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Objective Analysis of Muscle Spasticity Level in Rehabilitation Assessment

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Abstract: In current practice, the assessment of upper limb spasticity is subjectively evaluated based on the experience and perception of therapists. This leads to inconsistency in assessment and could affect the efficacy of rehabilitation process. Thus, the aims of this paper are to study and extract relevant information from the torque and angle signal measured from the muscle of the arm and to select independent features in order to classify the level of spasticity of the muscle based on Modified Ashworth Scale (MAS) assessment tool. Data were collected from twenty-five subjects that met the criteria with consent. The data went through pre-processing stage and analyzed before the features extracted. The seven features extracted from the data forming the dataset which later used to train and feed into suitable classifier to classify the level of spasticity. One-way ANOVA test was run in order to evaluate the statistical significant differences among the level. Based on the results from the test, four features were selected out from seven. Linear Support Machine (SVM) based classifier accorded the highest performance with 84% accuracy compared to other classifiers.

Keywords: Modified Ashworth Scale, ANOVA test, Classification, Feature selection, Support Vector Machine.

1. Introduction

People with neurological disorder such as stroke, traumatic brain injury (TBI) and cerebral palsy (CP) will most likely experience spasticity of muscles which leads to difficulties in managing their activities of daily living (ADL) [1]–[8]. Hence, these people have to do training and exercise in order to reduce the stiffness of the muscle and improve their motor control. Recovery process needs an efficient strategy of training in order to get back to closest normal state [9]–[12]. The spasticity severity of affected muscle has to be assessed before undergoing training or exercise by therapist. The reason is for the therapist to monitor the recovery process of the muscle as well as to be able to plan the best rehabilitation training to be undergone. Currently, this is done on subjective basis. Even though there are standard tools to measure the level of muscle spasticity such as Modified Ashworth Scale, Modified Tardieu Scale and Fugl-Meyer Assessment [13]–[15], the assessment relies heavily on therapists' intuition, knowledge and experience [16], [17]. Thus, the appraisal is vulnerable to variation and this could postulate a challenge to screen the progress of the subject effectively especially if the preparing sessions are conducted by different therapists. In the long run, the problem could lead to the increase of cost, time and effort. This could be overcome by having the assessment done objectively using standard tool[18]. To date, assessment using measurable biomarkers has not been fully embraced by the mainstream physiotherapist. The approach however could be useful to complement the assessment done in subjective manner and to add objective weight to the assessment.

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Q. Peng et.al revealed from the elaboration in [19] that quantitative measurements of spasticity can lead to more accurate characterizations of pathological conditions and outcome evaluations contributing to better healthcare services. N.A.C Zakaria in [20] had formulated a derived spasticity Symptoms-oriented model based on the MAS tool in order to develop new principles of variable stiffness actuation in their system. However, the model only focused on MAS 0,1 and 1+ due to lack of subjects' parameters extracted.

Classifier is an approach to quantify the spasticity level of the muscle. The interaction between the features extracted, as input dataset and the structure of the classifier itself could also impact the performance of classification. Some combination of features may perform better than the others in term of accuracy and some may result in lower variance. [21] reported comparison between various feature selection algorithms for choosing an optimal feature set for land use classification based on SAR satellite images using different texture models. In addition, [22] compare the performance of Linear Discriminant Analysis, Linear Support Vector Machine and nearest neighbor classifiers with ten feature selection when training sample sizes are limited and the number of features is huge. The best result based on the LDA and comparisons of different feature combinations were not discussed in details. The algorithm discussed useful in order to determine the optimal accuracy based on the classifier models and the choice of the features numbers.

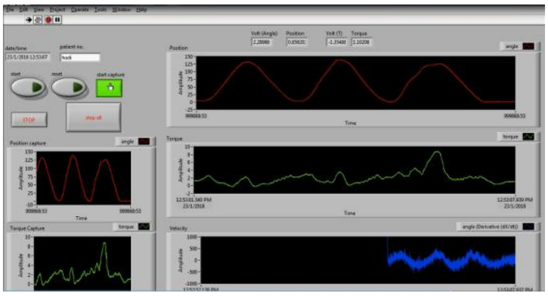
This paper is presented as follows. In section II, the subject selection and system configuration is discussed. In section III, the data pre-processing and analysis will be elaborated. The subsequence section presented and discussed on the experimental results.

