Suitability of Single-channel Acoustic Myography for Classification of Individual Finger Movements

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***Abstract*—Acoustic Myogram (AMG) is the vibration or sound signal produced during muscle contraction and relaxation. A simple system like a condenser microphone is enough to capture an AMG signal from muscles, unlike complex systems that are used in surface Electromyography (sEMG). Moreover, AMG signal is not highly sensitive to sensor placement like sEMG signal. Therefore, Acoustic Myography is a potential research area to find an alternative to complex and bulky sEMG system. This work focuses on verifying the suitability of single-channel AMG for the classification of individual five finger movements. AMG data were recorded from 14 subjects at two different sites on hand, namely forearm muscle and wrist. Temporal, Spectral, and Cepstral features were extracted from the collected data after required pre-processing. Two Machine learning algorithms: Support Vector Machine and K-Nearest Neighbors were applied to classify the features. From this analysis, three main outcomes were achieved: Independent five finger movements cannot be differentiated precisely using single-channel AMG data solely, whether they are from the forearm or wrist. Class reduction and grouping of some fingers increase the classification accuracy, which infers that vibrations due to different finger movements have very similar attributes. AMG from both forearm and wrist yielded similar classification accuracy, with no evidence of a site being significantly better.**

Contribution: This research reveals the competence of single-channel Acoustic Myography (AMG) in classifying individual hand finger movements.

Keywords– Acoustic myography, single-channel AMG, finger movement classification, Phonocardiograph, sEMG alternative

I. Introduction

Acoustic Myogram (AMG) refers to the vibration signal produced due to muscle movement. It is also known as Mechanomyogram (MMG), Phonomyogram (PMG), or Vibromyogram (VMG). Fig. 1 depicts that sounds are produced during both contraction and relaxation of the muscle. When an action potential propagates down a muscle, it contracts. This contraction results in a vibration, which has a resonant frequency detectable through acoustic sensing [1]. This resonant frequency depends on muscle length that changes as a function of contraction [1]. Furthermore, the results of Blaho's 2018 project [2] show that there is an obvious correlation between acoustic properties and muscle contraction in the human arm and it can be quantified.

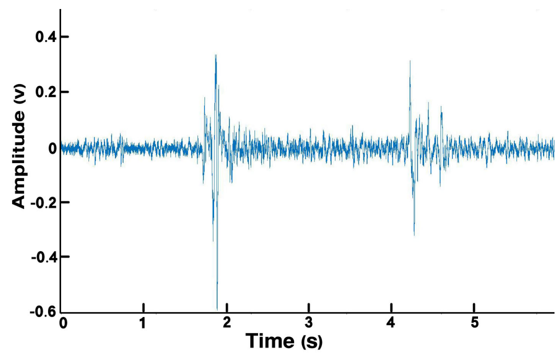

Fig. 1. An AMG signal from forearm muscle. The first amplitude burst represents muscle contraction while the second burst represents relaxation.

In applications like diagnosis of muscle dysfunction, controlling prosthetic limb, and recognizing gestures, surface Electromyography (sEMG) is widely used [3]. Different sEMG signals with unique features are generated for unique hand movements. Studies show that higher classification accuracy is achievable using machine learning [4], [5], [6], [7]. But identifying individual finger movements is a more complex challenge. Several channels and complex machine learning techniques are required to successfully classify individual finger movements using sEMG [8], [9]. Complications like proper sensor position, associated numerous artifacts, etc. give rise to the need for complex circuitry and precise signal processing in sEMG [10]. Alternatives to sEMG are being explored to address its limitations and complexity. Acoustic Myography as well as Electroencephalography (EEG), accelerometer data, pressure sensor, vision, etc. are several alternatives and inclusions studied along with sEMG.

AMG devices nowadays have the potential to assess patients with neuromuscular and musculoskeletal complaints correctly in clinics, home monitoring, and sports settings [11]. This work also predicted the potential of AMG as a technique to diagnose and monitor patients with Parkinson's disease, rheumatic diseases, Huntington's disease, myopathy, cerebral palsy, fibromyalgia, ALS, etc. It was also pointed out that if sEMG is to be accepted as a clinical tool, there is a need for

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improvement in existing techniques. A single channel AMG was successfully used to differentiate the lameness of proximal suspensory ligament between healthy and injured horses [12]. Integration of single-channel AMG with EMG was found to be a useful method for noninvasive assessment of force production and fatigue of the quadriceps muscle [13]. The ratio of AMG and sEMG was used as a diagnostic method for pediatric muscle disease and AMG was found to show good impact on increasing the efficiency of diagnosis [14].

