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Motor recovery monitoring in post acute stroke patients using wireless accelerometer and cross-correlation

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***Abstract*— Stroke is a major reason for physical immobility and death. For effective treatment of stroke, early diagnosis and aggressive medication in the form of thrombolytic drugs is shown to be essential. In order to provide proper care, the patient should be kept under continuous monitoring during the first few hours after subjecting thrombolytic drugs and based on the response of the patient to the medication, line of treatment should be changed. In our previous work [1], we have shown the proof of principle by monitoring the motor activity of the stroke patient using accelerometer fitted on patient's arms. Based on preliminary analysis, we proposed methods using resultant acceleration signal and showed its effectiveness in predicting National Institute of Health Stroke Scale (NIHSS) stroke index. In this paper, novel technique based on cross-correlation of accelerometer values along different axes is developed for predicting the NIHSS index. An overall increase in prediction accuracy by over 7% compared to the earlier method is obtained. A multi-class support vector machine (SVM) classifier for cross correlation features is also designed and an overall prediction accuracy of 93% is achieved.**

I. BACKGROUND

Stroke is the rapid loss of brain function due to disturbance in the blood supply to the brain caused by blockage (thrombosis or arterial embolism) of one or multiple arteries. This causes brain cells to die due to lack of oxygen. Stroke is a major cause of morbidity and mortality worldwide. In Australia alone, there are annual incidents of 48,000 new strokes and the risk of death is 25 to 30% [2]. Of those who survive, majority of them become disabled for the rest of their life. Thrombolytic drugs are a category of drugs used to dissolve blood clots. A 24 hour monitoring and regular examination of patient by a stroke neurologist is required while using thrombolytic agents for acute stroke patients, as there are dangerous mimics of stroke and wrong diagnosis by a non-specialist can significantly affect the patients condition. This translates to missed treatment opportunities in decreasing the morbidity and mortality associated with acute stroke [3]. Patients who do not show early motor recovery can benefit from more advanced and aggressive treatment. In practice this monitoring is being done manually, which is time consuming and suffers from inter-personal bias. Hence, there is a need for continuous monitoring of post-thrombolytic patients.

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Recent advances in low power integrated circuits with enhanced sensing capabilities have made it possible to use these type of devices for patient management applications [4]. This has also become one of the key area of research in biomedical engineering, where a wearable Wireless Body Area Network (WBAN) provides us the opportunity of continuous monitoring of patient's physiological condition [5] and help in making better clinical decisions. Bonato emphasized on the impact of technological advances in the area of sensors and sensor networks on the area of biomedical engineering in his editorial overview about wearable systems in 2003 [6].

The National Institutes of Health Stroke Scale (NIHSS) [7] is a tool used by stroke neurologists to objectively quantify the impairment caused by stroke. It provides a numerical measure of the severity of the stroke. It is used as a clinical assessment tool to determine severity of the stroke, appropriate treatment line and predicting patient outcome. The NIHSS is composed of 11 distinct items to access effect of stroke. Each item scores a specific ability between 0 and 4, where, a score of 0 typically indicates normal function, while a higher score is indicative of some level of impairment. Out of these 11 conditions, we are focused on motor activity score. Table I defines the various scale provided for motor activity based on movement analysis.

TABLE I: NIHSS motor activity analysis scale

Scale	Status	Description
0	No arm drift	The arm remains in the initial position for the full 10 seconds.
1	Drift	The arm drifts to an intermediate position prior to the end of the full 10 seconds, but not at any point relies on a support.
2	Limited effort against gravity	The arm is able to obtain the starting position, but drifts down from the initial position to a physical support prior to the end of the 10 seconds.
3	No effort against gravity	The arm falls immediately after being helped to the initial position, however the patient is able to move the arm in some form.
4	No movement	Patient has no ability to enact voluntary movement in this arm.