2. Subject Selection and System Configuration

Data from twenty-five subjects were collected from International Islamic University Malaysia Medical Centre (IIUMMC) and Physical Rehabilitation Centre of Kulliyyah of Allied Health Science, IIUM, after getting ethical clearance from IIUM Research Ethics Committee. The selection of subjects is based on criteria that they have abnormality in motor control with hemiparesis condition due to cerebral palsy, stroke and traumatic injury. The subjects are within the age of 18 years and above and have given full consent before their data been collected.

A 1-DOF platform was designed to invoke signal from the subjects when the assessment of muscle spasticity was conducted. The system is equipped with a custom-designed torque sensor to measure the impedance dynamics around the joint elbow involving (name of the muscle) muscles. A single turn potentiometer is used to measure the flexion angle at the elbow joint. The remaining part of the system is composed of arm plate, a lever to orient the arm plate, and a laptop with Labview software connected to data acquisition card (NI DAQ card USB-6211). A more detail description of the system can be found in [23]. Before the measurement of spasticity was conducted using the platform, the level of muscle spasticity for each subject was first accessed by therapist using manual method which is based on the MAS tool. Under the supervision of the therapist, the subject was then asked to place his arm on the platform. The armed is flexed around the elbow joint in passive motion using the lever as shown in Fig 1(a). The idea here is to simulate the action done in manual assessment by the therapist while recording the necessary data. In order to monitor and record the measured data from the subjects, a dedicated graphical user interface (GUI) was developed in NI LabVIEW as shown in Fig.1 (b). For every subject, on top of their identification and profile, the data recorded are composed of torque signal, position signal and velocity of the arm throughout the full functional range of motion (ROM). The assessment by the therapist is repeated for three times and three times using the platform. The system and procedure conducted is able to record more consistent information that is necessary to assess the spasticity more objectively. The correlation between the position of the limb and torque generated due to muscle spasticity is analyzed and classified to get to the muscle spasticity level based on MAS tool.

(a)



(b)

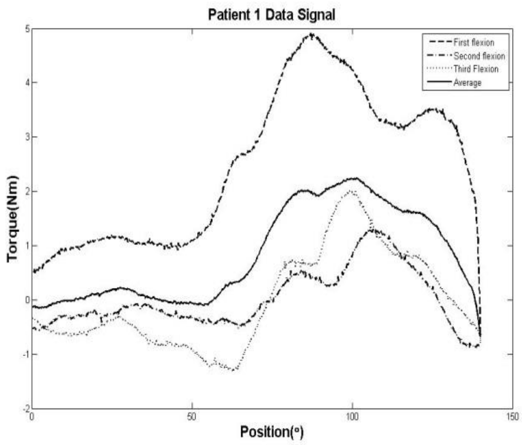
Fig. 1 - (a) Data collection procedure using Automatic Muscle Spasticity Assessment System (AMSAS) (b) Graphical User Interface of data acquisition

3. Data Pre-processing and Analysis

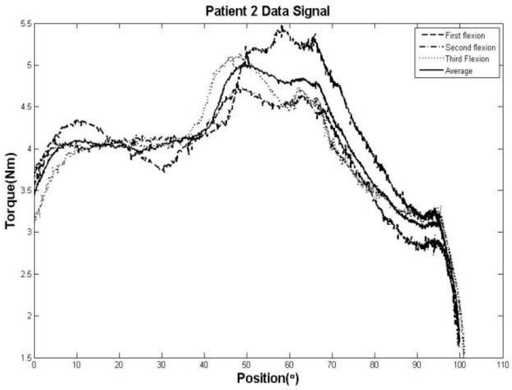
The algorithm in extracting the features from the recorded data consists of two stages namely signal preprocessing and feature extraction stages. All data extracted were the tabulated to form a dataset. In this research work, the twenty-five data samples are recorded to train the classifier. Raw data is made up of flexion movement repeated three times. One set of data signal is transform to be one signal by averaging them. One-way ANOVA test was adopted to eliminate dependent and redundant features using feature significant measurement.

