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Classification of EMG Signal Based on Human Percentile using SOM

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Abstract: Electromyography (EMG) is a bio signal that is formed by physiological variations in the state of muscle fibre membranes. Pattern recognition is one of the fields in the bio-signal processing which classified the signal into certain desired categories with subject to their area of application. This study described the classification of the EMG signal based on human body percentile using Self Organizing Mapping (SOM) technique. Different human percentile definitively varies the arm circumference size. Variation of arm circumference is due to fatty tissue that lay between active muscle and skin. Generally the fatty tissue would decrease the overall amplitude of the EMG signal. Data collection is conducted randomly with fifteen subjects that have numerous percentiles using non-invasive technique at Biceps Brachii muscle. The signals are then going through filtering process to prepare them for the next stage. Then, five well known time domain feature extraction methods are applied to the signal before the classification process. Self Organizing Map (SOM) technique is used as a classifier to discriminate between the human percentiles. Result shows that SOM is capable in clustering the EMG signal to the desired human percentile categories by optimizing the neurons of the technique.

Keywords: Biceps brachii, classification, electromyography, human percentile, pattern recognition, self organizing map

INTRODUCTION

Research on EMG classification is essential in the field of ergonomics, sports science, rehabilitation, medical research and human technology interaction. It required a strong foundation of the neuromuscular system, signal properties and impact of the tools used during signal acquisition in order to collect meaningful data.

Historically, human percentile is used to establish the portion of user population for specific design. It allow the subjects with specific percentile to fit on any critical dimensions Human percentile is an anthropometric dimensions for each population that are ranked by size. For instance, 5th percentile represents smallest measurement while 95th percentile represents largest dimensions (Scott and Erin, 2006). Different human percentile definitively varies the arm circumference size. Variation of arm circumference is due to fatty tissue that lay between active muscle and skin.

There are several external factors that could influenced the behaviour of EMG signal such as tissue characteristics, physiological cross talk, changes in the geometry between muscle belly and electrode site, external noise and selection of electrode and amplifiers. In this study, the focus is the tissue characteristics. Principally, human body is a very good electrical

conductor but the conductivity is highly dependent to the tissue characteristics. Several reasons that affect the tissue performance are thickness, type, physiological change and temperature. Thus, the EMG signals vary from subject to subject that avoid direct quantitative comparison of EMG amplitude (Peter, 2006).

This research used SOM technique to cluster the EMG signal according to the human body percentile. SOM is an unsupervised learning (learning by observation) refers to the method that learns by itself according to input attributes and also applies competitive learning that made the output nodes to compete to be activated. Only one of the node will activated at any one time or we called winning neuron (Bohari *et al.*, 2014). Such a competition can be induced through negative feedbacks between neurons. All nodes are forced to be self-organized through the feedback path.

LITERATURE REVIEW

EMG classification field has been started since early 1970 where elementary classification technique such as linear discriminant analysis was used (Graupe *et al.*, 1978; Lee and Saridis, 1984). Then in 1990s, pattern recognition using Artificial Intelligent technique has been initiate using Artificial Neural Network (ANN) by analysing the nonlinear map between the

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EMG signal and the arm gesture movement (Wang and Buchanan, 2002; Hudgins *et al.*, 1993; Kelly *et al.*, 1990; Chiharu *et al.*, 2012). Tsuji *et al.* (1992) implement neural network based on statistics structure while Kentarou *et al.* (2006) use combination of chief ingredient analysis and fast fourier transform. Other uses the hybridization of multivariate auto regression model and hidden Markov Model (Joyce *et al.*, 2008). K-NN algorithm that has been used by Killer *et al.* (1986) is widely is for EMG classification which based on the distance similarity matching. This technique has advantage of simplicity but it cannot cater complicated features.

Simon (1999) use back propagation neural network that seems more robust because it can learn the relationship between inputs and desired outputs. However the downside of it is the complexity increased exponentially when the number of inputs increases. Chan *et al.* (2000) design a fuzzy inference that applied back propagation algorithm to train the fuzzy rules for classification. Hamed *et al.* (2012) used FCM techniques due to its flexibility, fast training, easy to use and low cost of calculation.

