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Human Breathing Classification Using Electromyography Signal with Features Based on Mel-Frequency Cepstral Coefficients

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Abstract: Typical method on assessing the human breathing characteristics is based on measurements of breathing air parameters. Another possible method for human breathing assessment is through the analysis of respiratory muscles electromyography (EMG) signal. The EMG signal from different breathing task will be analyzed in order to determine the characteristics of the EMG signal pattern. Thus, feature extraction need to be done on the EMG signals. This paper will look into the use of Mel-Frequency Cepstral Coefficients (MFCC) in providing the features for EMG signal. Analysis is done using different data analysis frame sizes. EMG signal classification is done using K-Nearest Neighbour. Results shows that MFCC is a good feature extraction method for this purpose with classification accuracy exceeds more than 90% for data analysis frame size of 2000 ms, 4000 ms, 5000 ms and 10000 ms.

Keywords: Electromyography, Human Breathing, Respiratory Muscles, MFCC

1. Introduction

The presence of electromyography (EMG) as representative of muscle activity is closely related to the work of nervous system. Electrochemical transmission between nerves starting from the brain produces action potential which propagates through nerve fibers. Action potential moves along nerve fiber will stimulate skeletal muscles which then create muscle contraction. This then results in movement of human limbs. Action potential acts on a single nerve. Since there are vast numbers of skeletal muscle fibers, the electrical potential from muscle recorded for EMG is actually superposition of action potentials acting on skeletal fiber muscles [1].

Study on EMG had been intense, especially for the last couple of decades, due to the use of modern electronic devices along with numerous emerging techniques in signal processing. With advancement in the area of signal processing, pattern recognition and machine learning, EMG signal can be further examined to obtain its characteristics according to the corresponding body movements and gestures. For example, muscles that enable movement of forearm are the biceps and triceps. Thus, acquiring EMG from these two muscles will enable the assessment of the characteristics forearm movement.

Similarly, for examining the characteristics of human chest movement due to breathing, EMG signal that corresponds to the breathing action could be used as the subject of study. There are several of such muscles located around the chest, neck and abdomen. Electromyography signal can be acquired from these muscles which then bring to the utilization of signal processing techniques.

Various studies had been done on human muscles through EMG signal. Biceps brachiii of the upper arm and brachioradialis of the forearm had been investigated on their role in elbow movement [2]. EMG of rectus femoris of the hip had been studied to investigate the effect under certain workload of leg exercise [3]. Other leg muscles such as vastus lateralis, biceps femoris and soleus had been chosen for study on its EMG activity during certain physical exercise [4]. Study on muscle pain during certain physical task or exercise could also utilize the EMG signal like the one that had been done on upper trapezius muscle [5]. Even facial muscle such as zygomaticus had seen its EMG application for human-machine interaction [6].

When represented in waveform, the EMG signal recorded from muscles activity seems fluctuates rapidly between maximum and minimum value. An example of EMG signal is shown in Fig. 1. Although the signal seems to be chaotic, it could contain information on muscle activity or characteristic. Usually, signal conditioning need to be performed to obtain much meaningful expression of EMG signal.

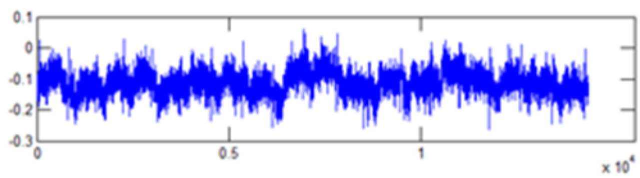

Fig 1 An example of EMG signal in time-domain waveform

Looking at the appearance of the EMG signal based on Fig. 1, if such signal needs to be analyzed, it is more

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convenient for it to be presented in much simpler form. This is where feature extraction comes into the picture.

Among the method that is used for EMG feature extraction are Mean Absolute Value, Root Mean Square, Simple Square Integral, Variance, Zero Crossing, Slope Sign Change and Willison Amplitude [7]. Root Mean Square (RMS) in particular, is the most popular method that is based on time domain feature. In RMS, each data point is squared and the sum is divided by the number of data point before the result is square rooted. In other way, RMS value would provide the representation of EMG amplitude. This type of feature usually applied in studies concerning muscle performance based on certain human motion activity [8, 9].

Time-domain based features are usually suitable for use on EMG signal that has obvious variation in its amplitude such as hand flexion and extension movement [10]. For this type of movement, the EMG signal would have a burst when the corresponding muscle contracts. The burst would also indicate increase in EMG amplitude [11].

