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# Classification of Myoelectric Signal using Spectrogram Based Window Selection

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**Abstract:** This paper presents a study of the classification of myoelectric signal using spectrogram with different window sizes. The electromyography (EMG) signals of 40 hand movement types are collected from 10 subjects through NinaPro database. By employing spectrogram, the EMG signals are represented in time-frequency representation. Ten features are extracted from spectrogram for performance evaluation. In this study, two classifiers namely support vector machine (SVM) and linear discriminate analysis (LDA) are used to evaluate the performance of spectrogram features in the classification of EMG signals. To determine the best window size in spectrogram, three different Hanning window sizes are examined. The experimental results indicate that by applying spectrogram with optimize window size and LDA, the highest mean classification accuracy of 91.29% is obtained.

**Keywords:** Electromyography, spectrogram, support vector machine, linear discriminate analysis and Pattern recognition.

## 1. Introduction

According to the statistics of National Limb Loss Information Centre, vascular disease and trauma were the main causes for upper limb loss [1]. Due to the loss of upper limb, trans-radial amputees have the difficulty to perform daily life tasks. Unlike healthy human, trans-radial amputees require a smart and multifunction myoelectric prosthetic to ensure they can execute many actions that people do in their everyday life [2]. In recent days, surface electromyography (EMG) has been widely used in upper limb myoelectric prosthetic. Advance rehabilitation indicates myoelectric prosthetic regained at least a significant part of lost hand functionality [3].

EMG is a natural source that contains the rich neural information to stimulate motion classification and myoelectric control [4]. Naturally, EMG measures the electric potential generated by the muscle cells when there is a muscular electrical activity such as hand motion [5]. Multichannel EMG recording offers a recognition of hand movement types corresponding to the specific pattern of myoelectric signal. However, the recognition of EMG signals is usually difficult due to the complex nature of the signal itself [6]. Additionally, EMG signals often contaminated by the heart electrical activity, motion artifact and noise [7], [8]. In such case, signal processing is preferred for analyzing the EMG signals.

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An increased in the time domain (TD) and frequency domain (FD) features improve the potential of EMG signal in discriminating multiple hand movements. However, TD features do not provide any spectral information in the analysis of EMG signal [4]. On the other hand, FD features describe the muscle characteristic but in the limited regular window size [9]. In other words, TD and FD features assume the EMG data as a stationary signal [10]. Hence, the time-frequency distribution (TFD) is introduced to overcome the limitation in TD and FD. TFD represents the time and frequency information of the signal simultaneously. In the previous research, most of the researchers evaluated the performance of healthy subjects in the classification of 4 to 12 hand movement types [2], [10]–[12]. Unfortunately, the number of hand movement in myoelectric control is often insufficient.

This paper aims to investigate the performance of spectrogram in differentiating 40 hand movements. Firstly, the EMG data are collected from 10 subjects through NinaPro database 4 (DB4). Then, spectrogram is applied to transform the signal into time-frequency representation (TFR). Next, ten features are extracted from each spectrogram. For performance evaluation, two popular machine learning algorithms namely support vector machine (SVM) and linear discriminate analysis (LDA) are utilized. To optimize the performance of spectrogram, three different Hanning window sizes, 128, 256 and 512 ms with 50% overlap are examined. Finally, the performance of EMG pattern recognition is discussed.

## 2. Material and Methods

### 2.1 Structure

In this study, the EMG database of Non-Invasive Adaptive Prosthetics (NinaPro) project is employed. NinaPro is a publicly access EMG database that contains a large number of EMG data recording from the intact and amputee subjects [3]. In addition, NinaPro database has been successfully applied in previous works [13], [14]. This study aims to investigate the performance of spectrogram in discriminating large number of hand movement types. For this reason, the EMG data of 40 hand movements (Exercise B and C) from NinaPro database 4 (DB4) are used [2]. Note that DB4 comprised of the EMG signals recorded from 10 intact subjects. Table 1 outlines the list of 40 hand movement tasks in NinaPro project. In the experiment, subjects were instructed to execute 40 different hand movements with 5 seconds each, followed by a resting state of 3 seconds. Each movement was repeated for six times. The EMG signals were acquired by using 12 surface electrodes. Eight electrodes were placed uniformly around the forearm. Another two electrodes were placed on the extensor digitorum superficialis and flexor digitorum superficialis, respectively. Finally, two electrodes were placed on the triceps and biceps brachii muscles, respectively. At the end of recording, a total number of 72 EMG signals (6 repetitions × 12 channels) were collected from each movement form each subject. The recorded EMG signals were sampled at 2k Hz with resolution of 16 bits. Nevertheless, in this study the EMG signals were initially sub-sampled by a decimation factor of 2. For pre-processing, the EMG signals were filtered by a Hampel filter to remove the 50 Hz power line interference. Moreover, the rest period was removed before signal processing.

