature extraction. Spectrograms generated from the wavelet coefficients were used for training a MobileNet network with 17 inverted layers for a 3-way classification. Training employed a cross entropy loss function and the Adam optimization algorithm. Learning rate was 0.001, and first and second moment decay rates were 0.9 and 0.999 respectively. Subject-specific test accuracies of 92.9%, 93.7%, and 96.4% were obtained for three subjects, while the cross-subject classification accuracy was 95.0%. As this is the first reported general purpose mobile percussograph reported in the literature, these results are state-of-the-art. This study has established the viability of implementing mobile percussionography in a standard, repeatable and accurate manner, which can lead to faster and more reliable medical percussion globally.

Keywords - MobileNet, Percussion, Percussograph, Percussography, Wavelets

1 INTRODUCTION

For centuries, physicians have depended on inquiry, auscultation, inspection, palpation, and percussion for examining patients. Inquiry is a question-and-answer exchange used to establish the relevant facts to the patient's condition. Auscultation is the process of listening to sounds emanating from the human body to evaluate the likelihood of various conditions being present (Alam et al., 2010). In inspection, the physician visually examines the body of the patient for clues to physical or diseased state, while in palpation, the sense of touch is engaged to determine size, shape, firmness or location of body features. Percussion is similar to auscultation as it involves aural discrimination between body sounds. In percussion however, the sounds are not naturally-occurring, but generated by the physician striking the relevant body part using a standard technique (Peng et al., 2014). The resulting sounds are generally classified as dull, resonant, or tympanic, with each corresponding to well-known underlying conditions.

All five methods share commonalities. First, interpretation depends on the subjective sensory assessment of the physician. Also, in their basic forms, they are all easily administered manually. In the case of auscultation, a passive amplification device (the stethoscope) is used to improve acuity. Unfortunately, globally-accepted standard instruments have not been developed for other examination modalities. For instance, inspection could be improved with an instrument making a greater portion of the radiofrequency spectrum (including infrared frequencies) available to the physician (Rowan et al., 2010). Percussion would also benefit from having a device to generate mechanical impulse in a standardized, reproducible manner.

An obstacle to the adoption of standardized instruments for inspection, palpation, or percussion is the issue of guaranteed availability. There is a reluctance to train doctors to depend on tools that may not always be available. Miniaturization provides a possible way around this. Despite the afore-stated reluctance, the stethoscope has evolved into a ubiquitous instrument whose availability can almost always be assumed by a physician. If some means can be found to develop instruments for other modalities in very portable form factors, they will similarly be embraced. Consequently, the development of mobile devices for inspection, palpation, or percussion would be of great value.

In this study, a mobile percussograph (PCSG) was developed for performing automatic percussion on patients. A standard mechanical impulse is generated by means of a push-pull solenoid, while an NVIDIA Jetson Nano development board acts as the processing unit which uses a deep architecture classifier to detect one of three classes of percussive sounds.

2 RELATED WORK

Percussion is a staple in Medical Sciences, being used to detect several conditions including cardiomegaly (Heckerling et al. 1991), abnormalities in the ventricles of the heart (Heckerling et al. 1993), pleural effusion (Guarino & Guarino 1994), lung abnormalities (Bohadana, Coimbra, and Santiago 1986; Rao et al. 2018; Sánchez Morillo, León Jiménez, and Moreno 2013), and abdominal conditions (Mansy, Royston, & Sandler 2002). Part of its popularity is due to the fact that it performs well when compared to palpation and auscultation (Bohadana et al. 1986; Heckerling et al. 1993). Not much work has been reported on the development of automated devices for medical diagnosis using...
percussion methods. Automated percussion has two important parts: the human interface, and the signal processing, classification / detection and computation algorithms.

Thierman (2007) created a mechanical device for medical percussion. It comprised a spring-loaded plunger coupled to a stethoscope so that the plunger is used to percuss while the person listens through the stethoscope. Pantea et al. (2012), on the other hand, used an air microphone with their plessimeter. Rao et al. (2018) used a surface exciter (a speaker without cone or frame) paired with an Eko Core digital stethoscope in their auscultatory percussion device.

A general purpose automatic percussography device was developed by Ayodele et al., (2020). In that device, a NI 6251 data acquisition device was used to acquire audio signals after mechanical impulse by a push-pull solenoid. An NVIDIA Jetson TX computer was used for signal processing and classification, which was on the basis of complex Morlet wavelets. Automatic three-class classification was done with a 17-layer MobileNet convolutional neural network architecture, leading to subject-specific accuracies of 91.7%, 93.3% and 95% for three test subjects and cross-subject accuracy of 95.6%. Similar classification pipelines were reported in Howard et al. (2017, 2019) and Sandler et al. (2018).

