International Journal of Engineering & Technology, 8 (1.7) (2019) 219-226

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper



Classification of EMG Signal for Health Screening Task for Musculoskeletal Disorder

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Abstract

Electromyography signal analysis and classification method for Health Screening Program for Social Security Organisation (SOCSO) Malaysia is the first time applied using time-frequency distribution (TFD). This paper presents the classification of EMG signals for health screening task for musculoskeletal disorder. A time-frequency method, i.e spectrogram is employed to obtain the data of time and frequency information of the EMG signal. Four machine learning classifier of k-Nearest Neighbor (k-NN), Linear Discriminant Analysis (LDA), Naïve Bayes (NB) and Support Vector Machine (SVM) are implemented to EMG signal. Three out of six tasks (axial rotational task, kneeling reach and kneeling to standing back reach) which focused on the upper limb was performed using Multi Sensor Management ConsensysPRO and functional range on motion (FROM). From the experiment, SVM classifier is outperformed others using the purposed extracted features from spectrogram which is more than 80% except NB with 73.33%. The finding of the study concludes that SVM is suitable to classify EMG signal and can help rehabilitation center to diagnose their patients.

Keywords: *Electromyography, Spectrogram, Machine learning classifier, Mean root mean square voltage*.

1. Introduction

Musculoskeletal Disorders (MSDs) are the second most common cause of disability in the work setting which give the impact of fatigue and the productivity of the workers [1], [2]. Social Security Organisation (SOCSO) Malaysia has reported that 25% of the worker in industries continued to suffer from upper limb injuries [3]. SOCSO has classified occupational diseases into hearing impairment, musculoskeletal disorder, vibration disorder, skin diseases and occupational asthma. Statistic of industrial accidents in Malaysia recorded 57,639 cases compared to 55,186 for the previous year. The musculoskeletal disorder is one of the critical occupational injuries and disabilities. In 2016, it showed an increment of 174% from 31 to 85 cases [2]. The effect of MSDs can be progressed from mild to severe disorder [4], [5].

There has been an increasing effort in recent years to investigate the causes of MSDs and to take action to prevent them. It is important to know the method that able to detect the symptoms that will contribute to MSDs problem in the body [2]. Recent years, electromyography (EMG) is widely used in the analytical study, clinical and rehabilitation areas of electrical activity produced by skeletal muscles [6], [7]. EMG signal is different between persons, and changes depending on physical condition even for the same motion of the same person [8]. Various techniques for handling EMG signals are used as pre-processing stages before the analysis and feature extraction to improve the accuracy and response time of the data controller [5]. However, previous researchers found that it is difficult to obtain high accuracy in classifying in the data analysis process [9], [10].

The previous EMG researcher used time domain features in the classification of EMG signal because of its better processing speed and simplicity [11]. It can be directly extracted without need more mathematical transformation [12]. However, it does not contain spectral information and needs more features to be classified with higher accuracy [3], [13]. Frequency domain analysis as Fourier Transform to gain frequency information, but it is reasonable to approach stationary signal, not for non-stationary as an EMG signal with variable amplitude and frequencies [14], [15]. Therefore, the time-frequency distribution is proposed to cater non-stationary signal. Wavelet Transform (WT) is one of the common techniques used for EMG analysis. This technique offers high time resolution for high-frequency component and high frequency resolution for low-frequency component such as transient [16], [17]. Though, this technique provides poor frequency resolution for high-frequency component and poor time resolution for low-frequency components as EMG signal. WT also has multi-resolution analysis and required neural network programming technique for classification which can increase computer memory and computational overhead due to the large number of features [18].

Nowadays, the application of machine learning is most significant in data mining. People are often to making mistakes analyses and also trying to establish the relationship between multiple features [19]. The algorithms are very often helpful to classify and predict whether a document represents a positive or negative sentiment [20]. The extracted features have been classified into four groups based on the three types of tasks performed. Four approaches of sentiment classification are very often used in literature, also known as binary sentiment