Fig 2(a) and (b) show the example of the signal recorded and the average of them. The plot shows the relation between the joint torque and the flexion angle from 0 degree to 99 degree of arm flexion for patient 1 and 0 degree to 140 degree of arm flexion for patient 2.

The signal analysis was done by analyzing the torque-angle signal. The seven features extracted are total work done for first half of region (TWD1), total work done for second half of region (TWD2), difference between total work done for first half and second half of region (TWDD), catch torque (T_c), catch position (P_c), stiffness of pre-catch (K_{pre}) and stiffness of post-catch (K_{post}). The governing equation for each feature extracted is as follows.



(a)



(b)

Fig. 2 - (a) Patient 1 raw signal (b) Patient 2 raw signal

$$TWD1 = \int_{i=1}^{L/2} f(x)\,dx \quad (1)$$

$$TWD2 = \int_{i=L/2}^{L} f(x)\,dx \quad (2)$$

$$TWDD = \int_{i=1}^{L/2} f(x)\,dx - \int_{i=L/2}^{L} f(x)\,dx \quad (3)$$

$$Tc = max(y) \quad (4)$$

$$Pc = x(Tc) \quad (5)$$

$$K_{pre} = \sum_{i=1}^{x(Tc)} (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=1}^{x(Tc)} (x_i - \bar{x})^2 \quad (6)$$

$$K_{post} = \sum_{i=x(Tc)}^{L} (x_i - \bar{x})(y_i - \bar{y}) / \sum_{i=x(Tc)}^{L} (x_i - \bar{x})^2 \quad (7)$$

Equation (1) is a TWD1 is a measure of area under curve for first half region where f(x) is a function of the signal and L denotes length of the signal while (2) is represents TWD2 which calculates area under curve for second half region where the symbols has same meaning as TWD1. The difference value between area under curve for first and second half region is expressed in (3). T_c and P_c indicates torque and position respectively during catch happened that can be found as global maxima of the signal which can be defined as in (4) and (5). Equation (6) and (7) was a stiffness that can be measured from slope of regression line right before and right after catch happened accordingly.

We are using MAS as a referral tool which consists of more than two groups. One-way ANOVA test was selected as the most suitable statistical test technique. The features were tested by the one-way ANOVA test in order to test whether there is any significant difference in mean value among the groups.

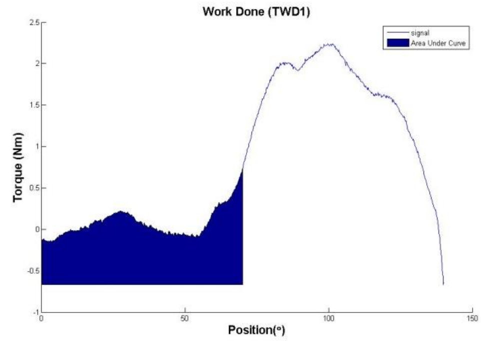
The ANOVA test was done per feature to test the significance of the feature statistically. Results for one-way ANOVA test of the dataset are tabulated in Table 1.

Table 1 - One-way ANOVA test results

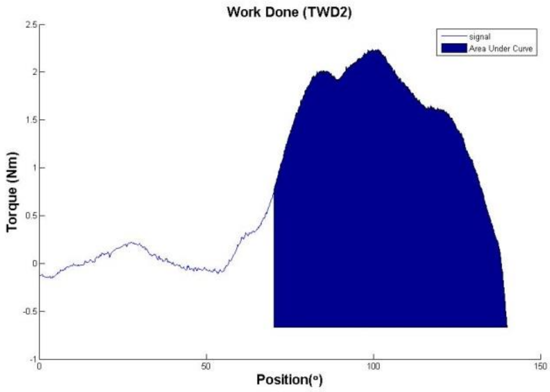
Features	p-values
TWD1	0.002
TWD2	0.004
TWDD	0.117
T_c	0.085
P_c	0.000
Stiffness of pre-catch	0.133
Stiffness of post-catch	0.033

