A Pilot Study on the use of Accelerometer Sensors for Monitoring Post Acute Stroke Patients

Jayavardhana Gubbi[1], Dheeraj Kumar[1], Aravinda S. Rao[1], Bernard Yan[2] and Marimuthu Palaniswami[1]

***Abstract*— The high incidence of stroke has raised a major concern among health professionals in recent years. Concerted efforts from medical and engineering communities are being exercised to tackle the problem at its early stage. In this direction, a pilot study to analyze and detect the affected arm of the stroke patient based on hand movements is presented. The premise is that the correlation of magnitude of the activities of the two arms vary significantly for stroke patients from controls. Further, the cross-correlation of right and left arms for three axes are differentiable for patients and controls. A total of 22 subjects (15 patients and 7 controls) were included in this study. An overall accuracy of 95.45% was obtained with sensitivity of 1 and specificity of 0.86 using correlation based method.**

I. Background

Stroke is a major cause of morbidity and mortality in Australia. There is an annual incidence of 48,000 new strokes and the risk of death is 25 to 30% [1]. Acute stroke is caused by a blockage of one of the arteries in the brain resulting in interrupted blood supply. Brain cells deprived of oxygenated blood die rapidly unless blood supply is restored. One of the milestones of modern management of acute stroke is the administration of a thrombolytic (clot-busting medication) in order to unblock the blocked artery [2]. It has been shown in international multi-center studies that patients who receive thrombolytic treatment have better clinical outcomes [2].

The delivery of thrombolytic agents to acute stroke patients require round-the-clock availability of a stroke neurologist to clinically assess the patient. Lack of continuous monitoring translates to missed treatment opportunities in decreasing the morbidity and mortality associated with acute stroke [3]. In addition, the monitoring of motor recovery is critical in the management of stroke patients. Patients who do not exhibit early motor recovery post thrombolysis may benefit from more aggressive treatment. It follows that a portable wireless motion detector would signify a major advance in patient management.

Assessment of the effect of thrombolysis is the core motivation to develop an automated monitoring tool for the assessment of post-stroke individuals' during the 'hot' period after stroke (while the patient is still in the hospital). The National Institute of Health Stroke Scale (NIHSS) is an international initiative to systematically assess stroke and provide a quantitative measure of all stroke related neurological deficit. The NIHSS scale is a 17-item neurological examination to evaluate the levels of consciousness, language, neglect, visual-field loss, extra ocular movement, motor strength, ataxia, dysarthria, and sensory loss. In our work, we are interested in motor strength assessment which is defined as in [4].

Recent technological advances in low-power integrated circuits and wireless communications have made available efficient, low-cost, low-power miniature devices for use in wireless sensing applications. Automated clinical decision making is one of the key research areas in biomedical engineering. A wearable body area network is a viable solution for unhindered monitoring of patient condition [5]. Wireless Body Area Network (WBAN) is one of the key emerging technologies for unobtrusive health monitoring [6]. In order to monitor stroke patients, low-cost hardware platform is necessary. Most major efforts have been in activity monitoring as a fitness aid using smart phones as the base platform. A good summary of the work using these sensors in activity monitoring can be found in [7] including a comparison of commercially available systems. Bouten et. al. [8] developed a basic activity monitoring system using a tri-axis accelerometer and proved the correlation of energy expenditure with the processed accelerometer sensor signal was high on healthy subjects. Often, the areas of focus have been in rehabilitation, which is a reactive response rather than a proactive response. Another area of research in post stroke assessment using accelerometer sensors is the Wolf Motor Function Test (WMFT) [9]. WMFT is a post stroke assessment procedure carried out within days after the onset of stroke. Parnandi et. al. [10], [9] have developed a wireless accelerometer system which replicates WMFT conducted by trained personnel. The assessment is based on 15 tasks rated according to time and quality of motion. They compare the scores obtained from their proposed method with therapist's scores and report an average error of 0.0667, which is excellent. Once again, researchers [10] are in post stroke assessment spanning days after the onset of stroke and falls under the post stroke rehabilitation category. However, the use of the accelerometer in the 'hot period' of stroke is virtually absent in the literature and this is the first attempt to monitor motor activity.