**Table 1 - List of hand movement tasks (M1-M40) in NinaPro project.**

| Index | Hand movement task | Index | Hand movement task |
|---|---|---|---|
| M1 | Thumb up | M21 | Index finger extension grasp |
| M2 | Extension of index and middle fingers, flexion of other fingers | M22 | Medium wrap |
| M3 | Flexion of ring and little fingers, extension of other fingers | M23 | Ring grasp |
| M4 | Thumb opposing base of little finger | M24 | Prismatic four fingers grasp |
| M5 | Abduction of all fingers | M25 | Stick grasp |
| M6 | Fingers flexed together in fist | M26 | Writing tripod grasp |
| M7 | Pointing index | M27 | Power sphere grasp |
| M8 | Adduction of extended fingers | M28 | Three fingers sphere grasp |
| M9 | Wrist supination (axis: middle finger) | M29 | Precision sphere grasp |
| M10 | Wrist pronation (axis: middle finger) | M30 | Tripod grasp |
| M11 | Wrist supination (axis: little finger) | M31 | Prismatic pinch grasp |
| M12 | Wrist pronation (axis: little finger) | M32 | Tip pinch grasp |
| M13 | Wrist flexion | M33 | Quad pod grasp |
| M14 | Wrist extension | M34 | Lateral grasp |
| M15 | Wrist radial deviation | M35 | Parallel extension grasp |
| M16 | Wrist ulnar deviation | M36 | Extension type grasp |
| M17 | Wrist extension with closed hand | M37 | Power disk grasp |
| M18 | Large diameter grasp | M38 | Open a bottle with a tripod grasp |
| M19 | Small diameter grasp (power grip) | M39 | Turn a screw (grasp the screwdriver with a stick grasp) |
| M20 | Fixed hook grasp | M40 | Cut something (grasp knife with an index finger extension grasp) |

Fig.1 illustrates the flow diagram of the pattern recognition architecture. Firstly, the EMG data are collected from 10 intact subjects. Next, spectrogram is employed to transform the signal into TFR. It is worth noting there are three window sizes, 128, 256 and 512 ms with 50% overlap are used. Then, ten features including SSE, SE, VAR, CM, Mean, $E_{SVD}$, MNF, MDF, RE and CoV are extracted from each TFR. After that, two widely used classifiers are utilized to evaluate the performance of spectrogram features in the classification of 40 hand movement types.

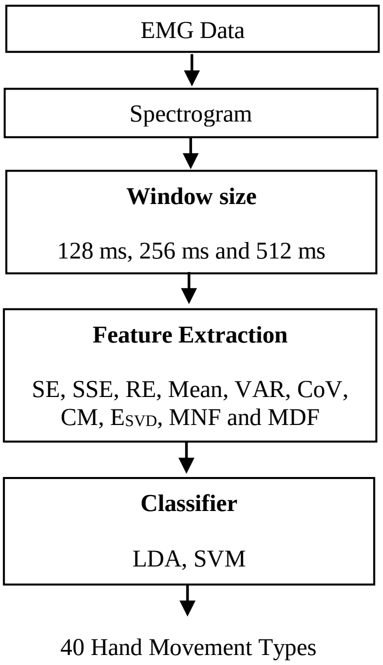


**Fig. 1 - Flow diagram of the pattern recognition architecture.**

## 2.2 Spectrogram

In signal processing, the application of TFD including spectrogram has been commonly used in the classification of EMG signals [4]. Nonetheless, spectrogram is the fundamental of TFD in analyzing signals, especially for noise and artifact reduction [15]. For biomedical signals such as non-stationary EMG signal, spectrogram overcomes the limitation of time and frequency representation. More specifically, time and frequency domain present the signal in limited regular window size [16]. To obtain the time and frequency information simultaneously, TFD is preferred.