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classification and multi-class sentiment classification [21]. There are classifiers algorithm of k-Nearest Neighbor (k-NN), Linear Discriminant Analysis (LDA), Naïve Bayes (NB) and Support Vector Machine (SVM) are implemented to EMG.
k-Nearest Neigbor (k-NN) is a simple yet effective widely renowned, method in data mining. However, the actual application of this model in the big data domain is not achievable due to time and memory restrictions [22], [23]. Though, it has successfully been developed in the real application, but with a large scale of the dataset. kNN needs to compute the distance (or similarity) of all training samples for each test sample in the process of selecting k nearest neighbors where n is the size of the training dataset and d is the dimensionality. It needs high cost because of the complexity is expensive for big data.
Linear Discriminant Analysis (LDA) is a statistical classification method which covers the boundary points and the different data points lie on the hyperplane. It is a common classification method used in EMG pattern recognition [24]. It is a supervised linear transformation based feature reduction strategy also able to provide information in high-dimensional feature vector to a low-dimensional space such that the ratio between maximised intra class scatter (within the class) SW and the inter class (between class) scatter SB [25]. The number of training samples are much lesser than the number of features and therefore the intra class scatter matrix would tend to be a singular matrix and the LDA computational will be so demanding [26].
Naïve Bayes (NB) is a machine learning method that predicts the density of the data set. NB is a truly qualified classifier due to its good behavior in the classification task [3], [27]. This class assumes class in independent conditions. Bayesian classifier predicts the probability of data belonging to a particular class. In order to predict probability, it uses the concept of Bayes' theorem. Bayes' theorem is useful in providing a way of calculating the posterior probability [28].
Support Vector Machine (SVM) classifiers are the most advanced ones, generally, designed to solve binary classification problems [27]. It just need small number of support vectors [29]. It is a well established machine learning method of classifying neuromuscular disease and pattern recognition process [30]. SVM has shown its superiority, especially for nonlinear and high dimensional pattern recognition [31]. However, the major drawbacks of the SVM are high computational time and selection of kernel function because its performance is based on the kernel function. Thus, it is one of the classify method can be used to classify the health screening task from the chosen parameter.
In this study, the performance of spectrogram is investigated to classify the tasks performed by the subject. The analysis will start with finding suitable features for EMG signal from spectrogram. Then, the features will be extracted from this method. The process continues with the classification method from machine learning. There are four different types of classification is used such as Naïve Bayes (NB), k-Nearest Neighbor (k-NN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) to classify the movement of the Health Screening Program. The finding of this research is able to assist SOCSO in evaluating the performances of their patients with more details compared to their current method.

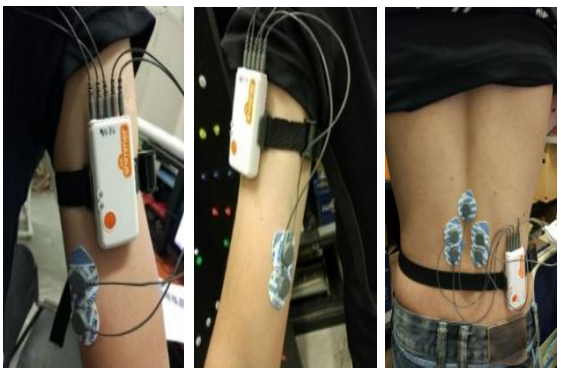
2. Procedure for data collection

One out of the five healthy subject with no previous injury from musculoskeletal disorder has selected to become the example of this paper's scope which is to evaluate the classification method for EMG signal. The subject with 58 kg and 166 cm is proposed to perform the experiment. There are some procedures implemented in earlier experiment, which are skin preparation and electrode placement based on the Surface EMG for non-Invasive Assessment of Muscles (SENIAM) standard.
Multi Sensor Management ConsensysPRO is used in configuring Shimmer sensors, streaming real-time data and managing collected data before the data analysis process. Shimmer sensor is interfacing with Consensys software to configure the data capture.
The acquired is filtered by using highpass filter. All the rest time are removed from the raw signal and exactly dataset is taken in the analysis process. For the data acquisition, the experiment would be performed to get the data before analysis would be a start. The selected method which is spectrogram is applied and four features have been extracted. There are four selected features extracted from the signal which are the mean root mean square voltage (Vrms), mean frequency (MNF), Variance (VAR) and standard deviation (STD). After that, the classification of k-NN, DT, LDA and SVM were applied to investigate the best classification with highest accuracy performed from the task. Thus, the performance of the task is identified.