Bartuzi *et al.* (2010) has conducted a study on the effect of the fatty tissue on EMG signal in young women. They describe the influence of fatty tissue on EMG signal as a function of force level. Fatty tissue layer also could cause inaccuracy in the measurement because it decrease the EMG signal amplitude and increase the cross-talk in muscles adjacent to activated muscle as well as attenuate the potential distribution present at muscle force. The tissue overlying the muscle, fatty tissue and skin thickness would change the EMG signal shape. When muscle is surrounded by fatty tissue, extracellular fluid and skin, the current field will be inflected and the level of impedance will be

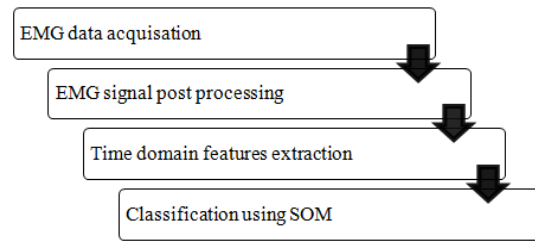


Fig. 1: Research strategy

varies because the skin tissue acts as a filter for a signal. Subject with great body fat will have more signals filtered before reaching the electrode that will cause the amplitude of the signal greatly drop.

METHODOLOGY

Figure 1 shows a flow diagram of our research methodology that consists of four major phases. It started with the EMG data acquisition. Second phase is EMG signal post processing. Third phase is the time domain features extraction and finally classification using SOM technique.

EMG data acquisition: Historically, human percentile is used to establish the portion of user population for specific design. It allows the subjects with specific percentile to fit in any critical dimensions. Human percentile is calculated based on the distribution of data which multiply the standard deviation *SD* by a factor *z* then add the product to the mean *m*. The formula is given as:

$$p = m + (z \times SD) \tag{1}$$

Table 1: Percentile of upper arm circumference (Frisancho, 1974)

Age group	Age midpoint years	No.	Arm circumference percentile, mm				
			5 th	15 th	50 th	85 th	95 th
			Males				
0.0-0.4	0.3	41	113	120	134	147	153
0.5-1.4	1	140	128	137	152	168	175
1.5-2.4	2	177	141	147	157	170	180
2.5-3.4	3	210	144	150	161	175	182
3.5-4.4	4	208	143	150	165	180	190
4.5-5.4	5	262	146	155	169	185	199
5.5-6.4	6	264	151	159	172	188	198
6.5-7.4	7	309	154	162	176	194	212
7.5-8.4	8	301	161	168	185	205	233
8.5-9.4	9	287	165	174	190	217	262
9.5-10.4	10	315	170	180	200	228	255
10.5-11.4	11	294	177	186	208	240	276
11.5-12.4	12	294	184	194	216	253	291
12.5-13.4	13	266	186	198	230	270	297
13.5-14.4	14	207	198	211	243	279	321
14.5-15.4	15	179	202	220	253	302	320
15.5-16.4	16	166	217	232	262	300	335
16.5-17.4	17	142	230	238	275	306	326
17.5-24.4	21	545	250	264	292	330	354
24.5-34.4	30	679	260	280	310	344	366
34.5-44.4	40	616	259	280	312	345	371

Table 2: Predefined subject details

Subject	1	2	3	4	5
Percentile	5 th	15 th	50 th	85 th	95 th
Age	30	28	27	27	29
Arm circumference, mm	260	280	310	344	366
Label	T13	T4	T12	T8	T3

Table 3: Sample subjects

Subject	Label	Status
1	T1	Random data
2	T2	Random data
3	T3	Predefined data for 95 th percentile
4	T4	Predefined data for 15 th percentile
5	T5	Random data
6	T6	Random data
7	T7	Random data
8	T8	Predefined data for 85 th percentile
9	T9	Random data
10	T10	Random data
11	T11	Random data
12	T12	Predefined data for 50 th percentile
13	T13	Predefined data for 5 th percentile
14	T14	Random data
15	T15	Random data

Survey conducted by Frisancho (1974) shows the relationship between the human percentiles with the right upper arm circumference for male and females. As the arm circumference increase, the subcutaneous fat also increase which affect the EMG signal behaviour. This is proved by the measurement done to the 5637 males and 6759 females aged 0 to 44 years. This study has produced a relationship between human body percentiles with average arm circumference size as shown in Table 1.