In general, spectrogram is the square magnitude of short time Fourier transform (STFT), which represents the signal in the energy distribution on time-frequency planes [4], [17]. Additionally, spectrogram exhibits the non-stationary nature of EMG signals in time-frequency analysis. Moreover, spectrogram offers the relationship between the EMG signal and muscle characteristic, thus presenting the muscle behavior of different muscle fibre [18]. Spectrogram can be expressed as:

$$S(t, f) = \left| \int_{-\infty}^{\infty} x(\tau)\, w(\tau - t) e^{-2\pi f \tau} d\tau \right|^2 \qquad (1)$$

where $x(\tau)$ is the EMG signal and $w(\tau\text{-}t)$ is the Hanning window function. Hanning is a window function in digital signal processing to execute the Fourier transform by selecting a series number of samples. In TFD, Hanning window varies the time and frequency resolution to obtain the useful information from the signal. Previous studies indicated lower window size affected the accuracy of frequency related information. However, a greater window size causes lower accurate in time related information [16]. In this analysis, Hanning window size of 128, 256 and 512 ms with 50% overlap are employed in order to determine the optimal time and frequency planes. Moreover, the number of Fourier points (nfft) is same as the selected window size.

## 2.3 Feature Extraction using Spectrogram

EMG signal in TFR. Nevertheless, TFR consists of high dimensional matrix and it is not well suited for direct classification. To obtain the valuable information from spectrogram, ten features are extracted and described as follow. Concentration measure (CM) is used to identify the concentration of energy distribution in TFD [19]. CM with a greater value shows that the energy is distributed in the entire time-frequency plane. CM can be defined as:

$$CM = \left( \sum_{n=1}^{L} \sum_{k=1}^{M} \sqrt{|S(n,k)|} \right)^2 \qquad (2)$$

where $S$ is the spectrogram, $L$ and $M$ are the length of time and frequency points, respectively.

Spectral entropy (SE) is a feature that used to measure the randomness of the energy distribution [19]. Generally, a lower value of SE indicates the power spectrum of spectrogram is more concentrating on the specific time-frequency plane. SE can be written as:

$$SE = -\sum_{n=1}^{L} \sum_{k=1}^{M} \frac{P(n,k)}{\sum_L \sum_M P(n,\mathrm{k})} \log_2 \left( \frac{P(n,k)}{\sum_L \sum_M P(n,\mathrm{k})} \right) \qquad (3)$$

where $P$ is the power spectral, $L$ and $M$ are the length of time and frequency points, respectively.

In general, Shannon entropy (SSE) is the fundamental of TFR feature. SSE underlines the medium tension and concentrates on the low intensities of energy in time-frequency distribution [20]. SSE can be expressed as:

$$SSE = -\sum_{n=1}^{L} \sum_{k=1}^{M} \frac{S(n,k)}{\sum_L \sum_M S(n,\mathrm{k})} \log_2 \left( \frac{S(n,k)}{\sum_L \sum_M S(n,\mathrm{k})} \right) \qquad (4)$$

where $S$ is the spectrogram, $L$ and $M$ are the length of time and frequency points, respectively.
The entropy based on singular vector decomposition ($E_{SVD}$) measures the magnitude and non-zero elements in SVD by decomposing the time-frequency distribution into signal and orthogonal sub-space [19]. $E_{SVD}$ can be defined as:

$$E_{SVD} = -\sum_{n=1}^{L} \frac{S_n}{\sum S_n} \log \left( \frac{S_n}{\sum S_n} \right) \qquad (5)$$

where $S_n$ is the singular value of TFD processed by singular value decomposition.

Mean frequency (MNF) is computed as the sum of product of power and its corresponding frequency divided by the total sum of power [19], [21]. In this work, the average of MNF is used as feature, where MNF can be expressed as:

$$MNF = \frac{\sum_{k=1}^{M} f_k P(n,k)}{\sum_{k=1}^{M} P(n,k)} \qquad (6)$$

where $P$ is the power spectral, $f_k$ frequency value of power spectral at frequency bin $k$, $L$ and $M$ are the length of time and frequency points, respectively.

Median frequency (MDF) is defined as the frequency at which the total power is divided into two equal parts [19], [21]. In this work, the average of MDF is used as feature, where MDF can be expressed as:

$$\sum_{k=1}^{MDF} P(n,k) = \sum_{MDF}^{M} P(n,k) = \frac{1}{2} \sum_{k=1}^{M} P(n,k) \qquad (7)$$

where $P$ is the power spectral, $L$ and $M$ are the length of time and frequency points, respectively.