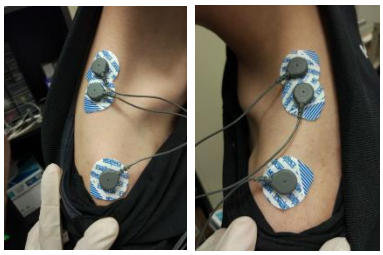
2.1. Electrode Placement

There are six muscles (upper limb) involved in this experiment which are as follows and Figure 1 shows the exact position of the muscles.

i. Right biceps brachii
ii. Left biceps brachii
iii. Right erector spinae (lumbar region)
iv. Left erector spinae (lumbar region)
v. Right Trapezius p. descendenz
vi. Right Trapezius p. descendenz



(a) (b) (c)



(d) (e)

Fig. 1: The positioning of the electrodes for EMG measurement (a) right biceps brachii, (b) left biceps brachii, (c) right and left erector spinae, (d) right trapezius and (e) left trapezius

2.2. Health screening task uses Functional Range of Motion

There are three tasks from six are selected to be tested in this research which are the axial rotational reach, kneeling reach and kneeling to standing back reach. Axial rotational reach is a function to determine a subject's ability to perform axial rotation activities in a standing position and performing functional reaching. Kneeling reach is performed to determine a subject's ability to perform kneeling activities with functional reaching and kneeling to standing back reach is to determine a subject's ability to perform activities requiring going into and out of the kneeling position and performing functional reaching.
Functional Range on Motion (FROM) is used for Health Screening Task (HST). It consists of 6 panels from left to right: 1, 2, 3, 4, 5 and 6. Each of these panels contains 45 holes of 5 different colours and three zones: A, B and C. Three types of HST with selected features and four types of classification method are discussed in this paper and the detailed procedures for this task is described below:

2.2.1. Axial rotational reach

1) As in Figure 2, The client is instructed to move five rows of pegs from Panel 6 (Zone B) to Panel 4 (Zone B).
2) The client should stand in the center of the board assembly (approximately 15 inches from the panel) while performing the test in order to achieve some back rotation.
3) The transfer process requires the subject to take the peg out of the hole with the left hand, transfer it to the right hand and then place the peg into the corresponding hole with the right hand (forward order)
4) Take rest 2 minutes, then repeat step 1 to 3 until 5 times

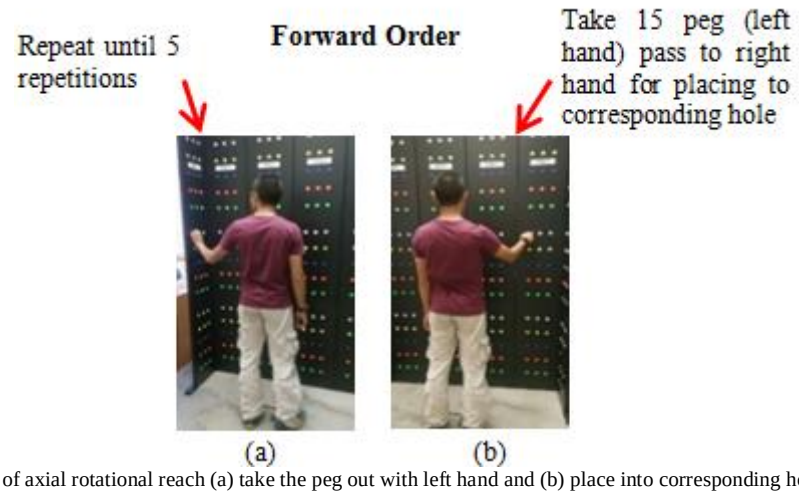


Fig.2: Procedure of axial rotational reach (a) take the peg out with left hand and (b) place into corresponding hole with right hand

2.2.2. Kneeling reach

1) Figure 3 shows the client is instructed to move five rows of pegs from Panel 2 (Zone C) to the corresponding row of holes in Panel 3 (Zone C).
2) The transfer process requires the client to take the peg out of the hole with the left hand, transfer it to the right hand and then place the peg into the corresponding hole with the right hand.
3) The process starts with the highest level row and then proceeds in order to the lowest level row.
4) Repeat procedure 2 and 3 until **FIVE (5)** repetition.



Fig.3: Procedure of kneeling reach (a) take the peg out with left hand and (b) place into corresponding hole with right hand

2.2.3. Kneeling to standing and back reach

1) The client is instructed to move a row of pegs from Panel 2 (Zone C) at the lowest row to the next highest row directly above the row from which the activity started as in Figure 4.
2) Only 3 pegs are used in this test. Two of the pegs must be moved with dominant hand and the third peg must be moved to the non-dominant hand.
3) The client must be in the standing position before start placement of the pegs in the lowest row of Zone B.
4) Once the pegs have reached the top row in Zone B, a test repetition has been completed.
5) The client then continues to move the pegs downward, one row at a time employing the same process.
6) The client must return to the kneeling position before starts placement of the pegs into the highest row of Zone C. Upon reaching the lowest row of holes in Zone C, another repetition has been completed.