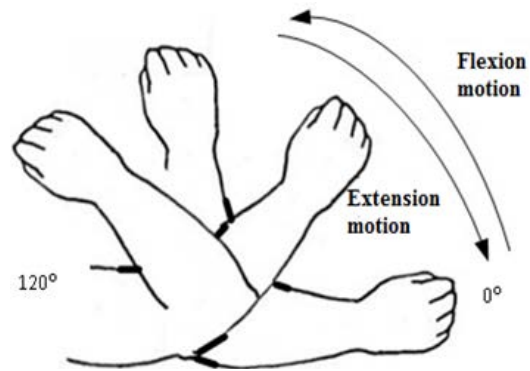
Three male subjects that represent five arm circumference percentiles which are 5, 15, 50, 85 and 95th, respectively are selected based on guidelines in Table 1. The EMG signals from these subjects are used as predefined data for signal classification later on. The subject's particular detail is tabulated in Table 2.

The predefined data is included randomly into sample of 15 healthy male subjects as shown in Table 3. From the human anatomy studies, the movements of upper limb with elbow as the reference is depend on relation of agonist and antagonist. In this study is focusing on the behaviour of biceps muscle as agonist and the triceps as the antagonist, respectively. Muscle that involved in this movement is biceps and triceps, however in this study to understand the electrical activity during muscle contraction, the biceps is the only muscle that taking into account. The movements' ranges in between position of arm flexion until arm fully extend.

The environment is in a room with low lighting especially the fluorescent light, any electromagnetic devices is away from the experiment equipment and the environment is in silent room. Then, the experimental is set up with the subject sit on the chair while the hand is on the table. The assistive devices (white in colour on Fig. 2a) helps to keep the position of the elbow joint



(a)



(b)

Fig. 2: (a) subject is set-up with arm assistive device for experiment, (b) simulation of subject's to lift up the dumbbell 2.268 kg of weight

and the wrist joint in line. Mostly, the EMG signal is obtained after several trials of the movements. These movements are specified from angle of 0° (arm in rest position), up to 120° (arm is fully flexion). The subject has to complete the task of lift up the dumbbell with 2.268 kg of weigh in Fig. 2b. Normally, the appearance of EMG signal is chaos and noisy depends on the type of electrodes also the noise factor. To simplify the difference of amplitude response for the motion, the dumbbell is functioned to amplify the amplitude in analysing the electrical activity during rest and contract. These electrodes are connected to the combination of Olimex EKG-EMG-PA and Arduino Mega for data collection (Jali *et al.*, 2014).

EMG signal post processing: After acquiring the raw EMG data as shown in Fig. 3a, post processing need to be performed to remove any unwanted noise. Noise comes from the environment need to be filtered accordingly to obtain the clean features. An extremely narrow notch filter in the range of 59.5-60.5 Hz is