For frequency-domain features, there are techniques such as Autoregressive Coefficients, Mean Frequency, Median Frequency and Fourier Transform [7]. Frequency-domain features show better performance in the study of muscle fatigue [12] with Mean and Median Frequency as the most popular technique for that particular purpose [13]. Autoregressive Coefficients on the other hand is normally used for signal modeling [14].

Another type of feature is time-frequency where Wavelet Transform is the most commonly used [15]. Apart from that, there are also Short-Time Fourier Transform, Wigner-Ville Distribution and Choi-Williams Distribution. A comparative study had been done by Karlsson et. al. where Continuous Wavelet Transform is compared with the other time-frequency domain techniques mentioned previously. This study concluded that Continuous Wavelet Transform is useful for the use on EMG signal [16].

For the scope of this paper, Mel-Frequency Cepstral Coefficient (MFCC) will be used to provide the features of the EMG signal. Even though MFCC is a very well-known tool for feature extraction in speech recognition, it had also been used for other type of signal such as electroencephalography [17], electrocardiography [18] and electromyography [19].

Example of previous works on application of MFCC on EMG is by Manabe and Zhang. They had used EMG signal to improve recognition accuracy of a speech recognition system. Instead of using speech signal, EMG signals from several facial muscles had been acquired and MFCC had been used as one of the feature extraction technique for the EMG [19]. This is an example of an EMG-based speech recognition system that utilizing the movement of facial muscle during speech.

2. EMG Data Source and Analysis

2.1 Respiratory Muscles

Movement of chest wall enables the human breathing mechanism, which is the expansion and shrinking of lung that allows inhalation and exhalation of air. Like other human limb, movement of chest is also related to action of muscles. There are several muscles that are working during the human breathing activity. These muscles are called respiratory muscles that mainly involve the diaphragm, rib cage and abdominal muscles [20]. Apart from that, there are also several other muscles that plays a minor role in human breathing mechanism. They are scalene and sternocleidomastoid that are located around the neck [21].

The respiratory muscles can be assessed through EMG measurement to investigate its characteristics that is associated with certain breathing tasks. Shown in Fig. 2 are the locations of respiratory muscles [22]. Listed in Table 1 are several respiratory muscles and its function in breathing mechanism. Diaphragm and intercostal muscles are the major muscle in breathing mechanism. Other muscles such as sternocleidomastoid, scalene and pectoralis major are considered as accessory muscles [23].

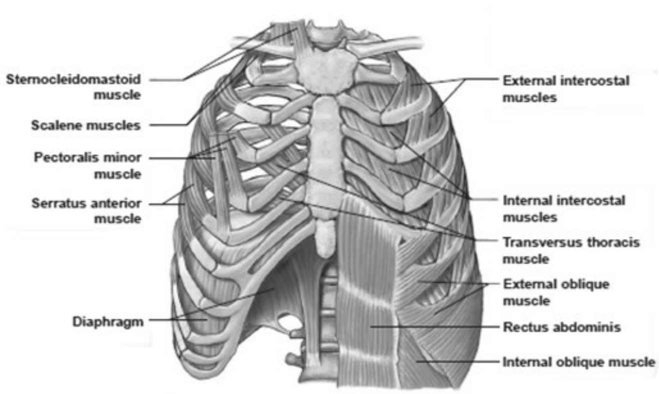

Fig. 2 Respiratory muscles location [22]

Table 1 Respiratory muscles and its function in breathing mechanism

Muscle	**Function**
Diaphragm	**Expands thoracic cavity.**
Intercostal	**Alter the configuration of the rib cage [26].**
Sternocleidomastoid	**Upward pulling of rib cage [23].**
Scalene	**Upward pulling of rib cage [23].**
Pectoralis Major	**Raising the ribs [27].**
Serratus Anterior	**Elevate rib cage during inspiration [28].**
Abdominal Muscles	**Increase abdominal pressure [26].**

Studies on EMG respiratory muscles had been done for various purposes such as investigating the respiratory muscle performance under certain breathing condition. For example, Reilly et al had done studies to examine the relationship between neural respiratory drive measured as the EMG of diaphragm and parasternal intercostal muscles during two different ventilatory loadings i.e. acute hypercapnia and inspiratory threshold loading [24]. Jung and Kim did a work on effects of different intensities of inspiratory muscle training where EMG is acquired from diaphragm, external intercostal and sternocleidomastoid [25].