Fig.4: Procedure of Kneeling to standing back reach (a) take the peg out with dominant hand in Zone C, (b) place into corresponding hole (Zone C), (c) stand to start placement of the pegs in the lowest row of Zone B and (d) standing position before start placement of the pegs in the lowest row of Zone B

3. Method

3.1. Analysis of EMG Signal

The raw EMG signal is collected in the time domain, however, it can transform into the frequency domain using fast-Fourier transforms [3], [19]. FFT has the limitation which not able to cater non-stationary signal whose it the signal characteristic change in time and frequency [20], [21]. The visual representation of the frequency spectrum for spectrogram is suitable to use because of the ability to overcome the imitation of FFT. EMG signals are transferred to time-frequency representation (TFR) and able to provide more information that needed to analyse the signal. EMG signal is really sensitive to noise, thus Hanning window is suitable to use because of its usefulness for noise measurement with a better frequency resolution than some other windows [22]. Spectrogram with Hanning window 1024 was selected to be applied to each channel. Spectrogram formula can calculate as in (1):

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

where $x(\tau)$ is the input signal and $w(\tau - t)$ is referring to the observation window which is Hanning window function.
Spectrogram analysis is able to have superior accuracy in challenging task color model, which is having multiple color to identify the magnitude, red for the highest magnitude and blue for the lower magnitude [23]. This technique roughly described on how frequency content changes over time. An optimum frequency resolution is useful for extracting features of any signals for further analysis, including EMG signals [24]. Smaller size window produces better time resolution, but reduces frequency resolution. The window width that has been chosen is maintained, which gives fixed frequency and time resolution for all frequencies. In this technique, the window size will affect time resolution and frequency resolution to produce the optimum presentation of the signal. The suitable size window should be selected for the optimum result of EMG signal because the fixed window will provide easier interpretation in terms of harmonics but effect on time-frequency resolution [27].

3.2. Feature Extraction

Features and extraction process is more crucial to know the suitable method for each different type of signal. Four types of features are chosen to present the information about the signals. There are the mean root mean square voltage (Vrms), mean frequency (MNF), Variance (VAR) and Standard Deviation (STD). All of this result also can be present in statistical method. V_{rms} is able to use for providing fatigue features and energy information. (2) shows the Vrms expression as follow:

$$Vrms\,(t) = \sqrt{\int_0^{fmax} S(\,t,f)\,dt} \quad (2)$$

where $S(t,f)$ is the time-frequency distribution and f_{max} is the maximum frequency of interest.
Mean (RMS) Voltage is used to indicate the strength of the muscle used in manual lifting task. Mean $V_{rms}(t)$ is mentioned as (3):

$$x = \sum \frac{V_{rms}(t)}{n} \quad (3)$$

where $\bar{x}$ is mean value of $V_{rms}(t)$, n is the number of $V_{rms}(t)$ and Σ is the summation of $V_{rms}(t)$.

4. Result and discussion

In this part, the result of the experiment is presented. Data analysis using spectrogram and then features are extracted before proceed to the classification process. The spectral of the spectrogram is demonstrated. Four classifier method is applied to four different features to measure the performance of the best classifier due to the accuracy.

4.1. Time-frequency representation (TFR) of EMG Signal

The spectrogram in time-frequency representation (TFR) has provided information on time-frequency information. Figure 5 shows the flow of the result presented started from Figure 5 (a) is the raw signal for five repetitions of tasks performed, each signal is separated into each repetition, then it is divided it into two parts as Figure 5 (b). Part 1 is due to take the peg and part, then place the peg into the corresponding hole. Figure 5 (c) shows power spectral information. This example shows the highest amplitude of EMG signal is when the time is at 0.042 minutes with frequency 80 Hz. This frequency is acceptable, as the previous study reported 6-500 Hz is an efficient frequency component of EMG signal [28].