Renyi entropy (RE) is another entropy that identifies the time-frequency structure and achieves the energy information of the EMG signal [19]. A lower RE is achieved when the EMG signal is estimated to be a very low complexity, especially for single component signals. RE can be represented as:

$$RE = \frac{1}{1-\alpha} \log_2 \sum_{n=1}^{L} \sum_{k=1}^{M} \left( \frac{S(n,k)}{\sum_L \sum_M S(n,\mathrm{k})} \right)^{\alpha} \qquad (8)$$

where $\alpha$ is RE order, $S$ is the spectrogram, $L$ and $M$ are the length of time and frequency points, respectively. It is worth noting that the $\alpha$ should be odd integer and it must be greater than 2 [19]. In this work, $\alpha$ with value of 3 is applied.

Commonly, statistical features including mean, variance (VAR) and coefficient of variation (CoV) are defined as one dimensional statistical properties. However, they can be extended into two dimensions so that they can extract the information from time-frequency plane. Two-dimensional mean, variance and CoV can be written as:

$$Mean = \frac{1}{LM} \sum_{n=1}^{L} \sum_{k=1}^{M} S(n,k) \qquad (9)$$

$$VAR = \frac{1}{LM} \sum_{n=1}^{L} \sum_{k=1}^{M} \left[ S(n,k) - \mu \right]^2 \qquad (10)$$

$$CoV = \frac{\sigma}{\mu} \qquad (11)$$

where $S$ is the spectrogram, $\mu$ is referred to the mean, $\sigma$ represents standard deviation, $L$ and $M$ are the length of time and frequency points, respectively.

## 2.4 Classification of EMG Signal

To evaluate the capability of spectrogram features in differentiating 40 hand movement types, the machine learning algorithms are employed. In this study, two popular and widely used classifiers namely support vector machine (SVM) and linear discriminate analysis (LDA) are utilized.

Support vector machine (SVM) has been recognized to be one of the best and efficient machine learning algorithm in EMG pattern recognition [19]. Recently, SVM has grown up as a high potential classifier, which offers more accurate results compared to others [22], [18]. On the hyperplane, SVM makes use of the concept of separation to partition the data set so that all data can be divided linearly [23]. Additionally, SVM maps the data on the high dimensional space and provides the optimal classification function for classifying different classes in spectrogram feature set [24]. However, SVM has the limitation in the selection of kernel function and high computational cost [22]. In the previous research, radial basis function (RBF), linear, polynomial and Gaussian function are commonly used in SVM. Concerning the classification accuracy, RBF offers a better performance as compared to linear and polynomial [22], [24]. For this reason, SVM with RBF kernel is applied in this work.

Linear discriminate analysis (LDA) is a well-established machine learning algorithm that gives robust results. A study of Phinyomark et al. [25] indicated LDA was able to provide a high consistent results for a long-term EMG effect. Additionally, LDA is known as a less problems machine learning algorithm, especially when overtraining. The feature vector variables in LDA are assumed to be a multivariate normally distributed [26]. The concept of LDA is pretty simple, LDA evaluates the parameter of discriminate function based on training data set. Then, the boundary space in the hyperplane between different classes is assessed [6]. In this work, LDA with pseudo-linear function is implemented.

After selecting the proper classifiers, the data is divided into training and testing sets for performance evaluation. In this work, six-fold cross validation method is used. Cross validation is a popular statistical technique that has been widely used in classification and regression [10]. Cross validation aims to test the whole data set by partitioning the data equally into six parts. Each part is used for testing in succession while the rest are used for training session.

# 3. Results and Discussion

In this section, the results of the performance of spectrogram features are discussed. In the experiment, ten features are extracted from each TFR. In total, 120 features (10 features × 12 channels) are extracted from each movement from each subject. The features are then normalized so that they have zero mean and unit variance.

In the first part of the analysis, the optimal Hanning window size of spectrogram is examined. Fig.2 demonstrates spectrogram with 128, 256 and 512 ms with 50 % overlap. As can be seen, the time information is reduced as the window size increased. On one side, the frequency information is reduced as the window size decreased. Certainly, spectrogram has the limitation in the tradeoff of time and frequency distribution and it has been mentioned in the literature. To balance the information content of time and frequency domains, the selection of window size is considered. Note that the total number of features for three different window sizes are the same.