Effect of head posture and respiratory pattern on respiratory muscle had been studied by Koh and Jung. They had chosen EMG from the sternocleidomastoid and scalene with subjects performing maximal respiration [29]. Another study done by Santos et al performs certain breathing exercises to evaluates the influence of incentive spirometry and forward leaning on inspired tidal volume and EMG activity of diaphragm, external intercostals, sternocleidomastoid and scalene [30]. There was also comparison study to differentiate EMG activity of certain respiratory muscles between mouth breathing and nasal breathing of adults. This had been done by Trevisan et al by choosing the diaphragm and accessory inspiratory muscle as the EMG target muscles [31].

EMG respiratory muscles are also examined on patients with certain pathological condition especially those that related to respiratory diseases. A study by Kim et al on chronic obstructive pulmonary disease (COPD) patients had acquired EMG from respiratory muscles of scalene and sternocleidomastoid to determine the effects on EMG activity due to breathing maneuver and sitting posture of the patients [23]. In another study on several patients with acute respiratory failure, EMG of extradiaphragmatic inspiratory muscles was analyzed to determine any correlation with dyspnea when patients are mechanically ventilated [32].

Another most well-known disease related to respiration is asthma. In a research done by Silva et al using EMG of sternocleidomastoid and diaphragm, finding shows lower EMG activity on both muscles for asthmatic group of adult subject compared to their normal counterpart [33]. Cystic fibrosis is another respiration type disease. There is a work comparing EMG parameter of patient with the disease and healthy subjects upon cycling exercise. EMG was taken from diaphragm and parasternal intercostal muscle [34]. Parasternal intercostal muscle had also been utilized to assess respiratory load in children. This had been done by MacBean et al where analysis on EMG of parasternal intercostal shows that it is feasible in both healthy and diseased children [35].

Another interesting study regarding human respiration is on the human breathing type i.e. the way a person breath. Several literature records a study on two types of human breathing namely upper costal and costo-diaphragmatic [36].

2.2 Feature Extraction of EMG

Feature extraction is one of an essential stage in signal analysis. In case if there is a huge sample of data with random stochastic and non-stationary signal, feature extraction is essential to reduce the number of data points that need to be processed. Thus, the purpose of feature extraction is to represent a complex or chaotic data into a simpler form. For example, an EMG data such shown in Figure 1 could be analyzed easier if the signal is simplified by showing its amplitude envelope.

Another purpose of feature extraction is for signal classification [37]. Having a set of simplified data where the number of data points had been reduced from the original signal; it is much easier for the data to be differentiated to classes of specific feature values. Classification can be done either through supervised or unsupervised learning approach.

Some of the EMG feature extraction techniques that were used had been mentioned earlier in Section 1.0. A literature by Phinyomark et al had listed out a number of EMG feature extraction technique with the corresponding equations [37].

2.3 Mel-Frequency Cepstral Coefficient

The name MFCC is derived from the use of Mel-scale triangular filter bank. First step of MFCC is Fast Fourier Transform (FFT) on the signal. If the data is divided into window segments with window function, w and length L, FFT is formed by :

$$X(k) = \sum_{n=0}^{L-1} x[n]w[n]e^{-j(2\pi n/N)k} \qquad (1)$$

Equation (1) is Discrete Time Fourier Transform with frequency denoted by k. Given k = 0 ... N -1, where N is the number point of the FFT. Then the Mel-scale filter is derived with frequency transformation given by :

$$f_{mel} = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \qquad (2)$$

Frequency transform in Equation (2) is done for the highest and lowest frequencies from the normal frequency scale of X(k). Suppose the normal frequency scale is f, then f(i) ϵ [flow , fhigh] where i = 1,…,N with N is the number of FFT length.

Then, the cut-off frequencies for each of the triangular filters in the filter bank are obtained from :

$$f_m(m') = f_{mel}(low) + m'\left(\frac{f_{mel}(high) - f_{mel}(low)}{M+1}\right) \qquad (3)$$

Here in Equation (3), $f_{mel}(low)$ is the lowest frequency value in the Mel-scale associated to the lowest frequency in the normal scale and $f_{mel}(high)$ is its highest frequency value counterpart. M is the number of Mel-scale filters with m' = 1,…,M+1. These cut-off frequencies in Mel-scale are then retransformed back to normal frequency scale using the inversed expression for f in Equation (2). The retransformed frequencies are denoted as $f_n(m')$.