Hence, the p-value of TWD for first half region, TWD for second half region, Difference between TWD of first and second half of region, catch torque, catch position, stiffness of pre-catch and stiffness of post-catch are 0.002, 0.004, 0.117,0.085, 0.000, 0.133 and 0.003 respectively. The rejection value was set at $p < 0.05$. The p-value is determined to correlate a significant difference in dependent variables. In ANOVA test, the null hypothesis is the mean is the same of all groups. As for TWD for first half of region, TWD for second half of region, catch position and stiffness of post-catch have p value less than 0.05, the null hypothesis has been successfully rejected. Combination of these four optimum features was used to train classifier models in order to classify the level of MAS.

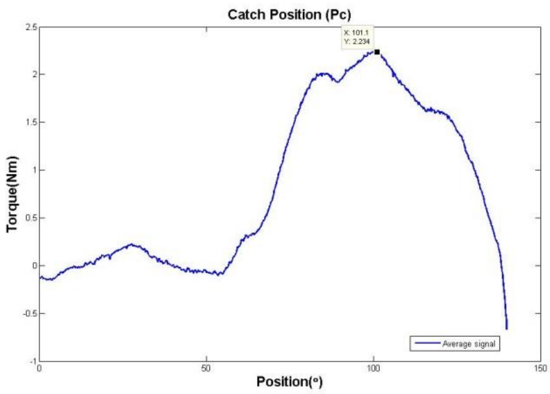
Fig.3 (a)-(e) pictures the selected features which are TWD1, TWD2, P_c and K_{post} respectively. The first and second half of region is obtained by dividing the full range of motion by two. Area under curve was then calculated based on each division that assigned as TWD1 and TWD2. The third feature selected is position when catch happened by determine the catch as maximum value of torque signal. Last feature is slope of regression line that measured right after catch occurred.



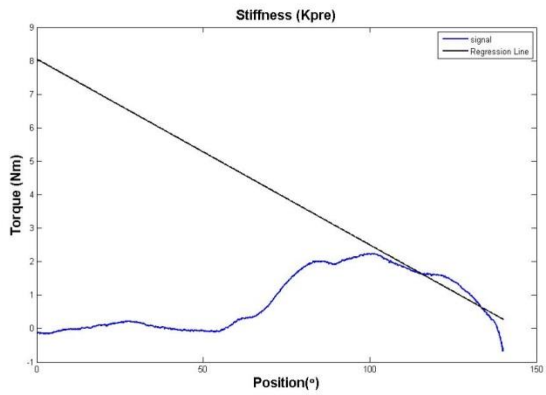
(a)



(b)



(c)



(d)

Fig. 3 - Selected features extraction for torque-angle signal (a) Total Work Done for first half of region (b) Total Work Done for second half of region (c) Catch position (d) Post-catch of stiffness

4. Experimental Result

In this study, twenty-five subjects with different level of spasticity are distributed as follows; 7 subjects from MAS 0, 10 subjects from MAS 1 and 8 subjects from MAS 2 as shown in Fig.4.

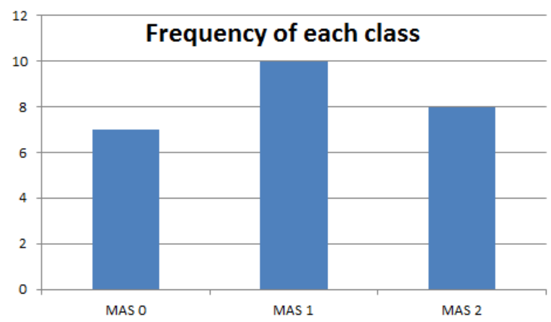


Fig. 4 - Number of samples within classes

Rule of thumb in balancing the number of samples for each group is the differences between higher and lower number of sample in group is not more than 2.0. In this case, the imbalance number of samples between classes is 1.5 which is applicable for the classification later.

The input dataset is made up of four features extracted from twenty-five subjects and saved in a four by twenty-five matrix. The features are listed in the Table 2.