Table 2 outlines the classification accuracy of spectrogram features for window size of 128, 256 and 512 ms with 50% overlap. A higher mean classification accuracy of 91.29% (LDA) and 90.29% (SVM) are achieved for 256 and 512 ms window, respectively. The result of T-test shows that there is no significant difference ($p$>0.05) can be found between the classification performance of 128 ms (LDA) and 256 ms window (SVM). By applying LDA, 256 ms window shows an increment of 0.37% and 0.58% mean classification accuracy compared to 128 ms and 512 ms. In short, it has been found that 128 ms window achieves the best performance in LDA. On the other hand, 512 ms window offers the optimal performance when SVM is employed. Evidently, the accuracy of spectrogram features is varied according to the window size. This means that the optimal window size provides a better classification performance. Therefore, the analysis of the optimal window size in spectrogram is critically important.

In term of computational time, spectrogram (per subject) with 128, 256, 512 ms cost 12.839s, 6.804s and 4.271s, respectively. It shows that as the window size increases, the computational cost reduced. From the results, it is observed that 256 ms window (LDA) and 512 ms window (SVM) are more appropriate to be used in the EMG signals classification. Considering the classification accuracy, computational cost and consistency, it is concluded that spectrogram with 256 ms window and LDA is the best combination in current work.

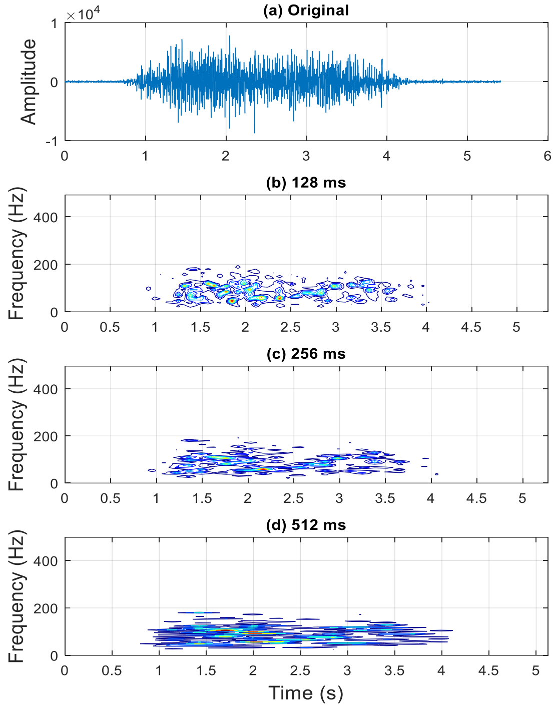


**Fig. 2 - Spectrogram of EMG signal with three different Hanning window sizes. (a) EMG signal (b) 128 ms (c) 256 ms (d) 512 ms.**

**Table 2 - Classification accuracy of three different window sizes (128, 256 and 512 ms).**

| Subject | Classification accuracy (%) | | | | | |
|---|---|---|---|---|---|---|
| | 128 ms window | | 256 ms window | | 512 ms window | |
| | SVM | LDA | SVM | LDA | SVM | LDA |
| 1 | 96.25 | 93.75 | 93.75 | 95.42 | 95.83 | 94.58 |
| 2 | 92.08 | 93.33 | 92.50 | 92.92 | 92.92 | 94.17 |
| 3 | 85.00 | 82.92 | 85.42 | 86.67 | 87.08 | 87.92 |
| 4 | 89.58 | 92.08 | 90.42 | 89.58 | 90.83 | 90.42 |
| 5 | 85.42 | 89.17 | 86.67 | 88.33 | 88.33 | 87.50 |
| 6 | 92.50 | 92.08 | 92.92 | 95.83 | 92.92 | 93.75 |
| 7 | 88.33 | 90.42 | 88.75 | 92.50 | 90.42 | 92.08 |
| 8 | 87.50 | 91.25 | 86.25 | 89.58 | 85.83 | 87.08 |
| 9 | 90.00 | 91.25 | 89.58 | 91.67 | 88.75 | 89.58 |
| 10 | 89.58 | 92.92 | 90.42 | 90.42 | 90.00 | 90.00 |
| Mean | 89.63 | 90.92 | 89.67 | 91.29 | 90.29 | 90.71 |
| SD | 3.393 | 3.129 | 2.905 | 2.956 | 3.005 | 2.813 |