Knowing the cut-off frequencies, triangular filters can be generated based on relationship in Equation (4). Filter index number is symbolized as m'' where m'' = 1,…,M.

$$H(m'') = \begin{cases} \dfrac{f(i) - f_n(m')}{f_n(m'+1) - f_n(m')}, f_n(m') \le f(i) \le f_n(m'+1) \\ \dfrac{f_n(m'+2) - f(i)}{f_n(m'+2) - f_n(m'+1)}, f_n(m'+1) \le f(i) \le f_n(m'+2) \end{cases} \tag{4}$$

Next is applying these filters to the frequency spectrum X(k) and the result from these operation can be expressed as X_H which is the mel frequency power spectrum. Finally, the coefficients of MFCC are obtained from the discrete cosine transform of the log of mel power X_H. The expression for MFCC coefficient is shown in Equation (5).

$$c(q) = \sqrt{\frac{2}{M}} \sum_{p=1}^{M} \log(X_H(p)) \cos\left(\frac{\pi(p-0.5)q}{M}\right) \tag{5}$$

Index number of the coefficient is given by q and again M is the number of Mel filter. These coefficients of MFCC will be used as the features for the EMG signal.

3. Methodology

3.1 Experimental Setup and Protocol

To obtain the EMG signal of human breathing, an experiment had been performed. It involves 11 human volunteers consists of healthy males aged between 23 to 35 years old. Muscles that are chosen for acquiring the EMG signals are sternocleidomastoid, scalene, second intercostal muscle and diaphragm. Pre-gelled Ag/AgCl disposable surface electrodes are used as the sensor to obtain the EMG signal. These electrodes will be patched on the muscles where each muscle will have two electrodes. The position of electrodes and thus the location of muscles are shown in Fig. 2

There will be four breathing activities that will performed by all the subjects. They are quite breathing, deep breathing, deep breathing with breath hold and fast breathing. The EMG signal for all the activities are recorded for 10 seconds. Each activity are consists of five trials. Fig. 3 shows the flow chart of the experiment protocol.

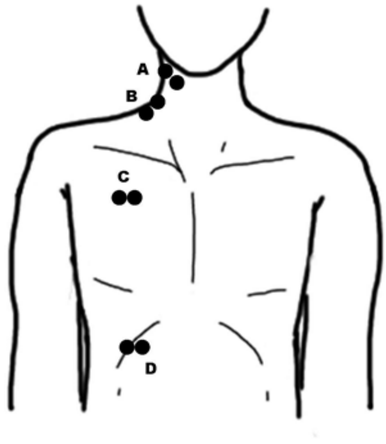

Fig. 2 Electrodes attachment on muscle locations. Label shown here indicates the musles which is defined as A : Sternocleidomastoid; B : Scalene; C : Intercostal Muscle; D : Diaphragm

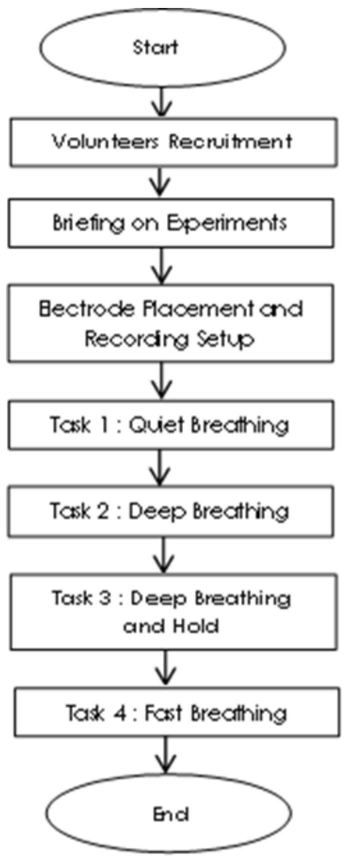

Fig. 3 Flow chart of the experiment protocol

Data acquisition is done using ADInstrument PowerLab 4/25T. It is equipped with amplifier circuit specific for bioelectrical signal measurement. To work with this device, is has to be connected to a computer that is installed with software called ADInstrument Lab Chart 7. The software is used to configure the settings for data acquisition device. It is also used for data recording configuration and real-time signal observation. Fig. 4 illustrates the experiment setup.