In this project, we propose to develop wireless accelerometer platform in order to monitor the motor recovery in acute-stroke patients. In our previous work [11], we have shown that the accelerometer data obtained from these sensors can be used for monitoring patients. However, the algorithm fails

[1]J. Gubbi, D. Kumar, A. S. Rao and M. Palaniswami are with the Department of Electrical and Electronic Engineering, The University of Melbourne, Parkville, VIC - 3010, Australia. Email:{jgl, palani}@unimelb.edu.au, {dheerajk, aravinda}@student.unimelb.edu.au

[2]B. Yan is with the Melbourne Brain Center, Royal Melbourne Hospital, Dept of Medicine, The University of Melbourne, Parkville, VIC - 3050, Australia. Email: Bernard.Yan@mh.org.au

to differentiate between patients and control. Hence, there is a need to create an efficient algorithm at the first stage to differentiate between patients and controls and then apply stroke index calculation algorithm at the second stage. In this paper, we present a new algorithm for classifying patients and control from the collected accelerometer data.

II. METHOD

A new system for continuously monitoring motor activity of arms based on wireless accelerometer attached to the patient is developed. A wireless sensor is attached to both the arms of the patient. These sensors transmit the accelerometer information to a base station, which is a sensor node capable to receive the data transmitted from the wireless sensors. The base station is attached to the computer via USB and it receives the activity data at 50Hz. The received data consists of time stamped x, y, and z axes data. The data is then pushed into a MySQL database server for further processing and analysis.

A. A wearable sensor platform

In this pilot study, off-the-shelf iMote2 platform is used. The Imote2.NET can be programmed in Microsoft's Visual Studio using C#. It is built around the low-power PXA271 XScale CPU. Furthermore, the system integrates an 802.15.4 compliant radio operating at 2.4 GHz bandwidth. The advantage of this platform is its modularity to interface sensors to its existing basic sensor board (ITS400). The ITS400 consists of a three-axis accelerometer ($\pm$2g) and a 12-bit, four-channel Analog to Digital (A/D) converter.

B. Data collection Protocol and pre processing

Human Research Ethics Committee approval has been obtained from Royal Melbourne Hospital Human Research Ethics Committee (HREC 2010.245). The data is collected at Melbourne Brain Center. Each data packet included a time stamp and the tri-axis accelerations. A typical plot for a control and patient are shown in Fig. 1. Careful observations

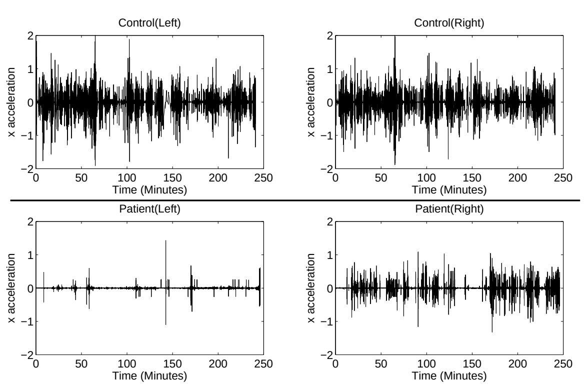

Fig. 1. Left hand and right hand x-axis acceleration values for a control (top) and a patient (bottom).

of the difference in the muscular activity between the hands indicate reduced activity in the patient (2^{nd} row in Fig. 1). In total, 22 subjects were used to develop the method that included 15 acute stroke patients (8 males, 7 females) and 7 controls (2 males, 5 females). The average age of patients is 69.8 ± 15 years and the average age of controls is 60 ± 16 years. The summary of the patient data is given in Table I. This signal was filtered using a Butterworth 6^{th} order high-pass filter with 1 Hz as cutoff frequency.

TABLE I

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 CLASSIFICATION

Based on the preliminary time and frequency domain analysis of the data collected [11], two new methods are developed for patient/control classification: (a) using cross-correlation of acceleration magnitude between arms over 10 minute window, and (b) using the difference in cross-correlation of the 3 axis of each arm. The methods are explained below:

A. Cross-correlation of magnitude

The hypothesis of this stage is that the correlation of the activities of the two arms varies between patients and controls. In order to prove our hypothesis, the resultant of the accelerometer data is divided into 10 minute windows. For each window, a 1024-point FFT is taken and the power is calculated. The maximum power that represents the highest activity for any frequency (arm movement) is recorded. This results in a time series of power readings for each arm. The correlation coefficient is then calculated between the left and the right arm, which reflects the difference in arm movements. For window size, 1 minute, 5 minutes and 10 minutes were tested before settling with a 10 minute window. A correlation coefficient threshold of 0.7 was empirically chosen for differentiating patients from controls.