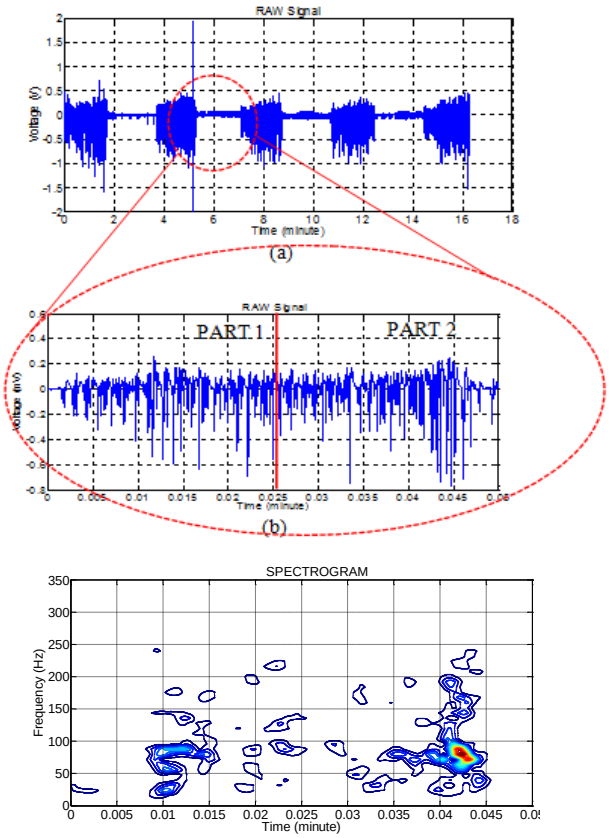


Fig.5: (a) Five repetition of the dataset, (b) one data set is separated and (c) spectrogram of the EMG signal

4.2. Classification of health screening task from extracted features

Table 1 shows the summary of classification accuracy for all selected features HST data with 5-fold cross validation. Using spectrogram, it can be observed that three of four classification methods achieved a good result which is 80% and above. k-NN, LDA and SVM are obtained 80, 86.67 and 80% respectively for better classification accuracy, however, NB classification is just under a good classification which 66.67%. The result is very important to determine the best feature and technique used in feature extraction for classification method.

Table 1: Classification accuracy for four different classifications for spectrogram features

Features	Classification (%			
	k-NN	LDA	NB	SVM
Mean(Vrms)	93.33	93.33	73.33	80.00
MNF	60.00	60.00	73.33	66.67
VAR	73.33	46.67	60.00	60.00
STD	80.00	60.00	66.67	60.00
Full Classification of features	80.00	86.67	66.67	80.00

Figure 6 illustrates the features classification accuracy for k-Nearest Neighbor (k-NN) classification method. This graph indicates the best classifier discriminate HSP is mean root mean square voltage (V_{rms}) with an accuracy of 93.33%. Standard deviation (STD), and full classification have the same accuracy for the second highest which is 80%. It is followed by Variance (VAR) with 73.33% and lowest accuracy is just 60%, which is 64% from the highest accuracy, mean frequency (MNF).

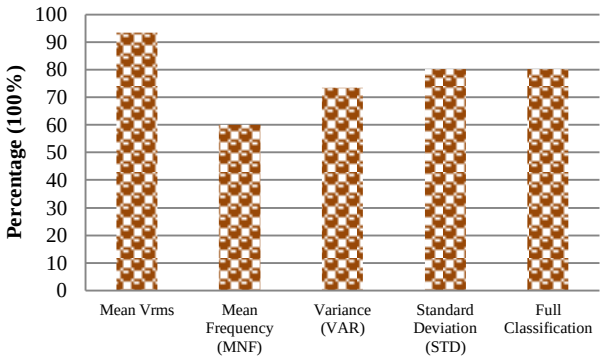


Fig.6: k-Nearest Neighbor (k-NN) classification of spectrogram feature set for HSP

The features classification accuracy of linear discriminant analysis (LDA) is shown in Figure 7. Mean V_{rms} is obtaining the highest classification accuracy as k-NN with 93.33%. Full categories of feature classification is 86.67%, which is the second highest of accuracy. It is lower accuracy is STD with the same value with MNF and then lowest is VAR with an accuracy of 60%, 60% and 46.67%. LDA is one of the most widely studied dimensionality reduction technique. The application of variants of LDA technique is able to solve the problem of small sample size.

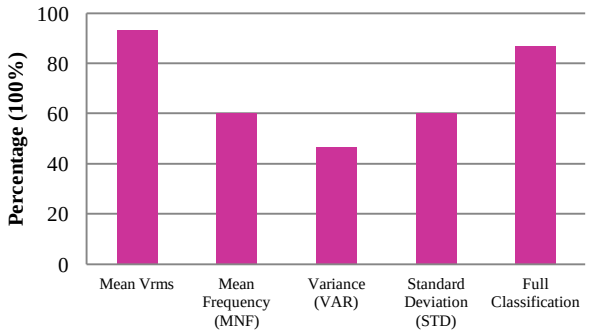


Fig.7: Linear Discriminant Analysis (LDA) classification of spectrogram feature sets for HSP

From Figure 8, the performance of classification for Naïve Bayes (NB) is illustrated. Mean V_{rms} and mean frequency (MNF) are the best with a classification accuracy of 73.33%. It is followed by STD with full classification of 66.67% accuracy, then the lowest is VAR with 60%. This classification is the lowest accuracy compared to three others classification method. This is because the naive algorithm of this classification method will assume the independence of features as features do not covary with each other [30]. This classifier is simple in its structure, and the speed of the learning algorithm it employs. The NB classifier assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature [31].