Major research in this area has been in the application of accelerometer in Wolf Motor Function Test (WMFT) [8], which is a post stroke assessment carried out after a few days of onset of stroke. It evaluates upper extremity performance in a time bound environment for chronic stroke patients. A wireless sensor network to replicate WMFT, which is being done by trained personnel is described in [9]. This shows excellent results for 15 tasks rated according to time and quality of motion. Similar system was developed in [10] for Functional Ability Scale (FAS) for stroke patients.

In contrast to most of the work described in literature, our work focuses on the the monitoring of stroke during the first 24 hours after the onset of stroke (hot period). In our previous work [1], three different methods (norm based index, signal magnitude area based index and average energy comparison based index) were proposed to calculate stroke index using overall resultant accelerometer signal. In this paper, a new method, cross-correlation between different acceleration axes is explored and a multi-class classifier using Support Vector Machines is designed for calculating stroke index. The proposed method is shown to provide better results using data collected from 15 patients and comparing it with the observed NIHSS scores of the stroke clinician.

II. METHOD

A new system for continuously monitoring motor activity of arms based on wireless accelerometer attached to the patient is reported. Briefly the procedure used for our analysis is as follows: The data is collected using a wireless sensor node attached to a 3-axis accelerometer. The data collected at a predetermined sampling rate is transmitted from both the arms to the base station. On the base station, the data is pre-processed using a basic high pass filter and the resultant activity in a 10 minute window is calculated. The activities of the two arms are compared and the stroke index is calculated.

A. Wireless Accelerometer Sensor Data Acquisition

Crossbow iMote2 is used as the sensor platform for collecting the acceleration data. It contains a three-axis accelerometer, which is mounted on each arm of the patient using an armband (Fig. 1) and the sensor readings are transferred wirelessly to an iMote2 base station. This enables the patient to move freely in a given perimeter. The sensitivity of the on board ST accelerometer is $\pm$2g.

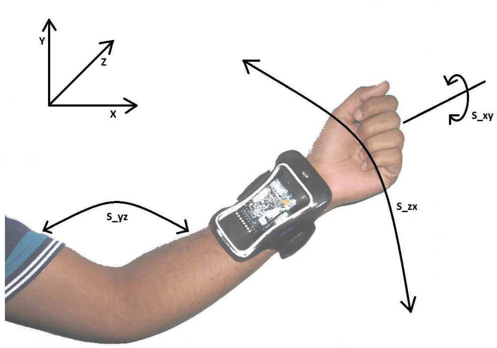


Fig. 1: Wrist band showing motions corresponding to S_{xy}, S_{yz} and S_{zx}.

B. Data collection and pre processing

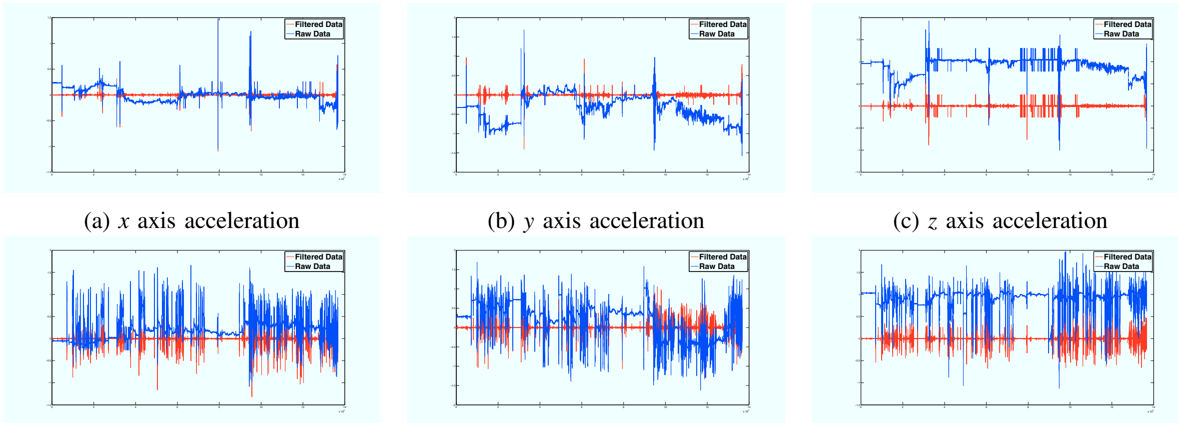
The data was collected in Melbourne Brain Center, Royal Melbourne Hospital, Australia. The research protocol was approved by Royal Melbourne Hospital Human Research Ethics Committee (2010.245). The experiment was carried out on 15 acute stroke patients (8 males, 7 females), having an average age of 69.8 ± 15 years. The summary of the patient data is given in Table II. The accelerometer data was collected for the first four hours after administering thrombolytic drugs and another one hour after 24 hours. An expert neurologist records the observed NIHSS motor scores and the observed NIHSS overall score at the time of onset (0^{th} hour), 1^{st} hour, 2^{nd} hour, 3^{rd} hour and at 24 hours. In total, six acceleration values were received at any given instant (2 arms $\times$ 3 axis). This signal was filtered using a Butterworth 6th order high-pass filter with 1 Hz as cutoff frequency. The original raw signal and the filtered output is shown in Fig. 2.