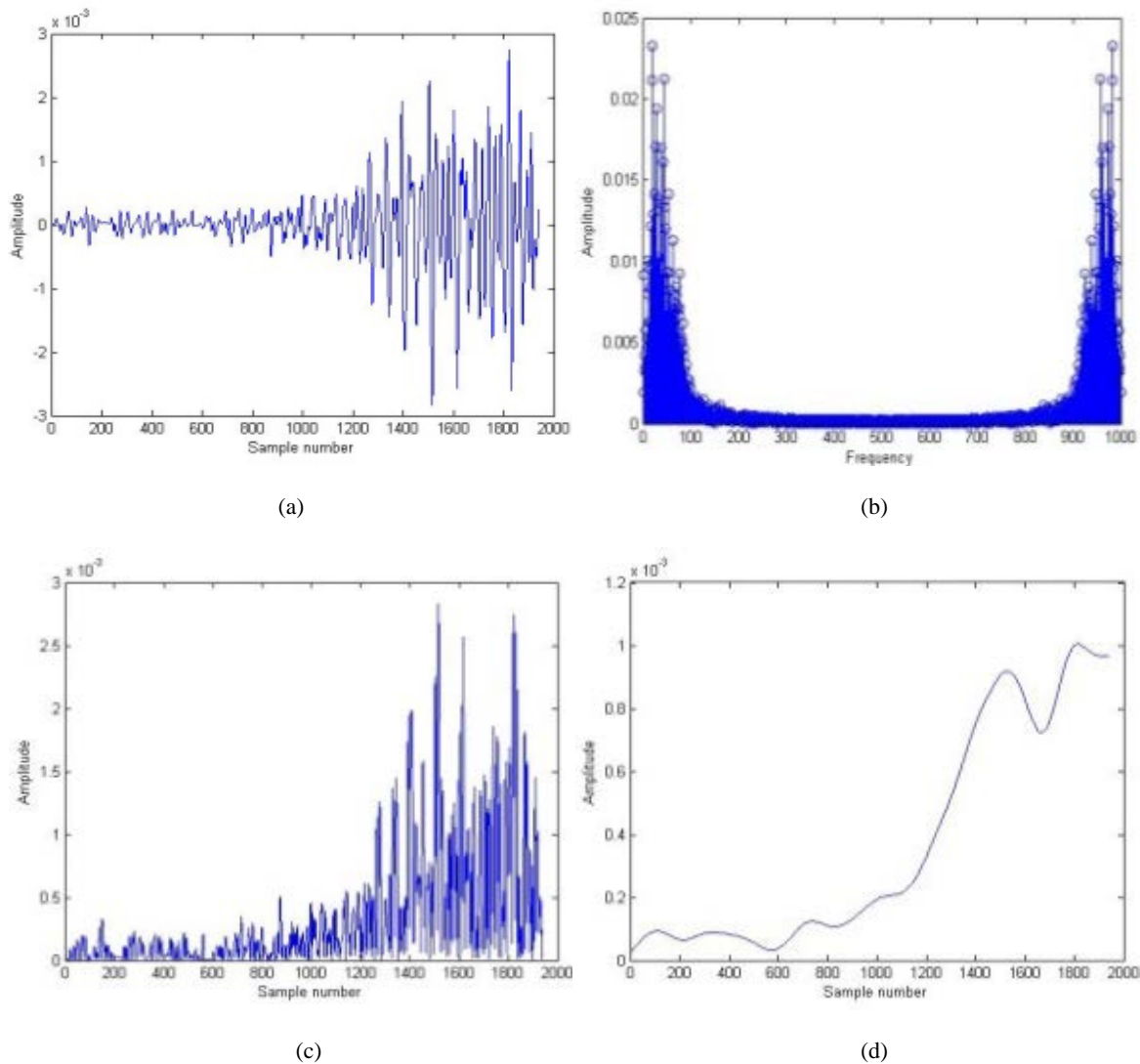


Fig. 3: (a) raw EMG signal, (b) power spectral density, (c) rectified signal, (d) smooth signal

applied to eliminate the interference from line AC and radio frequency. Then, a high pass filter in a range of 5-10 Hz is applied for DC offset. The filter preserves the wave shape of any filtered signals across the group delay in the pass band. The DC offset of the EMG signal is removed and rectified to obtain its absolute value as shown in Fig. 3c. In order to observe the variation of signal in different frequency components, the FFT signal is represented by Power Spectral Density (PSD). From the PSD we can describe how the signal energy or power is distributed across frequency. Figure 3b shows that most of the power is in the range of below 10 Hz. Finally, the signal is smoothed and normalized passing it through a 5th order Butterworth type low-pass filter with cut off frequency 10 Hz as shown in Fig. 3d.

Time-domain features extraction: In order to achieve an efficient EMG pattern recognition, multiple features

need to be employed as input to the classifier. Each feature reflects a unique character individually. Therefore, a combination of several features capable to describe the classification system more accurately (Ahsan, 2011). A feature extraction is very important to transform the raw signal into reduced representation set of features. These features could complement each other to exhibit the behavior of the EMG signal itself which is very useful for classification process. Five time domain feature extraction methods which are Standard Deviation (STD), Root Mean Square (RMS), Mean Absolute Value (MAV), Variance (VAR) and Zero Crossing (ZC) are chosen for this study.

The time domain features are the most commonly used by the researchers. One of the advantages of using time domain is it can be implemented in real time. There are many of features that related to time domain, below is described more on features in this study (Angkoon *et al.*, 2009).