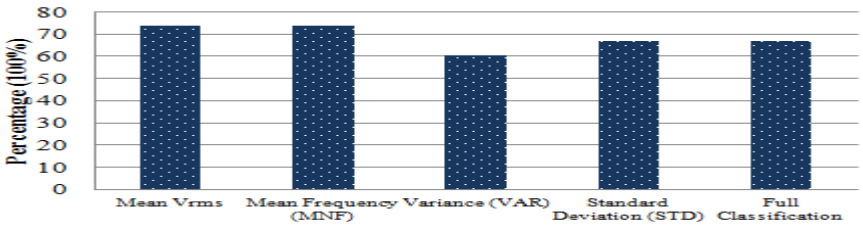


Fig.8: Naïve Bayes (NB) classification of spectrogram feature sets for HSP

In recent times non-linear approaches such as the support vector machine (SVM) have been applied to credit scoring and help to increase the accuracy and reliability of many credit scorecards [32]. The performance of the features for SVM classification method is presented in Figure 9. The best classification accuracy features are Mean V_{rms} and full classification due to the same value of accuracy which is 80%. MNF is the second highest with drastically decrease to 66.67%. Then the lowest is VAR and STD of 60% of classification accuracy.

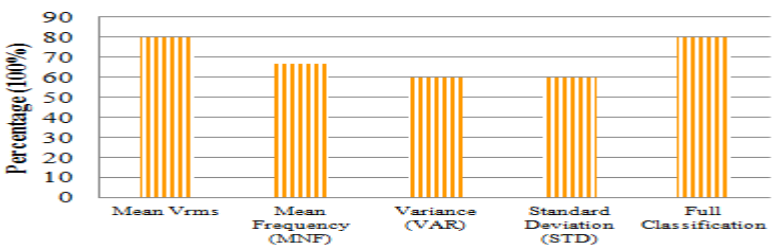


Fig.9: Support vector machine (SVM) classification of spectrogram feature set for HSP

The performance of the positive predictive (PPV) and false discovery rate (FDR) for each type of tasks for HSP is illustrated in Figure 10. The green box is directed for each feature is correctly classified to assign class which involved three tasks (axial rotational reach, kneeling reach and kneeling to standing back reach). Then, the red box is indicated for unable to classify the type of tasks. From Figure 10, the results show the axial rotational reach achieve the highest true positive which is 80% of correctly classified because another 20% is misclassified to kneeling reach. Second higher performance is kneeling to standing back reach with 60% of correct classified and 40% wrongly classified into kneeling to standing back reach. The third is kneeling reach with worse correct classified, with just 20%. Misclassified occurred 60% axial rotational reach and 20% with kneeling to standing back reach.

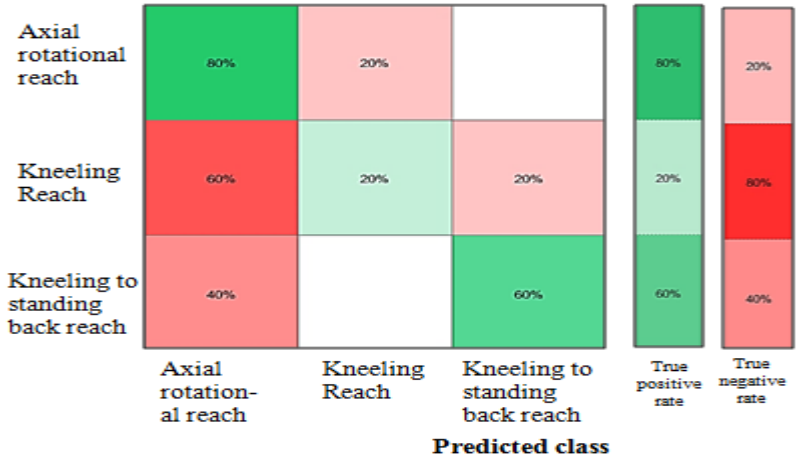


Fig.10: Positive predictive (PPV) and false discovery rate (FDR) for each type of tasks for HSP

5. Conclusion

This paper has presented the classification of EMG Signal for health screening task for musculoskeletal disorder which the performance of spectrogram is demonstrated. The features were extracted from this technique and it shown that it is suitable to be applied to the EMG signal analysis, then feature extraction and classification. Either four demonstrated a classification method, it is clearly shown that support vector machine (SVM) is able to perform the highest classification accuracy. The overall features extracted which is 80% and above for k-NN, LDA, SVM accept NB in just 73.33%. It is shown that SVM will be suitable to be applied in the future to classify EMG signal as HSP. This result is able to be implemented in a rehabilitation center as SOCSO for assessment and easier classified the performance of their patient.