Barry et al. [15] performed a comparative study on AMG and sEMG, which showed some noticeable advantages of AMG over sEMG. Alwin de Rooij [16] assessed the ability of machine learning techniques to classify arm gestures for different levels of muscle force. Moreover, several studies show that AMG and other forms of Mechanomyogram (MMG) can be used to classify wrist movements and other basic hand movements [17], [18]. AMG combined with sEMG has also been used to discriminate finger motions [19]. But the classification of finger movements solely from AMG has not been explored, which is the target of this study.

In this research, Acoustic Myogram (AMG) data were collected from forearm muscles and wrist. Features extracted from the collected data were used to classify individual five finger movements. This classification problem was approached using two extensively used machine learning algorithms: SVM and KNN. Collecting AMG data from forearm muscles is obvious since finger movements are controlled by forearm muscles [20]. In another study, it was proved that wrist-mounted pressure sensors can be practically used to classify hand gestures and they work better than wrist-mounted sEMG sensors [21]. Very recently acoustic signals from human wrist along with accelerometer and gyroscope data were used in hand gesture recognition [22]. These studies inspired collecting AMG data from the wrist along with forearm in this work. Here, the focus was to validate whether a single-channel AMG from the forearm or wrist alone is enough to classify individual finger motions or not.

This paper is organized as follows. Section II is divided into six subsections. In these subsections, the steps and equipment in data acquisition and the methods used in data processing, feature engineering, and classification are explained successively in detail. Then section III describes the results along with illustrative explanations and figures. Section IV explains what problems are addressed in this work and how it is different from previous related works. Section V summarizes the outcomes and suggests future studies based on the outcomes.

II. Material and Methodology

A. Subjects

14 healthy subjects with no known diseases of the musculoskeletal system were informed of the experimental procedure and they gave their consents. Data were collected from 10 male (average age: 28) and 4 female (average age: 25) human subjects aged between 24 and 40 years old.

Fig. 2. Phonocardiograph used for AMG data collection. It was developed by Bi-BEAT Ltd., Bangladesh. It is a modified stethoscope with a condenser microphone inside and connected to a USB sound card.

B. Equipment

Bi-BEAT Ltd's Phonocardiograph or digital stethoscope was used to collect AMG data [23]. Two phonocardiographs as shown in Fig. 2 were placed on forearm muscle belly and wrist to collect data simultaneously. The forearm sensor was placed on the forearm flexor muscle and the site was identified using simple muscle palpation. On the other hand, the wrist sensor was placed centered on the Palmaris Longus tendon of the wrist.

Freeware 'Audacity' was used to record AMG data in *.wav audio format. Two PCs were used to collect data in parallel from both sites. A camera was used to record finger movement actions for synchronization during data processing.

C. Setup and Data Acquisition

Some step by step protocols were followed for setting up the system and collecting data. These are as follows:

1) Subjects were asked to sit in a relaxed sitting position stretching hand on the table as shown in Fig. 3.
2) Both sensor sites were cleaned with alcohol pads to remove dust and dead cells.
3) Viscous gel was applied at the sensor-skin interface to reduce acoustic impedance.
4) Musk tape and Gauge bandage were used to fix the stethoscopes in position as shown in Fig. 3. This also helped reduce external environmental audio noise.
5) Subjects were asked to keep still and silent as much as they could while performing the finger movements.
6) Subjects were instructed visually by gestures on when to contract and relax the fingers. Thus a similar gap of roughly 5 seconds was maintained among iterations.

All the subjects performed 5 classes of finger movements. They were individual five finger flexion as shown in Fig. 4.