Root mean square: The RMS represents the square root of the average power of the EMG signal for a given period of time. It is known as a time domain variable because the amplitude of the signal is measured as a function of time:

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N EMG(i)^2} \quad (2)$$

Mean absolute value: The MAV is the computer calculated equivalent of the Average Rectified Value (ARV). The MAV is known as a time domain variable because it is measured as a function of time. It represents the area under the EMG signal once it has been rectified, it is defined by the negative voltage values have been made positive. The mean absolute value is calculated using a moving window. It is calculated for each window of data according to the equation:

$$MAV = \frac{1}{s} \sum_1^s |f(s)| \quad (3)$$

Standard deviation: The STD of a set of data is the square root of the variance, where \bar{x} refers to the mean of the sample. The STD is often used as the fluctuation for a sample when data is being collected in an experiment. The results taken from data are frequently written as the mean \pm STD:

$$STD_{n-1} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (4)$$

Variance: VAR is a feature that utilizes the EMG signal power. It takes the mean value of the square of the deviation. However, mean of EMG signal is close to zero. In consequence, variance of EMG can be calculated by:

$$VAR = \frac{1}{N-1} \sum_{n=1}^N X_n^2 \quad (5)$$

Zero crossing: ZC is a feature that represents the number of times that the amplitude value of EMG crosses the zero y-axis. It provides an approximation of frequency domain properties. The threshold condition is used to abstain from the background noise. It can be formulated as:

$$ZC = \sum_{N=1}^{N-1} \left[\begin{array}{l} sgn(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \\ \geq threshold \end{array} \right]$$

where,

$$sgn(x) = \begin{cases} 1, & \text{if } x \geq threshold \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

Classification using SOM: Based on neurological studies, all human sensory inputs are mapped onto

certain areas at the cerebral cortex that form a map called Topographic Map (Bohari *et al.*, 2014). It has two most essential assets:

- At each stage of processing, every each information is reserved in its proper environment.
- Close related information nodes will be close to each other to ensure short synaptic connections.

SOM primary purpose is to transform incoming input patterns into a one or two dimensional discrete map. This process must be performing in orderly approach. In this study, SOM is used to classify the EMG signal that has been randomly collected from 15 subjects according to their body percentile.

For this SOM clustering hexagonal lattice is selected and numbers of neurons is increased from 100 to 300 to optimize SOM result. Normalization method used in this research in 'range' normalization. The performances of each combination of feature are evaluated according to their quantization error, topographic error and training time.

Architecture of SOM network: SOM structure built from two main layers; input and output layer that sort in two-dimensional preposition. SOM algorithms resemble Learning Vector Quantization (LVQ). In LVQ all neurons are arranged on a grid together with selected neurons whereas SOM has a feed-forward structure with a single computational layer arranged in rows and columns. Each neuron is fully connected to all the source nodes in the input layer. Neighbouring nodes will be updated to perform neurons order. This indicates that SOM as a multidimensional scaling method from input space to two-dimensional output space. Visual format of SOM help researcher to define clusters, relations and structures in complex input database (Bohari *et al.*, 2014).

Best Matching Unit (BMU): Number of neuron may vary from a few dozen up to several thousands. Each neuron is represented by a d-dimensional weight vector (prototype vector, codebook vector) $m = [m_1, \dots, m_d]$, where d is dimension of input vectors. Neurons connected to the adjacent neurons through neighbourhood relation that dictates its topology.

SOM is then subjected to iteration for training the network. In the iteration process, one sample vector s from the input data will be selected randomly and the distances between all the nodes are then calculated by particular distance measures. The neurons that have closest weight vector to the selected sample s is called Best Matching Unit (BMU) and denoted by c :

$$\|s - m_c\| = \min_i \|s - m_i\| \quad (7)$$

where,

c : Euclidean distance measure

Upon determining BMU, SOM weight vectors are updated so that the BMU will be closer to the input vector in input space. This adaptation process will stretch the BMU and its topological neighbours towards the sample vector (Bohari *et al.*, 2014).

RESULTS AND DISCUSSION

In order to optimize the SOM performance, different numbers of neurons are simulated until achieved the satisfactory results. Satisfactory result is defined as the best tradeoff between each performance variable. For instance, the lowest value of topographic error, quantization error and training time does not mean the number of neurons is the best performance unless the U-Matrix mapping result shows the best

quality in term of clarity of separation and boundary between the SOM clustering.