In the nutshell, from positive predictive (PPV) and false discovery rate (FDR), it's shown that the percentage of correct classified accuracy can be more higher and the additional of other suitable features is needed to increase the potential for correct classification of machine learning.

Acknowledgement

A grateful thank to the Ministry of Higher Education Malaysia (MOHE) and Universiti Teknikal Malaysia Melaka (UTeM) for Zamalah Scheme and PJP/1/2017/FKEKK/H19/S01526 as the funding research. Thank also to support team of this project from Centre of Robotic & Industrial Information (CeRIA) and specially gratefully thanks to the Faculty of Electrical Engineering of Universiti Teknikal Malaysia Melaka (UTeM) for giving the cooperation to do this project.

References

[1] Daneshmandi, H., Choobineh, A. R., Ghaem, H., Alhamd, M., & Fakherpour, A. (2017). The effect of musculoskeletal problems on fatigue and productivity of office personnel: a cross-sectional study. *Journal of preventive medicine and hygiene*, 58(3), pp. 252-258.

[2] Zawawi, T. T., Abdullah, A. R., Jopri, M. H., Sutikno, T., Saad, N. M., & Sudirman, R. (2018). A Review of Electromyography Signal Analysis Techniques for Musculoskeletal Disorders,11(3), pp. 1136-1146.

[3] Too. Jingwei, A.R Abdullah, Norhashimah Mohd Saad, N. Ali, And T.N.S Tengku Zawawi (2018). Application of Spectrogram and Discrete Wavelet Transform For EMG Pattern Recognition. *Journal of Theoretical & Applied Information Technology*, 96(10), pp. 3036-3047.

[4] Buckley, P. (2016). Work-related Musculoskeletal Disorder (WRMSDs) Statistics, Great Britain 2016. *Health and Safety Executive (HSE)*, pp. 1-20.

[5] Nazmi, N., Abdul Rahman, M., Yamamoto, S. I., Ahmad, S., Zamzuri, H., & Mazlan, S. (2016). A review of classification techniques of EMG signals during isotonic and isometric contractions. *Sensors*, 16(8), 1304.

[6] Ruchika, Shalini Dhingra. (2013). An explanatory study of the parameters to be measured from emg signal, *International Journal of Engineering and Computer Science* , 2(1), pp.207–213.

[7] Y. Ning and Y. Zhang, (2017). A new approach for multi-channel surface EMG signal simulation, *Biomedical Engineering Letters*, 7(1), pp. 45–53.

[8] Kiguchi, Kazuo, and Yoshiaki Hayashi, (2012). Estimation of joint torque for a myoelectric arm by genetic programming based on EMG signals, *In World Automation Congress (WAC)*, pp. 1-4. IEEE.

[9] S. Thongpanja, A. Phinyomark, F. Quaine, Y. Laurillau, C. Limsakul, and P. Phukpattaranont, (2016). Probability Density Functions of Stationary Surface EMG Signals in Noisy Environments, *IEEE Transactions on Instrumentation and Measurement*, 65(7), pp. 1547–1557.

[10] R. H. Chowdhury, M. B. I. Reaz, M. A. B. M. Ali, A. A. A. Bakar, K. Chellappan, and T. G. Chang,(2013). Surface electromyography signal processing and classification techniques, *Sensors*, 13(9), pp. 12431–12466.