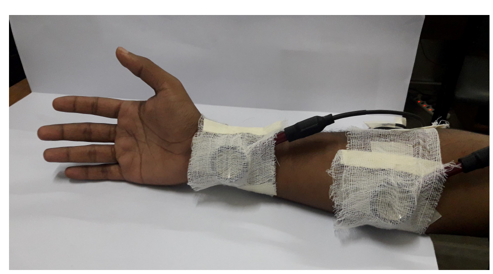


Fig. 3. Experimental setup for AMG data acquisition

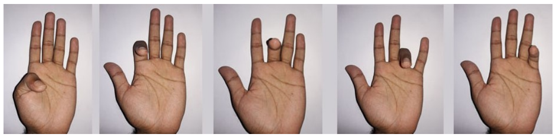


Fig. 4. Flexion of 5 individual fingers. These 5 flexions represent 5 classes.

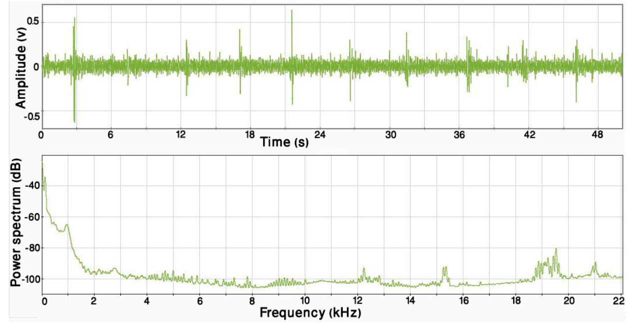
Every subject iterated each movement 5 times. So, the number of samples collected per class from 14 subjects were $14 \times 5 = 70$ samples. So, there were $70 \times 5 = 350$ samples for 5 classes of movements recorded from 14 subjects.
Five iterations for each finger were recorded at a stretch. Then a 1-minute gap was given for the subject to relax muscles before starting data acquisition from the next finger. Around 45 minutes was spent per subject for preparation and data acquisition.

D. Data Processing

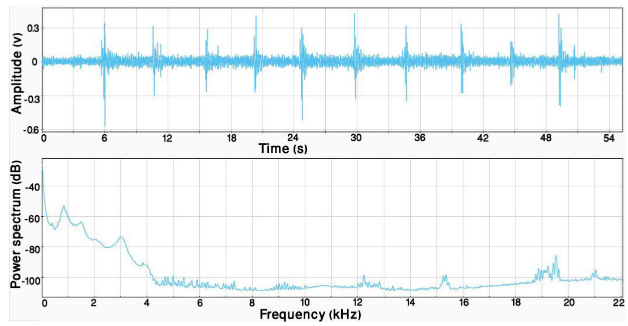
Fig. 5 displays time-domain signals from the forearm and wrist and their corresponding frequency responses. Amplitude bursts are noticed during contraction and relaxation of the muscle. For example, in Fig. 5(a) each pair of amplitude burst represents one flexion incident of the thumb (i.e., one contraction and corresponding relaxation) collected at the forearm. There are 5 such incidents recorded. Similarly, Fig. 5(b) represents the same for wrist data. AMG data were collected at a sampling rate of 44.1 kHz.

Several studies indicate that vibration generated due to muscle movement has a frequency response around 20 Hz [24], [25]. A sampling rate of 44.1 kHz is very high considering the 20 Hz frequency of AMG. Yet, data were sampled at this high rate to explore if any noticeable high-frequency content was found. Power spectrums of the signals in Fig. 5 show that significant frequency contents are below 1 kHz. So, a Low Pass Filter (LPF) with a cut-off frequency of 1 kHz was used to filter the signal. The stopband attenuation of the filter was set to 100 dB. Moreover, the steepness of the filter was set to 0.99 to get a steep roll-off at the cut-off. No further processing was performed on the data.

In this paper, the main focus was to classify the contractions of muscles only. Contraction is the onset of flexion movement while relaxation is the end of that movement. For practical application, the flexion movements need to be detected and classified at their onset. Hence, the classification of the contraction signals due to different finger movements was crucial. So, the relaxation parts of the signals were ignored and contraction parts were analyzed first. To separate the contractions from relaxations, each signal was segmented into 10 equal parts since each signal had 5 pairs of contraction and relaxation. So, the segmented odd-numbered parts were contractions and even-numbered parts were relaxations. After that, the segmented contraction parts were stored. These stored segmented signals contained unnecessary baseline signals along with the target amplitude bursts. To extract the amplitude burst from each segment, further segmentation was performed.