From Table 4, it can be seen that training time keep on rising when the number of neurons increase. However based on simulation, training time surge abruptly up to 8 sec when the number of neurons larger than 300. Thus, the simulation stops at the number of neurons 300. Training time of 5 sec is still acceptable because it produce value of both quantization and topographic error around zero. Further investigation need to be conducted in term of U-Matrix mapping to select the best number of neurons.

Figure 4a to f depicted U-Matrix mapping result that represent the number of neurons of 100, 150, 200, 250, 280 and 300, respectively. By using hexagonal topology, it can be observed that the clarity of

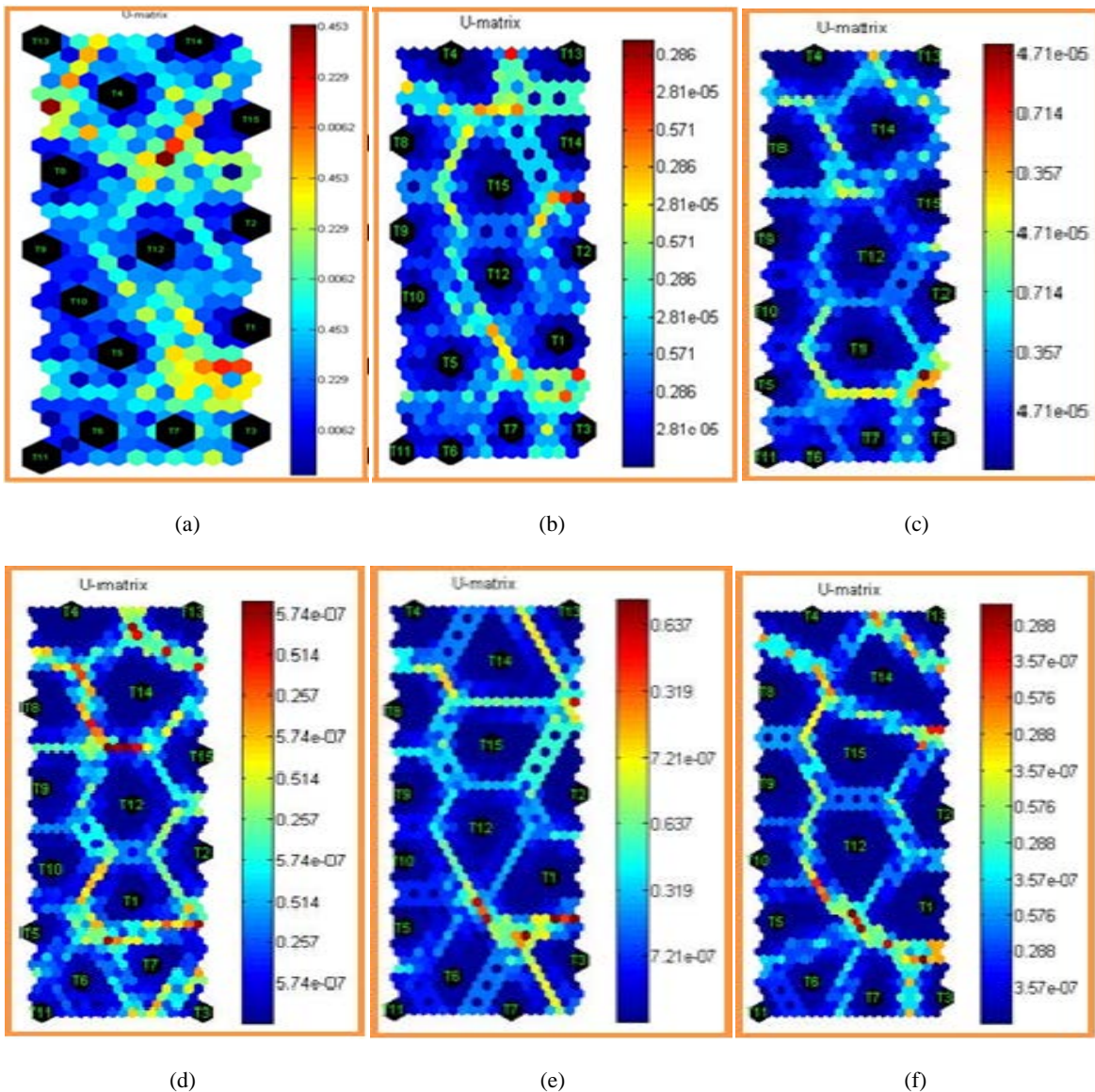


Fig. 4: U-matrix for number of neurons (a) 100, (b) 150, (c) 200, (d) 250, (e) 280, (f) 300