The diagonal confusion matrix of 10 subjects are averaged to evaluate the performance of 40 hand movement tasks. Fig.3 illustrates the confusion matrix of the best classification performance in this work, which is spectrogram (256 ms) + LDA. From the confusion matrix, spectrogram features have successful recognize the 40 hand movement types with the class-wise accuracy of above 80% except M29. Through the confusion rate, M17 (100%) is the most correct predicted. By contrast, the highest misclassification rate can be found in M29 (78.95%). The experimental results validate the potential and efficiency of spectrogram features in the classification of EMG signals.

## 4. Conclusion

This study shows the potential of spectrogram in the classification of multiple hand movement types. In the first step, the analysis for the optimal selection of Hanning window size was done. It is observed the spectrogram with window size of 256 ms and 50% overlap offered the best recognition rate when LDA is used. The experimental results indicated that the combination of spectrogram features and LDA gives the best mean classification accuracy of 91.29%. Indeed, the hand movements of intact subject have been classified properly. In future, the performance of amputee needs to be done to develop an accurate multifunctional myoelectric prosthesis.

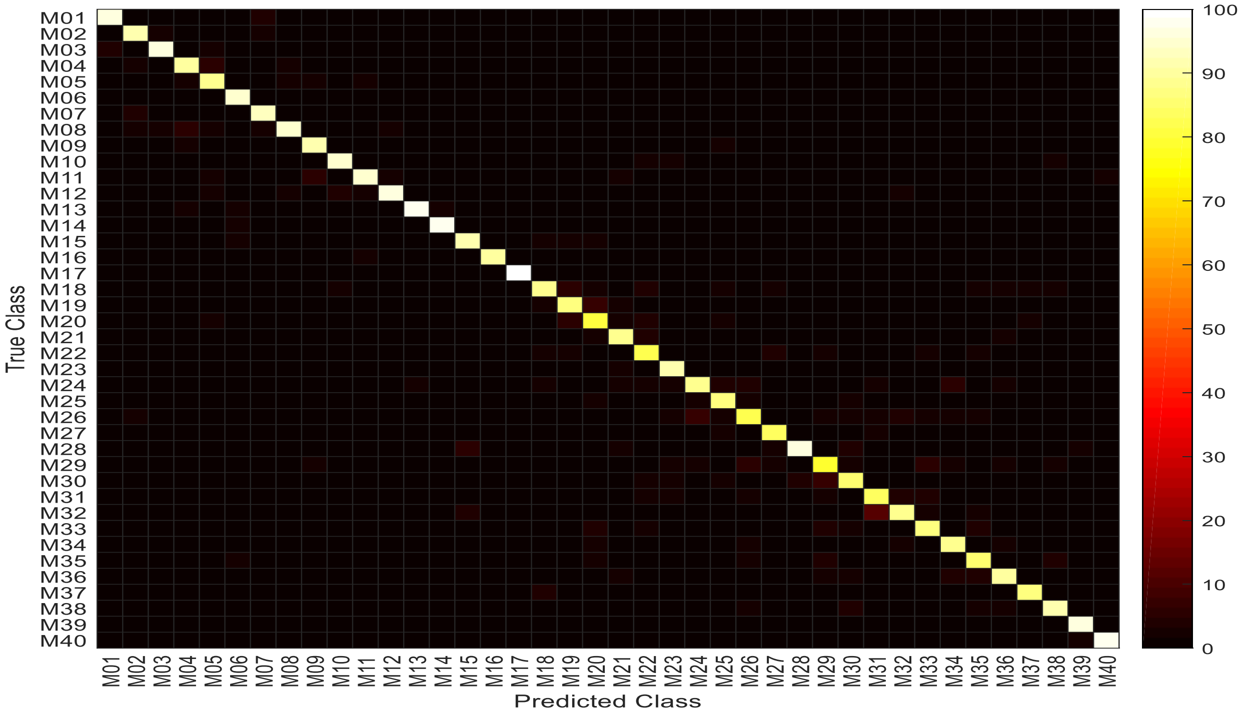


**Fig. 3 - Confusion matrix of spectrogram (256 ms) + LDA of 40 hand movement types across 10 subjects (%).**

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