TABLE II: Summary of the patient data collected

Patient details						Data collected	
Sl. No.	Age	Sex	Diabetic	Smoking	Hyper-tensive	Stage 1 (Mins)	Stage 2 (Mins)
1	87	Male	No	No	Yes	184	61
2	59	Male	No	No	Yes	274	69
4	44	Male	Yes	Yes	No	130	27
5	47	Male	No	No	No	239	83
8	61	Male	No	No	Yes	249	68
9	81	Female	Yes	No	Yes	246	72
10	88	Female	No	No	Yes	243	×
12	78	Female	Yes	No	Yes	246	90
13	52	Female	No	No	No	260	69
15	59	Female	No	Yes	No	251	66
16	81	Female	No	No	Yes	245	68
17	85	Female	No	No	No	245	70
18	76	Male	No	No	Yes	244	60
19	81	Male	No	No	No	253	75
20	69	Male	No	No	Yes	253	77

III. SIGNAL ANALYSIS AND CALCULATION OF STROKE INDEX

For the automated prediction of NIHSS stroke index, the relative motion of two arms is the signal of interest as stroke reduces the mobility of one side of the body. The motion of the two arms would be significantly different for the patient suffering from stroke and this difference is directly proportional to the severity of the stroke. From the relative movements of the arms, a score equivalent to NIHSS score is derived. As the assessment of the NIHSS score by the stroke clinician is being carried out every hour and as it takes approximately 10 minutes to complete the assessment, a 10 minute window is considered for the calculation of motor activity using the proposed system. In our previous work [1], we have used three indices namely (a) norm based index, (b) signal magnitude area (SMA) based index and (c) average energy comparison based index for calculating NIHSS score and found that average energy based index correlates best with the observed index. The focus of this paper is to arrive at better stroke scores than average energy based methods.



(a) x axis acceleration (b) y axis acceleration (c) z axis acceleration

(d) x axis acceleration (e) y axis acceleration (f) z axis acceleration

Fig. 2: Raw (blue) and filtered (red) accelerometer values of right (bottom row) and left arm (top row) - left arm affected patient

A. *Cross correlation based index*

It is observed that the stroke patients are not comfortable performing rotatory motion from their stroke affected arm, for example, rotating a door knob or rotating their arm around elbow or shoulder joint. This forms the basic motivation of the presented work and it is based on finding the cross correlation between acceleration values along x, y and z axis. Fig. 1 shows corresponding hand movements associated with different cross correlation coefficients.