B. Cross-correlation between the 3 axis

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, whereas healthy persons can do them with ease. This forms the basic motivation of the developed method and it is based on finding the cross-correlation between acceleration values along x, y and z axes. We consider a 10 minute window as discussed earlier and the following procedure is used: We first take 2 second Hamming window with 50% overlap. Then, correlation of 3 pairs of axes - x and y (eq. 1), y and z (eq. 2), z and x (eq. 3) are calculated to obtain three correlations. The cumulative integral of correlated signals within 10 minutes 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}.

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

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

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

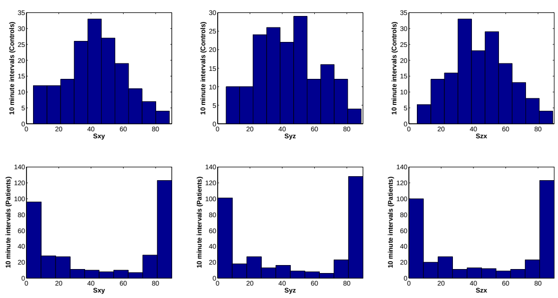

Fig. 2. Histogram of S_{xy}, S_{yz} and S_{zx} values for controls (top) and patients (bottom)

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 being affected and close to 90° represent left arm being affected. Fig. 2 shows the histogram of S_{xy}, S_{yz} and S_{zx} for controls (top) and patients (bottom) respectively. The histograms also reinforce our belief that value of correlations is close to 45° for controls and close to 0° or 90° for patients (based on the side affected by stroke). After obtaining the correlation values, a binary classification based on linear thresholding is performed. An individual is declared as control or patient based on rules presented in Table II.

TABLE II

RULES (THRESHOLDS) FOR PATIENT-CONTROL CLASSIFICATION

Condition	Decision
$45^\circ - TH_1 < S_{xy} < 45^\circ + TH_1$	Control
$(S_{xy} < 45^\circ - TH_1)$ OR $(S_{xy} > 45^\circ + TH_1)$	Patient
$45^\circ - TH_1 < S_{yz} < 45^\circ + TH_1$	Control
$(S_{yz} < 45^\circ - TH_1)$ OR $(S_{yz} > 45^\circ + TH_1)$	Patient
$45^\circ - TH_1 < S_{zx} < 45^\circ + TH_1$	Control
$(S_{zx} < 45^\circ - TH_1)$ OR $(S_{zx} > 45^\circ + TH_1)$	Patient

IV. RESULTS AND DISCUSSION

The development of diagnostic protocol for monitoring acute stroke, which involves programming the nodes, data collection, analysis and classification of patients and controls is presented. 22 subject data using wireless accelerometer sensor including 15 patients and 7 controls is collected. Table III shows the overall results of patient classification using the two proposed methods. An overall accuracy of 86.36% is obtained with sensitivity of 0.87 and specificity of 0.86 using cross-correlation of magnitudes between arms. Further, the second method is based on difference in correlation between 3 axes is proposed. As it can be seen from Table III, an accuracy of 95.45% is achieved with significant improvement in sensitivity (1) and specificity (0.86). In order to validate our results using the second method, ROC curve (refer Fig. 3) for S_{xy}, S_{yz} and S_{zx} are plotted and area under curve of 0.84, 0.85 and 0.82 respectively is obtained.

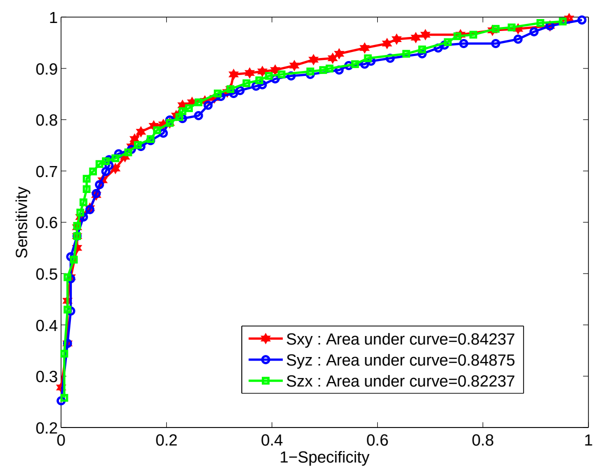

Fig. 3. ROC curve for S_{xy}, S_{yz} and S_{zx}

As the methods are implemented on low power nodes, use of non-linear classifiers like Support Vector Machines is deliberately avoided. It is important to note that the threshold values chosen in Table II will have significant effect on the classification. In order to justify this, accuracies obtained for different values of threshold is shown in Fig. 4. For more than 80% of the threshold values, the accuracy is over 90% demonstrating the robustness of the proposed linear classifier. The results in Table III are based on a threshold of 10° for S_{xy}, 9° for S_{yz} and 10° for S_{zx}.