[11] Zhang, Xu, and Ping Zhou, (2012). High-density myoelectric pattern recognition toward improved stroke rehabilitation, *IEEE Transactions on Biomedical Engineering*, 59(6), pp.1649-1657.
[12] Kakoty, Nayan M., and Shyamanta M. Hazarika, (2011). Recognition of grasp types through principal components of dwt based emg features, In *2011 IEEE International Conference on Rehabilitation Robotics (ICORR)*, pp. 1-6. IEEE
[13] D. Joshi, B. H. Nakamura, and M. E. Hahn, (2015). High energy spectrogram with integrated prior knowledge for EMG-based locomotion classification, *Medical Engineering and Physics*, 37(5), pp. 518–524.
[14] Jopri, M. H., A. R. Abdullah, M. Manap, T. Sutikno, and M. R. Ab Ghani, (2018). Harmonic Contribution Analysis of Electric Arc Furnace by Using Spectrogram, *Bulletin of Electrical Engineering and Informatics*, 7(2), pp. 236-243.
[15] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin, (2006). Techniques of EMG signal analysis: detection, processing, classification and applications, *Biol. Proced. Online*, 8(1), pp. 11–35.
[16] Tengku Nor Shuhada Tengku Zawawi, Abdul Rahim Abdullah, Isa Halim, Ezreen Farina Shair, and Saleha Mohamad Salleh, (2016). Application of spectrogram in analysing electromyography (EMG) signals of manual lifting, *ARPN Journal of Engineering and Applied Sciences*, 22(5), pp. 3603-3609.
[17] Andreotti, A., A. Bracale, P. Caramia, and G. Carpinelli, (2009) Adaptive Prony method for the calculation of power-quality indices in the presence of nonstationary disturbance waveforms, *IEEE Transactions on Power Delivery*, 24(2), pp. 874-883.
[18] Kotsiantis, Sotiris B., I. Zaharakis, and P. Pintelas,(2007). Supervised machine learning: A review of classification techniques, *Emerging artificial intelligence applications in computer engineering*,160, pp. 3-24.
[19] Tripathy, Abinash, Ankit Agrawal, and Santanu Kumar Rath, (2015). Classification of sentimental reviews using machine learning techniques, *Procedia Computer Science*, 57, pp. 821-829, 2015.
[20] NQ Zainal Abidin et al, (2012) Leakage current analysis on polymeric surface condition using time-frequency distribution. In: *2012 IEEE International Power Engineering and Optimization Conference (PEOCO) Melaka,Malaysia*,. IEEE. pp. 171–175, 2012.
[21] Maillo, Jesus, Sergio Ramírez, Isaac Triguero, and Francisco Herrera, (2016). kNN-IS: An Iterative Spark-based design of the k-Nearest Neighbors classifier for big data, *Knowledge-Based Systems*,117, pp. 3-15.
[22] Deng, Zhenyun, Xiaoshu Zhu, Debo Cheng, Ming Zong, and Shichao Zhang, (2016) Efficient kNN classification algorithm for big data. *Neurocomputing*, 195, pp. 143-148.
[23] G.Venugopal, M. Navaneethakrishna, and S. Ramakrishnan, (2014). Extraction and analysis of multiple time window features associated with muscle fatigue conditions using sEMG signals", Expert Systems with Applications, 41(6), pp. 2652–2659.
[24] Khan, Salabat, Muhammad Hussain, Hatim Aboalsamh, and George Bebis,(2017). A comparison of different Gabor feature extraction approaches for mass classification in mammography, *Multimedia Tools and Applications*, 76(1) , pp. 33-57.
[25] P. Bermejo, J. A. Gámez, and J. M. Puerta, (2014). Speeding up incremental wrapper feature subset selection with Naive Bayes classifier, *Knowledge-Based Systems*, 55, pp. 140–147.
[26] Wang, Lipo, ed. (2005). Support vector machines: theory and applications. Springer Science & Business Media, 177.
[27] J. Yousefi and A. Hamilton-Wright, Characterizing EMG data using machine- learning tools (2014), *Computers Biology and Medicine*, 51, pp. 1–13.
[28] H. Xu and G. Chen, (2013). An intelligent fault identification method of rolling bearings based on LSSVM optimized by improved PSO, Mechanical Systems and Signal Processing, 35(1), pp. 167– 175.
[29] A.-C. Tsai, J.-J. Luh, and T.-T. Lin, (2015). A novel STFT-ranking feature of multi-channel EMG for motion pattern recognition, Expert Systems with Applications, 42(7), pp. 3327–3341.
[30] Gao, Vance, Fred Turek, and Martha Vitaterna, (2016). Multiple classifier systems for automatic sleep scoring in mice, *Journal of neuroscience methods*, 264, pp. 33-39.
[31] Wang, Hua, and Yanchun Zhang, (2016). Detection of motor imagery EEG signals employing Naïve Bayes based learning process, *Measurement*, 86, pp. 148-158.
[32] Harris, Terry, (2015). Credit scoring using the clustered support vector machine," *Expert Systems with Applications*,42(2), pp. 741-750.