Table 4: SOM clustering performance

No. of neurons	Quantization error	Topographic error	Training time (sec)
100	0.017	0.000	0
130	0.004	0.067	1
150	0.004	0.000	1
180	0.004	0.133	1
200	0.001	0.000	2
230	0.001	0.000	3
250	0.000	0.067	3
280	0.000	0.133	4
300	0.000	0.067	5

Table 5: Distribution of samples for each percentile

Group	Label	Status
1	T13	5 th percentile
2	T4, T14	15 th percentile
3	T1, T2, T12, T15	50 th percentile
4	T5, T6, T7, T8, T9, T10, T11	85 th percentile
5	T3	95 th percentile

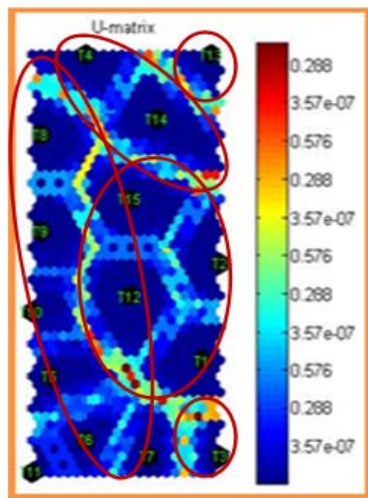


Fig. 5: U-matrix that has clustered into five groups

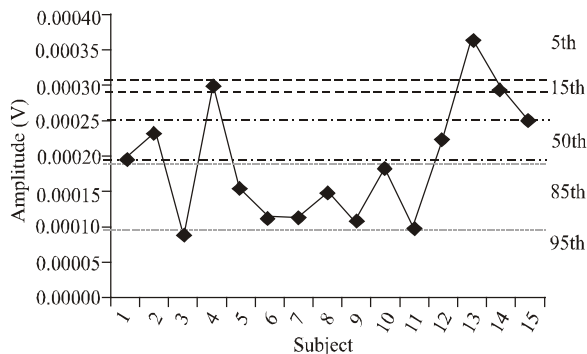


Fig. 6: Maximum EMG amplitude of the subjects and band categories of human percentile

separation and boundary of the mapping is improved when the number of neurons increases. Since we were targeting to classify the EMG signal into five categories, Fig. 4f that represents number of neurons of

300 is the best contender for the U Matrix mapping result. The clarity and quality of mapping is the best since it produce the clearest boundary or separation between different categories produced by SOM clustering. Figure 5 shows a clearer view of U-Matrix that has been clustered into five groups.

Next, the predefined data that has been declared earlier is utilized to identify the group that has been clustered fall under which categories of human percentile. Table 5 summarize that the distribution of the samples is distinguishable for each percentile.

Finally, the SOM classification result needs to be verified to ensure that all subjects have been clustering in an appropriate category. Based on the literature that has been described in the early section, the higher human percentile would definitively have the bigger arm circumference size. The size of the arm circumference is due to the fatty tissue lay between skin and active muscle. Fatty tissue would cause the amplitude of EMG signal decreased. Figure 6 shows the maximum amplitude of each subject. It shows direct relationship between EMG signal amplitude and the human percentile by taking into account the subject that has been clustered in a group by SOM techniques in Table 5. The subject above the green band represent 5th percentile, green band represent 15th percentile, yellow band represent 50th percentile, blue band represent 85th percentile and finally below the blue band is 95th percentile.

CONCLUSION

Based on the experimental result, it can be concluded that the SOM technique has successfully classify the EMG signal into the appropriate human percentile categories. The number of neurons needs to be optimized to produce the best SOM clustering result. In this research, number of neurons of 300 has produced the best tradeoff between the performance parameters as well as the U-Matrix mapping result. In addition, the clustering result also has been verified with the correlation of EMG signal amplitude with the human percentile size. Thus, it is proven that the SOM classification technique is capable to clustering the EMG signal based on the human percentile. It is recommended to enhance the features extraction for the classifier input to improve the U-Matrix clarity on the separation and boundary for each cluster.

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