Initially, a hamming window of acceleration along three axes of 2 second duration with 50% overlap (1 second) is considered. Then, correlation of x and y (eq. 1), y and z (eq. 2), z and x (eq. 3) signal windows is calculated to obtain three correlation *vs.* time signals. Next, a 10 minute interval is chosen and the cumulative integral of correlated signals is calculated to obtain velocity signal. The area under the velocity signal for 10 minute duration gives us R_{xy}, L_{xy}, R_{yz}, L_{yz}, R_{zx} and L_{zx}. Cross correlation based index is given by following equations:

$$S_{xy} = \frac{180}{\pi} tan^{-1}\left(\frac{R_{xy}}{L_{xy}}\right) \tag{1}$$

$$S_{yz} = \frac{180}{\pi} tan^{-1}\left(\frac{R_{yz}}{L_{yz}}\right) \tag{2}$$

$$S_{zx} = \frac{180}{\pi} tan^{-1}\left(\frac{R_{zx}}{L_{zx}}\right) \tag{3}$$

Values of S_{xy}, S_{yz} and S_{zx}, near to 45° represent less severity whereas away from 45° and close to 0° or 90° represent more severity of stroke, with close to 0° represent right arm affected and close to 90° represent left arm affected.

IV. Conversion to stroke index

S_{xy}, S_{yz} and S_{zx} are the calculated correlation values and they should be converted to equivalent scores ranging between 1 and 3 similar to NIHSS scores. This can be achieved by calculating 2 thresholds - $T1$ and $T2$. For different values of $T1$ and $T2$ across a meaningful range, the prediction accuracies are calculated. Fig. 3 shows percent accuracy of assigned stroke index (S_{xy}) as a function of $T1$ and $T2$. A Comparison of scores obtained using the threshold scheme and the NIHSS score given by a experienced doctor shows accuracy of the range of 80% - 90%. From Fig. 3, highest accuracy has been achieved for $T1 = 30°$ and $T2 = 40°$, which are used as thresholds.

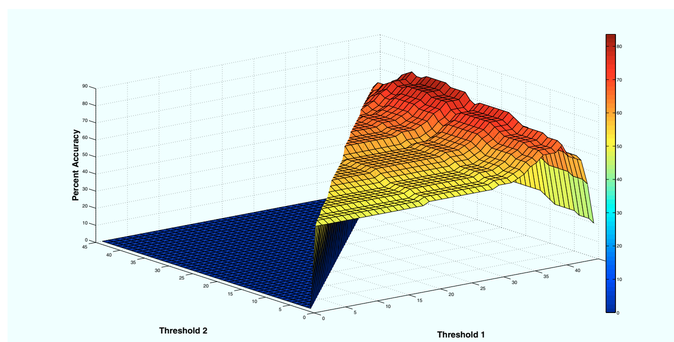


Fig. 3: Percent accuracy for S_{xy} as a function of Threshold 1 (T1) & Threshold 2 (T2)

A. *SVM classification*

A support vector machine classifier is designed to improve the calculations using S_{xy}, S_{yz} and S_{zx} as features. The data-set was randomly divided into training (80%) and testing (20%) groups. A radial basis function with gamma value of 0.5 and cost function (C) of 1 was used to train the SVM. The SVM analysis was carried out using LIBSVM toolkit [11].

V. Results and Discussion

Table III shows the result obtained using correlation based index S_{xy}, S_{yz} and S_{zx} after choosing suitable threshold. The mismatches are shown in bold. Stroke affected arm is predicted on the basis of continuous arm activity. We keep a continuous record of S_{xy}, S_{yz} and S_{zx} for each patient and predict the stroke affected arm on the basis of average of correlation