V. CONCLUSION

Use of accelerometer sensors for monitoring activity has become one of the key research areas in biomedical research. In this paper, a new algorithm for classifying stroke patients and controls is proposed. There is significant different in arm activity between the stroke affected arm and the normal arm in spite of varying degrees of paralysis. This fact is used to develop two algorithms: using the cross-correlation of activity between arms (resulting in an accuracy of 86%) and

TABLE III

RESULTS OF PATIENT-CONTROL CLASSIFICATION FOR THE 2 PROPOSED METHODS. ERRORS ARE HIGHLIGHTED.

		Cross-correlation of magnitude		Cross-correlation between the 3 axis					
No.	Observed	Energy correlation	Predicted	Average (S_{xy})	Predicted	Average (S_{yz})	Predicted	Average (S_{zx})	Predicted
1	Patient	0.683295	Patient	34.07	Patient	28.96	Patient	34.78	Patient
2	Patient	0.637615	Patient	58.18	Patient	59.36	Patient	59.03	Patient
4	Patient	0.187034	Patient	8.92	Patient	8.80	Patient	9.32	Patient
5	Patient	0.444135	Patient	9.50	Patient	10.75	Patient	8.17	Patient
8	Patient	0.552598	Patient	79.53	Patient	80.77	Patient	80.71	Patient
9	Patient	-0.222172	Patient	7.91	Patient	8.06	Patient	8.28	Patient
10	Patient	0.344284	Patient	83.93	Patient	83.53	Patient	81.66	Patient
12	Patient	-0.199177	Patient	35.16	Patient	35.64	Patient	35.13	Patient
13	Patient	0.588152	Patient	8.93	Patient	11.28	Patient	12.47	Patient
15	Patient	-0.405482	Patient	84.47	Patient	84.31	Patient	83.95	Patient
16	Patient	-0.761099	**Control**	82.29	Patient	82.41	Patient	81.93	Patient
17	Patient	0.445221	Patient	11.80	Patient	10.94	Patient	10.78	Patient
18	Patient	NAN	Patient	87.12	Patient	87.71	Patient	86.79	Patient
19	Patient	-0.076763	Patient	81.17	Patient	84.37	Patient	83.63	Patient
20	Patient	0.934955	**Control**	7.68	Patient	8.00	Patient	8.41	Patient
22	Control	0.964547	Control	62.69	**Patient**	67.25	**Patient**	62.94	**Patient**
23	Control	0.836076	Control	35.15	Control	38.69	Control	37.28	Control
24	Control	0.84554	Control	42.84	Control	47.42	Control	45.60	Control
25	Control	1	Control	37.53	Control	36.77	Control	38.85	Control
26	Control	0.23073	**Patient**	45.18	Control	45.40	Control	48.32	Control
27	Control	0.926019	Control	37.95	Control	44.21	Control	42.54	Control
28	Control	0.956752	Control	37.25	Control	37.66	Control	35.53	Control
% Accuracy		86.36%		95.45%		95.45%		95.45%	
Sensitivity		0.87		1		1		1	
Specificity		0.86		0.86		0.86		0.86	

using cross-correlation of activity along three different axes of movement. An overall accuracy of 95.45% is obtained with sensitivity of 1 and specificity of 0.86 using correlation between 3 axes. This study is useful in detecting stroke patients non-invasively and further useful in continuous monitoring.

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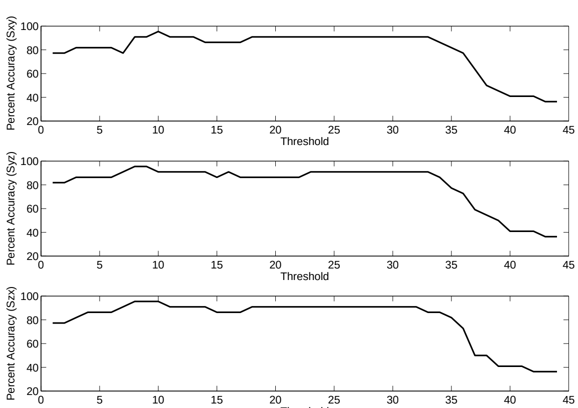

Fig. 4. Classification accuracy for S_{xy}, S_{yz} and S_{zx} as a function of Threshold (TH_1)

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