(a)



(b)

Fig. 5. Time-domain and frequency-domain plot of AMG data, recorded during flexion of thumb from (a) forearm and (b) wrist.

Each segmented signal was squared and then the index of the maximum amplitude of the squared signal was located. This location was the most prominent point of the amplitude burst. Then a window was selected around this location. A few trials were performed on different segments from different subjects for varying classes to find out the best-fit window. For the 44.1 kHz sampling rate, a window of 30,000 samples was found to be the best fit to accommodate the contraction (i.e., the amplitude burst) from every segment. This window neither excluded any major part of the amplitude burst nor included baseline noise. Since every subject iterated each movement five times, five samples were extracted from every subject per class. Finally, extracted samples were arranged in a subject-invariant class-based format for feature extraction.

E. Feature Extraction and Reduction

Initially, 40 temporal features and 81 spectral and cepstral features were extracted from the samples. There were three types of features mainly:

1) Statistical features like Mean, Variance, RMS, Fundamental frequency, etc.,
2) features usually used for surface Electromyography (sEMG), e.g., Zero-crossing, Willison amplitude, Mean Absolute Value (MAV), Log detector, etc., and
3) since AMG is a sound signal, a few sound processing features were extracted too. These include Mel Frequency Cepstral Coefficient (MFCC) and Gamma Tone Cepstral Coefficients (GTCC).

TABLE I
LIST OF FINALLY SELECTED FEATURES IN ORDER OF IMPORTANCE

Features for forearm data	Features for wrist data
Lyapunov exponent	Difference Absolute Standard Deviation Value (DASDV)
Approximate entropy	Peak prominence
Peak value	Maximum fractal length
Mean instantaneous frequency	Band power
Mean spectral entropy	*Log detector*
Minimum spectral slope	Correlation dimension
Maximum GTCC	Mean GTCC
Slope sign changes	Minimum GTCC
Bandwidth	Maximum spectral slope
Peak width	*Mean MFCC*
Standard deviation	*Mean spectral entropy*
Root sum of squares	Minimum spectral spread
Mean frequency	Lower index of cumulative sum
Mean MFCC	Minimum spectral skewness
Mean spectral slope	*Lyapunov exponent*
Range of GTCC	*Slope sign changes*
Log detector	Minimum instantaneous frequency
	Range of instantaneous frequency
Median absolute deviation	*Bandwidth*
Skewness	*Mean frequency*
Kurtosis	*Mean spectral slope*

$*$*Common features are mentioned in Italic font*

So, in total $40 + 81 = 121$ features were extracted per sample. A 'One-way Analysis of Variance (ANOVA)' model was used to rank all the features based on their importance. As mentioned earlier, a total of $14 \times 5 \times 5 = 350$ samples were collected from 14 subjects for 5 classes at 5 samples per class format. Since 121 features were extracted per sample, the dimension of the feature vector became 350×121. One-way ANOVA analyzed the differences among class-wise means from the whole feature set.

The first 80 features ranked using one-way ANOVA were taken for further analysis. Then from these 80 features, the best features were selected by manually feeding each feature one by one. Change in classification accuracy was checked for adding each feature. A feature was selected for positive change and discarded for a negative change of accuracy. After feature reduction, significant 20 features were exploited for forearm data and 21 features were considered for wrist data. They are enlisted in Table I. The features are listed in descending order of importance from top to bottom. As evident from Table I, 8 features were found common for both forearm and wrist data.

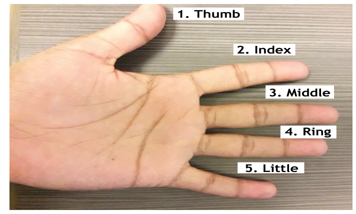


Fig. 6. Five individual fingers are assigned to five unique classes.

F. Classification

For ease of operation, each finger movement was assigned to a number as shown in Fig. 6. Variants of Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) were explored for classification. Five-fold cross-validation method was utilized at 70%/30% - train/test format. Both forearm and wrist features enlisted in Table I were separately used for classification. Three criteria of classification were analyzed, namely:

1) Classification of individual five fingers,
2) Classification with a reduced number of classes and
3) Classification for different combinations of finger groupings.