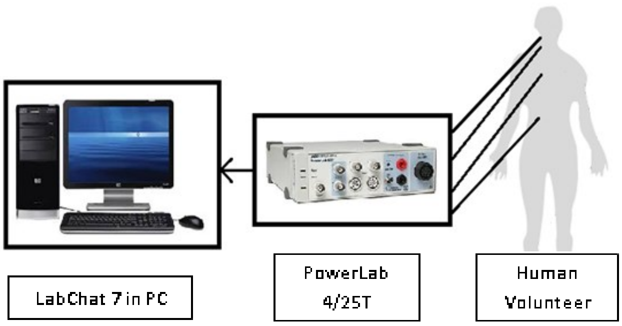

Fig. 4 Experiment's equipment setup

3.2 Signal Pre-processing

Pre-processing is necessary to improve the acquired data quality from noises and inappropriate information. The process could enhance the pattern recognition performance. This pre-processing usually involves filtering which is mainly for removal of noise and any unwanted signal.

Earlier, during the experiment and data acquisition, the raw data is recorded without any pre-filtering through the data recording software i.e. LabChart 7. This is to make sure that all necessary information on the EMG signal is recorded before deciding on which signal is undesirable and thus would be considered as noise.

There are several types of noise that could contaminate the EMG signal. The work in this paper will be focusing on three categories of noise. First is baseline wander and movement artifact [38]. Both are in similar form where the center of the signal is not fixed at the baseline of 0 volt. In most cases, the signal appears wavy. It also appears that DC offset is present since the signal is shifted either to positive or negative y-axis region. The presence of this kind of noise is mostly related to physical motion of the electrode and electrode's cable. It could also happen due to subject's movement.

Second type of noise is signal that comes from other bioelectrical signal sources such as ECG. In case of respiratory muscle EMG, several spikes similar to the ECG's QRS profile would appear especially when signal is acquired near to the part of chest where the heart is located. In some other cases, EMG signal from adjacent muscle could also interfere. This is called electrical cross-talk and it usually occurs when using electrodes that are placed on a region where different muscles are quite close together [39]. For the purpose of this paper, ECG would be the signal that needs to be removed. The pulses or spikes that consistent with the heartbeat are seen clearly in intercostal muscle and diaphragm.

Then there is also noise due to the power line frequency. Since the data acquisition device used in the data collection requires AC power source, such noise would be inevitable.

In this work, filtering of the EMG signals involves 6th order Butterworth high-pass filter with cut-off frequency of 20 Hz. This would be enough to remove the movement artifact, DC offset and also the spikes due to heartbeat that resembles the ECG. Then, for the power line interference, a notch filter is implemented with center frequency of 50 Hz. This filtering stage is done offline using MATLAB programming tools.

3.3 Feature Extraction

Feature extraction using MFCC is done with different analysis frame sizes. The frame sizes ranges from 1000 ms up to 10000 ms with overlapping of 50% from the frame size. For the window function, Hamming window is used. Number of Mel filter banks is 20 and the number of cepstral coefficients is 12.

EMG data from subjects is taken for 10 seconds. There are five trials for each task where data from all five trials are considered for feature extraction and classification. Thus the total EMG data length from each subject for each task is 50 seconds. Since there are four tasks undergone in the experiment, there will be 200 seconds of EMG data per subject.

Result from feature extraction is given as value of cepstral coefficients that obtained from the window frame analysis. Classification would then be based on these coefficient values.

3.4 Classification Using K-Nearest Neighbour

K-Nearest Neighbour (K-NN) is chosen as the classification tools to classify the EMG features based on the breathing tasks. K-NN is a method of classification based on closest training example [40]. Given an unlabeled sample x, K-NN will calculate the distance between x and all the data point in training data and assigns its class according to the nearest neighbor of K training samples, where K is a positive integer.

In this work, the calculation of distance is based on Euclidean and K is fixed at 1. Result of K-NN classification will be in form of percentage of classification accuracy, which is the measure of samples that is classified correctly. The number of classes is four that is corresponds to the number of breathing tasks in the experiment.