3 METHODOLOGY
3.1 INSTRUMENTATION
The block diagram of the overall PCSG instrumentation system is shown in Fig. 1, and a photograph of the device is presented in Fig 2. A plessor is a device that generates a mechanical movement to strike the skin of the patient. A microphone picks up the resulting sound, which is then processed and interpreted by a processing unit.

The block diagram of mobile percussograph

The energization of the linear actuator mechanically driving the plessor is initiated by a switch operating through T1, and R5|R6 provide a resistive divider producing a 3.3V logic HIGH that is transmitted via a GPIO pin on the microprocessor, thus initiating the percussion process.

Once the plessor strikes the skin, the generated sound is captured by the microphone. Since the generated signal is very weak, it is amplified using A transimpedance amplifier (Fig. 4), making it more suitable for digitization. The amplifier was designed to have a maximum gain deviation of -0.1 dB over the frequency band of interest. An inverting amplifier configuration was selected to allow the use of single supply system; the non-inverting input of the amplifier is biased to mid-supply point of the supply system by the resistive divider of R3|R5.
C2 compensates for parasitic capacitance at the inverting input of the amplifier to avoid instability, and R2 determines the signal gain while the noise gain is determined by the ratio of R2 to R1. The combination R2 and C2 forms a low pass filter with the corner frequency set to 98 kHz. The value of R1 was chosen to allow optimal operation of the electret microphone (2.0 V to 3.0 V) using the microphone’s maximum current consumption.

R1 and C3 form a high pass filter with corner frequency set to 2 Hz. Resistors R5 and R3 were chosen to set the non-inverting input of the amplifier to the midpoint of the supply voltage, a value of 100 kΩ was chosen to minimize power supply current drawn by the resistive divider. C6 forms a high pass filter with R3||R5, setting the corner frequency to about 2 Hz. Capacitor C5 was chosen to remove any DC component present in the amplified signal, while R6 was selected to avoid charge build up in the capacitor which might cause signal distortion, the combination of C5 and R6 form a high pass filter with corner frequency set to about 1Hz. OPA358 precision amplifier was selected because of its excellent noise performance and its ability to operate on low voltage supply systems delivering rail-to-rail output which increases the dynamic range of the signal.

A low pass filter with cutoff frequency set at 10 kHz and gain of 0 dB was designed to attenuate frequencies well above half the sampling frequency, this enables matching the high band width of the amplifier to the sampling frequency of the analog to digital converter. This also reduces signal misrepresentation as a result of frequency transformation. The filter topology was based on Sallen-Key filter architecture (Fig. 5). The filtering was done in two stages, the first stage has a quality factor of 0.54 with its cutoff frequency of 10 kHz, the second stage of the filtering was achieved with a filter with quality factor of 1.31, cut off frequency of 10 kHz and minimum gain bandwidth of 1.31 MHz. From Fig. 5, R5/C6 and R6/C7 form two passive poles of frequency 73 kHz in the transfer function, this enhances the high frequency characteristics of the filter. The filter was designed to improve the signal to noise ratio of the signal to meet the specification of the Analog to Digital Converter (ADC).

Band limited signals from the low-pass filter were sampled at 22.1 kHz, high sampling rate was used to study the possible presence of high frequency components in the percussion signal. Analog to digital conversion was performed using Analog Devices AD7860 at 16-bit resolution. AD7860 best suits the application because of its high sampling rate, low voltage operation and ultra-low power dissipation.

### 3.3 Signal Preprocessing and Classification

Digitized sounds were acquired by an NVIDIA Jetson Nano computational device and segmented into epochs of 62.5 ms duration each.

As shown in Bhuiyan et al. (2012) and Bhuiyan et al. (2015), a percussion sound can be accurately modelled as a sum of finite exponentially damped sinusoidal components:

\[
f(t) = \sum_{i=1}^{N} a_i e^{-\alpha_i t} \sin(2\pi f_i t + \phi_i)
\]

where, \(a_i\) is an attenuation factor, and \(f_i\) the frequency of the \(i^{th}\) damped sinusoid component. In extracting features from such a signal, time-frequency methods have been found to outperform frequency domain methods, with wavelet decomposition in particular being excellent for signals that can be modelled by Eq. 1 (Bhuiyan et al., 2012; Bhuiyan et al., 2015). Consequently, wavelet transform was chosen for feature extraction process of the percussograph in this study.