III. RESULTS

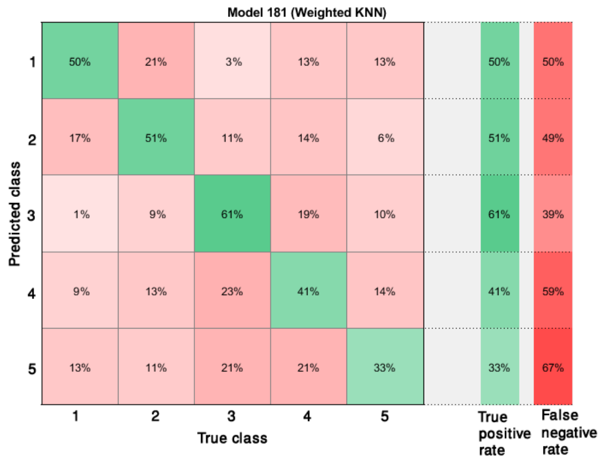
A. Classification of individual five fingers

Fig. 7 depicts the confusion matrices of the classification results for both forearm and wrist features. The best average classification accuracy was found for the weighted KNN model among all the variants of SVM and KNN explored. The average accuracy for the forearm was 47.4% and for the wrist was 44%. So, there is no significant difference found between the forearm and wrist features.

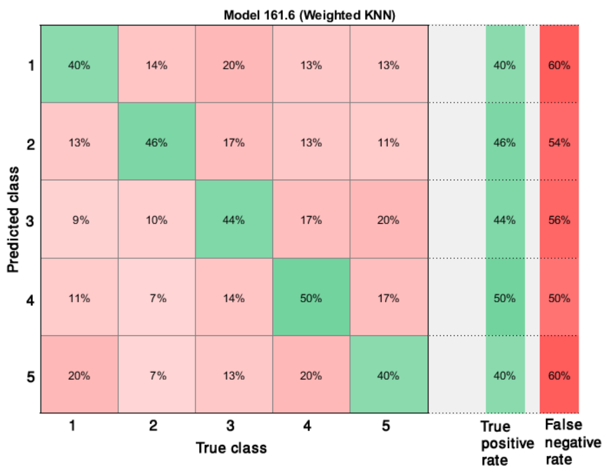
From the confusion matrix for forearm data in Fig. 7(a), it can be seen that class-1 has the highest confusion with class-2 and vice versa. As well as, class-3 shows the highest confusion with class-4 and the other way around for class-4, while class-5 shows the highest confusion with both class-3 and class-4. Overall, the model is mostly confused between class-1 and class-2 as well as among class-3, class-4, and class-5. On the other hand, from the confusion matrix for wrist data in Fig. 7(b), no such confusion pattern is perceivable. It is also evident that maximum accuracy is achieved for class-3, which indicates that the model can separate class-3 (i.e., movement of the Middle finger) better than other classes.

B. Class reduction

As evident in Fig. 7, the average classification accuracies are below 50%, which is an indication of poor efficiency of the whole system. However, from the confusion matrix for forearm data in Fig. 7(a), a confusion-pattern can be seen as



(a)



(b)

Fig. 7. Confusion matrices for classification of individual 5 finger movements from (a) forearm and (b) wrist data. Average classification accuracy is (a) 47.4% and (b) 44% respectively.

discussed previously. Accordingly, an initial assumption was that signals for different finger movements being originated from the same muscle group caused such a confusion-pattern. To verify this, classification was performed again by reducing classes. Each class was removed in turn as well as various pairs of classes were removed. Among them, four categories of class reduction demonstrated a notable increase in accuracy. These are:

1) Thumb flexion, i.e., class-1 was removed: Classification was performed for Index, Middle, Ring, and Little fingers only. Eventually, average accuracy was increased up to 51%.
2) Little finger flexion, i.e., class-5 was removed: Classification on the remaining four fingers showed about similar accuracy as removal of class-1 as mentioned above.
3) Both Thumb and Little finger flexion, i.e., class-1 and class-5 were removed: Remaining 3 finger movements were classified and average accuracy was increased up to 61%.
4) Ring and Little finger flexion, i.e., class-4 and class-5 were removed: In this situation, the accuracy was increased up to 63%.