4. Results and Discussion

Classification is done to classify all sets of EMG data into four different breathing tasks. There are 10 sets of EMG data with different analysis frame sizes and each data set contains features from 12 cepstral coefficients. K-NN classification is performed on each of the

Table 1 K-NN Classification Accuracy Result

Frame Size (ms)	MFCC Classification Accuracy (%)											
	1	2	3	4	5	6	7	8	9	10	11	12
1000	34.85	34.85	31.69	27.84	27.50	29.10	28.76	28.59	27.21	26.64	26.29	27.04
2000	99.54	98.96	98.49	97.80	98.26	97.80	97.91	97.91	98.38	97.80	99.54	98.38
3000	80.99	85.26	81.35	76.02	77.26	73.18	67.85	65.72	65.72	65.54	65.01	63.94
4000	99.05	96.92	99.05	97.87	99.05	99.05	95.73	96.68	96.68	97.87	96.92	96.92
5000	98.50	100.00	100.00	95.51	97.01	95.51	97.01	98.50	97.01	98.50	97.01	95.51
6000	91.29	91.29	83.33	82.20	82.95	77.27	75.38	70.83	66.67	67.42	66.29	65.15
7000	92.11	95.61	89.04	94.30	88.16	82.89	77.19	74.56	68.42	70.61	62.28	66.67
8000	90.67	95.85	89.64	91.71	85.49	85.49	84.46	75.13	81.87	77.20	80.83	75.13
9000	93.75	95.45	90.91	92.61	89.20	84.66	77.84	67.05	56.25	64.77	64.20	64.77
10000	97.47	94.30	97.47	91.77	100.00	97.47	94.30	92.41	91.77	97.47	92.41	91.77

coefficients. In total, there are 120 classification results based on frame size and coefficients.

The accuracy results are shown in Table 2. Three coefficients show 100% accuracy i.e. frame size 5000 ms at 2nd and 3rd coefficients; and also frame size 10000 ms at 5th coefficient. K-NN classification accuracy exceeds 90% for all coefficients for frame size 2000 ms, 4000 ms, 5000 ms and 10000 ms. The remaining frame size has accuracy varies from 25% to 90% with frame size 1000 ms having the lowest accuracy for all coefficients i.e. between 26.29% to 34.85%. If the average accuracy from all coefficients is taken into consideration, it is calculated that frame analysis of 2000 ms gives the highest value.

Based on the result, it is shown that maximum accuracy could be achieved using MFCC to classify the EMG signal of respiratory muscle based on different breathing tasks. However, it requires frame size 5000 ms and 10000 ms which is relatively huge. In certain application, the analysis frame size is required to be in short duration. This is necessary especially in real-time system where the analysis frame duration is as low as 20ms [41]. The high accuracy of huge frame size is probably due to less number of frames along the 50000 ms data.

For example, frame size of 5000 ms will results in 19 number of frames divided along the original data. Thus the number of features that corresponds to the 50000 ms data size is less compared to when the analysis frame size is shorter. This then would make the classification not to complex due to less number of feature samples.

In the case of a shorter analysis frame size, 1000 ms for instance, it would divide the original data into 99 frames which is more huge compare to the previous example on 5000 ms frame size. Therefore there would be more misclassified samples in the classification task.

5. Summary

Previous works related to this paper had investigated the EMG signal classification of respiratory muscles using four time and frequency domain features techniques which are root-mean-square, zero crossing, mean frequency and mean power frequency using Anova [42] and Feedforward Multilayer Perceptron [43]. This paper on the other hand, used MFFCC as feature extraction tool. It is concluded that MFCC technique in obtaining features of EMG signal could provide a good accuracy of signal classification. However the high classification accuracy is obtained at relatively long duration of data analysis frame size. The classification become inefficient at lower duration of frame size where in this work, 1000 ms gives relatively low accuracy. This perhaps due to number of features that is obtained based on the analysis frame where larger frame size would give less number of feature which is then easier to classify.

The aim of this work is to classify the EMG signal from respiratory muscles into different breathing tasks. Thus, to discriminate the EMG profile based on the breathing pattern, the easier way is to look at longer duration rather than a short period of time. With short period of time, there is not much information that could be obtained to determine the pattern of the EMG.

Using MFCC, the emphasis is on frequency domain analysis. In order to obtain better representation for the EMG features, a longer period of analysis frame is needed so that the EMG frequency profile could be observed with more information. However, in certain application such as online classification and real-time pattern recognition, analysis in short period of time frame is required as the information need to be obtained in small time duration.

As a future recommendation, it is proposed that the low classification accuracy at small size of data analysis frame should be overcome. For the purpose of breathing tasks classification based on EMG signal, analysis in short time duration of data frame could enable implementation of an online classification module that could be applied on an automatic rehabilitation device system.

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