Table 2 - Selected Features Extraction

Subjects	Feature 1/TWD1 (Nm.˚)	Feature 2/TWD2 (Nm.˚)	Feature 3/P_c (˚)	Feature 4/K_{pre} (Nm/˚)
1	110.6108	97.7919	59.6824	-0.0351
2	369.8279	173.3738	15.4844	-0.0824
3	26.0161	-22.213	44.5336	-0.0417
4	79.1103	288.1627	129.3192	-0.6728
5	33.4506	98.6089	138.8485	-0.8519
6	6.801	136.809	142.8394	0.1143
7	-29.3059	108.5497	103.7096	-0.0482
8	240.0738	473.1947	79.929	-0.0603
9	119.3591	97.8851	31.3802	-0.0289
10	210.2417	294.6903	75.8106	-0.0333

11	83.4588	103.5488	138.286	-0.6967
12	70.2287	168.4349	146.8171	-0.6285
13	34.6645	12.9563	45.5734	-0.0163
14	56.0517	23.7341	5.7081	-0.0166
15	106.0344	80.301	32.6709	-0.0284
16	109.3725	58.6218	33.1303	-0.0236
17	53.3272	34.1344	110.6174	-0.2595
18	112.4754	42.9765	110.3775	-0.2627
19	157.474	93.9323	7.323	-0.0185
20	207.9675	220.825	56.4229	-0.0478
21	132.1388	113.2256	59.6483	-0.0149
22	136.7498	107.8595	22.1249	-0.0094
23	65.45	32.3949	19.5009	-0.0177
24	71.277	30.7235	24.8271	-0.0158
25	66.2247	58.1338	34.2117	-0.0071

By using MATLAB software, the dataset was tested for classification and the results are shown in Table 3. The table shows the comparison of the accuracy of Linear Support Machine (Linear SVM), Linear Discriminant and Weight K-Nearest Neighbour (Weight KNN) classifier models and Linear SVM achieved the optimum performance. The classification process is performed using a standard toolbox to test the accuracy of the classifiers. Cross-validation of five folds is used to protects against over fitting by partitioning the data set into folds and estimating accuracy on each fold.

Table 3 - Performance of different classifiers in term of accuracy

Classifier	Accuracy
Linear SVM	84%
Linear Discriminant	80%
Weight KNN	76%

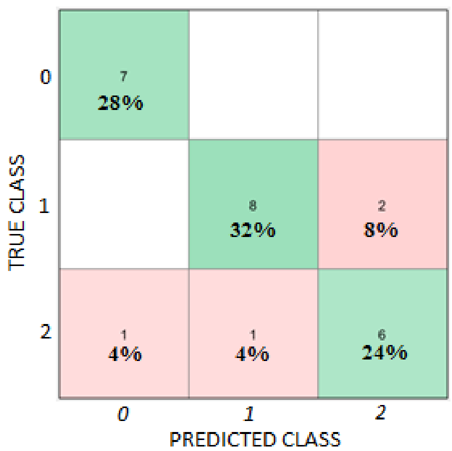


Fig. 5 - Confusion matrix for SVM classifier

Fig. 5 shows the confusion matrix that is often used to describe the performance of a classification model. The row and the column of this table represent the predicted and actual class respectively while class 0, 1 and 2 depicts of the MAS level 0, 1 and 2 accordingly. Overall accuracy of the linear SVM classifier is 84% which is a summation of true positive (TP) of each class divided by the total number of subjects in percentage form. 16% of the data were misclassified with 8% of class 1 were misclassified as class 2, 4% of class 2 were misclassified as class 0 and 4% of class 2 were misclassified as class 1. It is shown by confusion matrix that comparing among classes, class 1 obtained the highest precision of 88.9%, followed by class 0 (87.5%), and class 2 (75.0%).

5. Conclusions

The work reported in this paper has shown strong correlation between the four features namely TWD for the first half of region, TWD for the second half of region, catch position and stiffness of post-catch to the MAS level. This is indicated from the result of Linear SVM classifier. The idea purposely is meant for introducing a more objective and quantitative assessment on the level of muscle spasticity based on MAS assessment tool. For future study, more datasets will be collected in order to have a more generalize classification result.

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