Comparative details of the classification accuracy for different sensor sites (i.e., forearm and wrist) and different classifiers (i.e., KNN and SVM) are given in Table II and Fig. 8. From Table II, it is clear that accuracy was increased slightly up to 51% when only one class was reduced. However, when two classes were reduced, accuracy was increased further up to around 60%. The best accuracy 63.8% was found after removing class-4 (i.e., Ring finger) and class-5 (i.e., Little finger).

C. Grouping fingers

As mentioned earlier, the classifiers were mostly confused between class-1 and class-2 as well as among class-3, class-4, and class-5 for classification of individual five finger movements. So, the next approach was to group fingers in various combinations. For example, class-1 and class-2 can be considered as a single class, i.e., class-12. The sample number in this new combined class was normalized with other classes by random choice. Five combinations were found to achieve a significant increase in accuracy, these are:

1) Grouping-1: class-4 (Ring finger) and class-5 (Little finger) were merged together and treated as a single class. The other 3 classes were unaltered. Eventually, there were 4 classes then.
2) Grouping-2: class-3, class-4, and class-5 were combined together in one class. So, the total number of classes became 3.
3) Grouping-3: Thumb movement i.e., class-1 was considered as it was and all the other finger movements were grouped in one class. So, there were only 2 classes in this consideration.
4) Grouping-4: class-1 and class-2 were grouped together. Similarly, class-4 and class-5 were grouped together. The remaining class-3 was unaltered. Hence, a total of 3 classes were produced.
5) Grouping-5: class-1 and class-2 were grouped together in one class. Class-3, class-4, and class-5 were grouped together as well to form another class. Eventually, 5 classes were reduced to only 2 classes.

Details of the classification accuracy for grouping are presented in Table II and Fig. 8. The best accuracy of up to 70% was achieved for grouping-5.

D. Summary

Table II and Fig. 8 summarize the results. As evident, the AMG system considered here, could not effectively classify all the five finger movements. The average accuracy for both forearm and wrist data was less than 50%. However, after class reduction and grouping, accuracy increased. Around 60% accuracy was achieved for class reduction and around 70% accuracy was achieved for grouping. The comparative illustrations can be seen in Fig. 8. Fig. 8 also compares the

TABLE II
CLASSIFICATION ACCURACIES FOR VARIOUS CONSIDERATIONS

Classification criteria	Classes of finger movements considered	Average accuracy (in %)				Maximum accuracy (in %)			
		Forearm		Wrist		Forearm		Wrist	
		KNN	SVM	KNN	SVM	KNN	SVM	KNN	SVM
All 5 classes without modification	Flexion of individual 5 fingers	47.4	42.6	44	35.7	61	58	50	39
Class reduction	class-1 removed	50.7	51.8	42.9	45.7	66	54	47	49
	class-5 removed	51.4	51.1	42.9	42.9	60	60	47	49
	<u>class-1 and class-5 removed</u>	**61.4**	<u>58.6</u>	**58.1**	**59.5**	**70**	<u>71</u>	**60**	**61**
	class-4 and class-5 removed	<u>60.5</u>	**63.8**	<u>50.5</u>	<u>45.7</u>	<u>67</u>	**86**	<u>53</u>	<u>57</u>
Grouping fingers	Grouping-1: [class-4 + class-5]	48.9	49.3	41.8	38.6	<u>76</u>	56	51	43
	Grouping-2: [class-3 + class-4 + class-5]	55.2	57.1	50.5	49	63	66	56	57
	<u>Grouping-3: [class-2 + class-3 + class-4 + class-5]</u>	<u>63.6</u>	<u>68.6</u>	<u>57.9</u>	<u>55.7</u>	64	<u>73</u>	<u>64</u>	**74**
	Grouping-4: [class-1 + class-2] and [class-4 + class-5]	49.5	51.4	49	46.2	74	73	57	49
	Grouping-5: [class-1 + class-2] and [class-3 + class-4 + class-5]	**70**	**70**	**57.9**	**57.9**	**78**	**77**	**64**	<u>60</u>

$*$ **Best accuracies are mentioned in Bold font**
$**$ <u>2nd best accuracies are underlined</u>

results from the two sensor locations, i.e., forearm and wrist and no appreciable difference was evident.