In Ayodele et al. (2020), a complex Morlett base wavelet was employed for decomposition. The study however showed the Frequency B-Spline (FBSP) base wavelet was also very appropriate, particularly for signals with high attenuation factor, \(a_i\). In this study, each 62.5 ms epoch of digitized data was transformed using the FBSP at 512 scales corresponding to the frequency range of 50 Hz to 600 Hz. This allowed a spectrogram such as the one in Fig. 6 to be generated.
Classification thereafter proceeded as a 3-way image classification task using a MobileNet convolutional neural network with architecture shown in Fig. 7.

Percussion data were acquired from two male test subjects (A and B) of ages 19 and 30 years and a female subject (C) aged 10 years. The subjects were seated on a comfortable non-reclining chair, and signals were acquired from three locations: on the chest over the third intercostal space, over the liver, and over the abdomen. These regions are known to produce percussion sounds that are described as “tympanic”, “dull”, and “resonant” respectively. A total of 100 samples were acquired from each location per subject.

For classification, the acquired data were split for training, validation and testing in the ratio 60:15:25. Training used a cross entropy loss function and the Adam optimization algorithm. Learning rate was 0.001, and first and second moment decay rates were 0.9 and 0.999 respectively. Dropout with probability 0.3 and early stopping were used to prevent overfitting.

Classification accuracy was calculated using the following formula:

\[
A = \frac{\sum_{i=1}^{3} (tp_i + tn_i)}{3}
\]

Where \(tp_i\), \(tn_i\), \(fp_i\), and \(fn_i\) are the total number of true positive, true negative, false positive, and false negative classifications respectively for the \(i^{th}\) class out of 3 total classes.

### 4 RESULTS AND DISCUSSION

The frequency response of the microphone amplifier and filter is shown in Fig. 8. Tympanic spectral components are typically between 200 Hz and 600 Hz. Resonant sounds have spectral components that can be as low as 70 Hz, with prominent harmonics up to above 400 Hz. Finally, dull sounds do not have appreciable components below 100 Hz or above 600 Hz. The spectral response of the amplification system is therefore appropriate for the known spectral components of percussion signals.

The impact of the push-pull solenoid was measured for 8 consecutive strikes and tabulated in Table 1. The mean impact of 10.86 N is lower than what is generated in a typical manual performance of percussion, in which physicians generate up to 50 N. The lower force of the mobile PCSG in this study is however sufficient given that sound pickup is accomplished using a microphone located near the impact size, and is thereafter amplified. Consequently, signal to noise ratio is satisfactory even in the face of the lower impact force of the plessor.

A summary of the classification performance is presented in Table 2, while the confusion matrix is presented in Fig. 9. Table 2 shows that the test accuracies for both subject specific and cross-subject classifiers are generally (with the exception of Subject B) lower than the validation accuracies classifiers. This is common in classifier training and testing. drop, which is to be expected. Interestingly however, the test accuracy for the cross-subject classifier does not drop, as it remains 92% for both validation and testing. Of note is the fact that the cross-subject accuracy (95.0 %) was essentially identical to the mean subject-
specific accuracy (95.05±1.35 %), which is counter-intuitive. A likely explanation for this is the larger number of samples used for the cross-subject classifier, along with the likely lack of significant variability between the data acquired from the three subjects. This deserves further investigation.

Table 1. Impact forces generated by the plessor in 8 consecutive strikes.

| Strike Number | Force (N) |
|---------------|-----------|
| 1             | 10.5      |
| 2             | 11.1      |
| 3             | 11.2      |
| 4             | 10.9      |
| 5             | 10.7      |
| 6             | 10.8      |
| 7             | 10.9      |
| 8             | 10.8      |

These results compare favorably with previous studies. The only study not carried out by the authors that focused on automatic generation and classification of percussion sounds (Rao et al., 2018), achieved an accuracy of 92.3%. That device was however specifically for detecting pneumonia, and so was not general-purpose. The only other general purpose device reported in the literature (Ayodele et al, 2020) achieved subject-specific accuracies of 91.7%, 93.3%, and 95.0%, as well as cross-subject accuracy of 95.6%. Those figures are statistically similar to the values for this study, but for context however, the device reported in this study is mobile, which a total volume of less than 30% of the combined components of the previous device. Hence, a similar performance has been achieved along with added mobility. A future study will explore in depth the effect of different mother wavelets and other feature extraction techniques on classification or detection performance.

Table 2. Summary of validation and test accuracies

| Subject | Cross-Subject Accuracy (%) |
|---------|----------------------------|
| A       | Validation 94.7, Test 92.9  |
| B       | Validation 93.3, Test 93.7  |
| C       | Validation 96.4, Test 96.4  |

Fig. 9: Confusion matrices for testing data (a) Subject A-specific (b) Subject B-specific (c) Subject C-specific (d) Cross-subject

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