TABLE III: Results based on correlation based index

	Observed						S_{xy} based index						S_{yz} based index						S_{zx} based index					
Sl. No.	Affected Arm	T0	T1	T2	T3	T24	Affected Arm	T0	T1	T2	T3	T24	Affected Arm	T0	T1	T2	T3	T24	Affected Arm	T0	T1	T2	T3	T24
1	Left	1	1	0	×	0	Left	1	1	**2**	×	**1**	Left	1	1	**2**	×	**1**	Left	1	1	**2**	×	**1**
2	Left	1	1	1	×	1	Left	1	1	1	×	1	Left	1	1	1	×	1	Left	1	1	1	×	1
4	Left	3	3	3	×	3	Left	3	3	3	×	3	Left	3	3	3	×	3	Left	3	3	3	×	3
5	Left	2	2	2	×	2	Left	2	2	2	×	2	Left	2	2	2	×	2	Left	2	2	2	×	2
8	Right	1	1	1	×	1	Right	**3**	1	**3**	×	1	Right	**3**	1	**3**	×	1	Right	**3**	1	**3**	×	1
9	Left	3	3	3	3	3	Left	3	3	3	3	3	Left	3	3	3	3	3	Left	3	3	3	3	3
10	Right	2	2	2	2	×	Right	2	2	2	2	×	Right	**3**	2	2	2	×	Right	**3**	2	2	2	×
12	Left	1	1	1	1	1	Left	**2**	1	1	1	1	Left	1	1	1	1	**3**	Left	1	1	1	1	**3**
13	Left	3	3	3	3	3	Left	3	3	3	3	3	Left	3	3	3	3	3	Left	3	3	3	3	3
15	Right	3	3	3	3	3	Right	3	3	3	3	3	Right	3	3	3	3	3	Right	3	3	3	3	3
16	Right	1	1	1	1	1	Right	1	**3**	**3**	1	**3**	Right	1	**3**	**3**	**2**	**3**	Right	1	**3**	**3**	1	**3**
17	Left	3	3	3	3	3	Left	3	3	3	3	3	Left	3	3	3	3	3	Left	**2**	3	3	3	3
18	Right	3	3	3	3	3	Right	3	3	3	3	3	Right	3	3	3	3	3	Right	3	3	3	3	3
19	Right	3	3	3	3	3	Right	3	3	3	3	3	Right	3	3	3	3	3	Right	3	3	3	3	3
20	Left	2	2	2	2	1	Left	**1**	2	2	2	1	Left	2	2	**3**	2	1	Left	**1**	2	2	2	1
Accuracy							100%	86.96%					100%	84.06%					100%	84.06%				

based stroke index. As it is clear from Table III, all the three correlation indices are always successful in predicting the stroke affected arm. An accuracy of 88.96%, 84.06% and 84.06% was obtained using correlation between $x-y$, $y-z$ and $z-x$ respectively. The results are marginally higher than the average energy based method reported earlier [1]. Please note that × in Table III indicates data unavailability, caused either due to movement of patient outside the room or battery or communication error of iMote2, both of which lead to signal disruption.

The results using SVM is summarized in table IV. As it can be seen, the developed system has an overall classification accuracy of 90.03%. 9 out of 10 calculated indices are correct as compared to 8 out of 10 by previous methods [1].The main reason for this improvement is that the correlation features are representative of rotational movements carried out with elbow (Pronation-Supination (S_{xy}) and Flexion-Extension (S_{yz})) and shoulder (Abduction-Adduction (S_{zx})), which are more sophisticated features than previously used movement based measures. Also out of these three, Pronation-Supination of elbow (rotatory motion) is most difficult, hence highest accuracy for S_{xy}.

TABLE IV: Support vector machine recognition results

	S_{xy}	S_{yz}	S_{zx}	Concatenated features
Accuracy	92.31%	88.52%	87.64%	90.03%

VI. Conclusion

Continuous monitoring of motor activity is required for better management of stroke patients during the hot period. It has been shown that it can be effectively achieved using wireless accelerometer sensor attached to both arms of the patient. It provides doctors with more information about the recovery pattern of the patient and help to alter the treatment line or to make it more aggressive, in case patient does not respond to treatment. In this paper, a correlation based method is shown to be able to predict the arm motor activity index with an accuracy of around 87%, which is higher then what has been reported in literature [1]. Furthermore, the developed system is tested on 15 patients using support vector machine classifier and an overall accuracy of 90% is achieved.

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