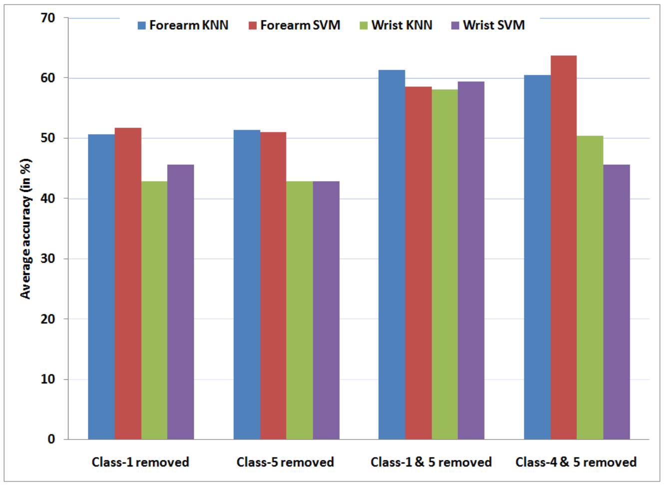
IV. DISCUSSION

Several studies show that Acoustic Myography (AMG) and other forms of Mechanomyography (MMG) can be utilized in finger movement classification as an inclusion to the conventional surface Electromyography (sEMG) technique [26], [19]. Moreover, multiple channels of AMG sensors have been used for classification of finger movements up to an offline classification accuracy of more than 80% [27], [28]. In contrast, this paper evaluates the capability of a single-channel AMG system for the classification of individual 5 finger movements. From Table II, it is evident that the system did not perform well in classifying all the five movements correctly. However, class reduction and grouping demonstrated an increase in accuracy.

Class reduction can increase classification accuracy to some extent. Table II shows that the removal of movements of Ring finger and Little finger can increase accuracy noticeably. This means that the single-channel AMG system can classify Thumb, Index, and Middle finger movements better than other types considered. Robust classification of these mentioned fingers can be utilized in many practical applications. Studies show that with the presence of opposable thumb, independent long finger movements are not essential [29]. Besides, most hand amputations are partial and the number of finger amputees is large [30]. Since accuracy increases for two or three fingers, this system has the potential to be used as a low-cost finger prosthesis for partial finger amputees. Moreover, with the advent of touch-screens and gestures in many aspects of technology, improving the identification of bezel gestures (e.g., zooming, swiping, pinching) is very important [31]. In classifying specific few fingers, this simple AMG system can be utilized as a compact wearable device.

Grouping fingers in different combinations showed an increase in classification accuracy as depicted in Table II. Especially, in Grouping-3 and Grouping-5 in Table II, about 70% accuracy was achieved. These results infer that signals generated due to Thumb and Index movements have very common characteristics. Similarly, signals from Middle, Ring, and Little fingers also have common features. This may be due to the fact that physiologically any finger cannot be moved without affecting another finger. Hence, classification of such closely correlated AMG signals requires a multi-channel or multi-sensor based system unlike the simple AMG system considered here.

Data acquisition using a single channel sEMG system requires a minimum of three patch-electrodes, two for differential data, and the remaining one as a reference electrode [32].



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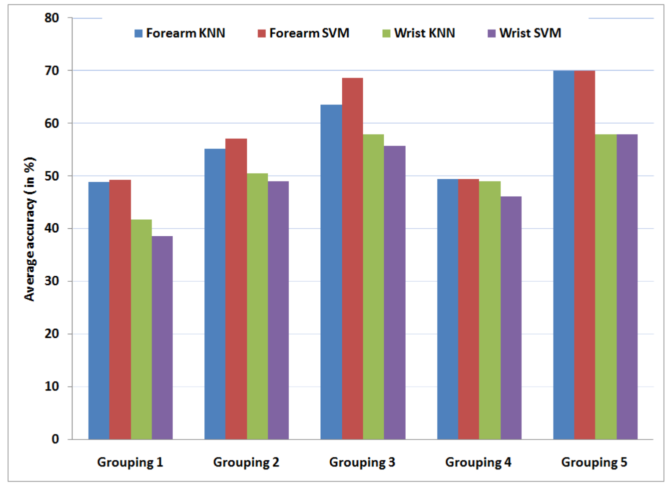

(b)

Fig. 8. Comparative illustration of results from Table II for (a) class reduction and (b) grouping fingers.

On the other hand, a single channel AMG device requires one small condenser microphone [33]. So, AMG sensors require significantly less space than sEMG electrodes. This makes it possible to mount AMG sensor on already available sEMG sensor [19]. Because of smaller size, the AMG sensor has the potential to be used in wristwatch as well and this inclusion may introduce more features and control in a smartwatch.

Many advantages of Acoustic myogram signal over surface Electromyography signal has already been proved experimentally in previous studies. For example, AMG is a pure signal while sEMG is a combined signal of muscle fiber depolarization and nerve signal; AMG signal is unaffected by sweating or sensor site preparation unlike sEMG; sEMG signal is prone to external electromagnetic fields, ECG, and other bodily electrical signals, etc. [11]. All these advantages are leveraged to develop AMG devices with significantly low cost preprocessing circuitry compared to sEMG devices. So, with further practical improvements, AMG devices have huge potential to be developed in a compact size with a lower cost than existing sEMG devices.

In this study, AMG data from both forearm frontal muscles and wrist were considered. From Table II, it is evident that there is no significant difference between the two sensor locations, i.e., classification accuracy for forearm and wrist data are quite similar. This indicates that one can wear a wearable-AMG-device on the wrist instead of wearing on the muscle. In contrast, wearable-sEMG-devices must be worn on the muscle belly which causes discomfort for the user. So, the AMG system has more commercial viability than sEMG in consideration of cost, size, and user comfort.

V. Conclusion and Future Works

Acoustic myogram is the vibration generated during muscle contraction and relaxation. It has been studied for a while as a non-invasive technique to interface with muscle. Many works have been performed to leverage AMG in clinical diagnosis purpose, prosthetic application, gesture recognition, Human-Computer Interfacing (HCI) and many more. Nowadays, identifying different finger movements for contactless device control, partial prosthesis, etc. has a growing need and AMG has been studied as an easier and cheaper method among others. Previous attempts in this area have achieved notable accuracy in finger movement classification using multi-channel AMG and combination of AMG with other techniques (e.g., sEMG). This paper pushed one step further and evaluated the suitability of a single-channel Acoustic Myography (AMG) for the classification of individual hand finger movements.

AMG data were recorded from the wrist and forearm flexor muscles of 14 healthy subjects (10 males and 4 females) simultaneously. Data for individual 5 finger movements were collected. After pre-processing and filtering the data, features were extracted from the data. Then essential features were selected using feature reduction techniques: One-way ANOVA and trial-error testing. These final features were fed in KNN and SVM classifiers.

Average classification accuracy was not appreciable for individual five finger movements, i.e., all five classes. However, combining multiple classes in one class offered a significant increase in classification accuracy. Removing one or two classes also increased accuracy. These indicate that classifying all five finger movements faces physiological challenges and limitations. So, the simple AMG system considered here needs to be upgraded. The upgrade may include adding more channels to the AMG system or, using an MMG sensor (e.g., pressure sensor, accelerometer sensor, etc.) along with the AMG sensor. Moreover, robust feature reduction techniques should be used (e.g., Fisher's discriminant ratio) and more data should be collected as well.

Overall, this work has not achieved significant classification accuracy. Hence, a single channel AMG system solely is not enough to differentiate unique features for individual finger movements whether the signal is recorded from forearm muscle or wrist. However, accuracies for class reduction and grouping inspire the analysis of basic hand movements (e.g., wrist flexion and extension, power grip, etc.) using this simple AMG system in the future. This simple system can be tailored further to be used for partial finger prosthesis as well. The comparative results between the forearm and wrist increased the reliability of recording data from the wrist. So, this work faced the practical challenges in the classification of finger movements, proposed applications based on acquired results, and suggested future modifications towards designing a simple system for the complex challenge in hand.

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