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Automatic Recognition of Postures and Activities in Stroke Patients

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Abstract— **Stroke is the leading cause of disability in the United States. It is estimated that 700,000 people in the United States will experience a stroke each year and that there are over 5 million Americans living with a stroke. In this paper we describe a novel methodology for automatic recognition of postures and activities in patients with stroke that may be used to provide behavioral enhancing feedback to patients with stroke as part of a rehabilitation program and potentially enhance rehabilitation outcomes. The recognition methodology is based on Support Vector classification of the sensor data provided by a wearable shoe-based device. The proposed methodology was validated in a case study involving an individual with a chronic stroke with impaired motor function of the affected lower extremity and impaired walking ability. The results suggest that recognition of postures and activities may be performed with very high accuracy.**

I. Introduction

STROKE is the leading cause of disability in the United States [1]. It is estimated that 700,000 people in the United States will experience a stroke each year and that there are over 5 million Americans living with a stroke [2]. Approximately one third of these individuals will be left with functional limitations as a result of their stroke [3]. Initially after stroke two thirds of individuals cannot walk or require assistance to walk. After three months one third of individuals who experience a stroke still require some form of assistance to walk or are not able to walk [3]. Many of those who do regain walking ability do no have sufficient locomotor capacity for independent mobility in the community.

Regaining the ability to walk is an important goal for individuals who have experienced a stroke and it is often a primary focus of the rehabilitation of these individuals. Individuals post-stroke who are independent walkers require less care and their level of disability is reduced as they are better able to participate in their societal roles. As walking ability is a primary goal of clients and focus of rehabilitation it is important that effective interventions are developed to improve walking ability in this population.

Current research suggests that rehabilitation strategies that are based on task oriented, intensive training are necessary to induce use dependent neurologic reorganization in order to enhance motor and functional recovery after stroke. Dean and colleagues [4] found that individuals with chronic stroke who participated in a task related lower extremity training program delivered in a circuit training class for 1 hour/day, 3 days a week for 4 weeks had a significantly greater improvement in locomotor capacity, as measured by gait speed and a 6 minute walk test, compared to a control group that received upper extremity training. The circuit training consisted of 10 lower extremity task oriented strength training and walking activities. The improvements in ambulation were maintained at a 2-month follow up. Yang and colleagues [5] had similar results using a 6 station task oriented lower extremity intervention delivered for ½ hour/day, 3 days a week for 4 weeks. These task oriented interventions were designed to increase the strength of the affected lower extremity in a functionally relevant way and to provide repetitive walking practice under various conditions.

Constraint induced movement therapy (CIMT) is another rehabilitation strategy that is effective for improving upper extremity motor function, activity and social participation in people with stroke. The CIMT intervention is based on three main elements: repetitive, task oriented training; adherence enhancing behavioral strategies; and restraining use of the less affected upper extremity [6]. Restraining the unaffected lower extremity is not practical for safety and functional reasons. The unaffected lower extremity is necessary for bipedal locomotion. Additionally, there is some indication that restraining the unaffected upper extremity makes only a small contribution in the overall outcome of CIMT [6,7]. Incorporating adherence enhancing behavioral strategies with task oriented, repetitive gait interventions is feasible, however it has not been reported in the literature.

We have developed a novel, shoe-based sensor that can be used as part of a comprehensive CIMT based intervention for the lower extremity in conjunction with task oriented interventions. The shoe based sensor will be able to monitor lower extremity activity, different postures and mobility tasks of an individual in their home and community. The information generated by the shoe sensor can provide feedback to the patient and therapist on real world mobility and affected lower extremity activity. Such information can also be incorporated into the CIMT program as part of the adherence enhancing behavioral strategies. The shoe based sensor has the added benefit in that the information it can gather in the patient's home and community (lower extremity activity, postural allocations, and walking activity) can be used as an outcome measure to assess the

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effectiveness of rehabilitation interventions.

The purpose of this paper is to report on the first steps in the development of this novel, shoe based sensor and its ability to monitor postural allocations and walking activity in a person with a chronic stroke.

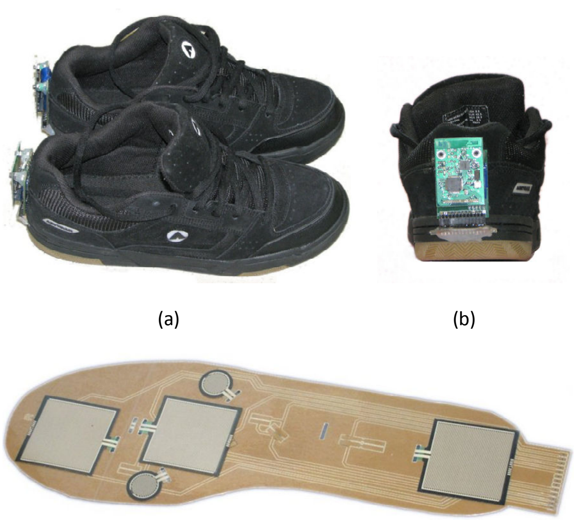
II. Methods

A. Wearable Sensors

The sensor data for this study were collected by a wearable sensor system embedded into shoes (Fig. 1). Each shoe incorporates five force-sensitive sensors embedded in a flexible insole and positioned under the critical points of contact: heel, metatarsal bones and the toe. Such positioning allows for differentiation of the most critical parts of the gait cycle such as heel strike, stance phase and toe-off. The information from the pressure sensors is supplemented by the data from a 3-dimensional accelerometer positioned on the back of the shoe. The goal of accelerometer is to detect orientation of the shoe in respect to gravity, to characterize the motion trajectory and to help characterize a specific posture or activity (for example, ambulation velocity).

Pressure and acceleration data were sampled at 25Hz and sent over a wireless link to the base computer. The wireless system used for data acquisition was based on Wireless Intelligent Sensor and Actuator Network (WISAN) [8] developed specifically for time-synchronous monitoring applications. Application of WISAN allowed for data sampling at exactly the same time from both shoes, thus avoiding potential complications that could be created in systems with varying time delay between sensors.

The battery, power switch and the WISAN board were installed at the back of the shoe as shown on Fig. 1(b). The sensor system is very lightweight and creates no interference with motion patterns in stroke patients. Collected sensor data were visualized and processed by using Matlab software.



(a) (b)

(c)

Fig. 1. Overall view of the shoe device (a); The back side view of a shoe including the accelerometer, battery and power switch (b); Pressure-sensitive insole (c).

(a) (b) (c)

Fig. 2. Examples of collected sitting postures: a) both legs on the ground b) crossed legs c) reaching forward.

(a) (b)

Fig. 3. Examples of other postures and activities: a) stand while reaching to the right b) walk.

B. Human Data Collection

Data collection was performed on a 66-year-old male subject who sustained a right cerebrovascular accident 18 months prior to data collection. The subject presented with left hemiparesis with resulting motor impairment of the left lower extremity (Fugl Meyer lower extremity motor score: 22/34). He used a cane and custom fit, articulated Ankle Foot Orthotic (AFO) to ambulate in the community, but only used the AFO in his home. His self-selected gait speed was 0.54 m/s. The study was approved by the Institutional Review Board at Clarkson University and informed consent was obtained from the subject.

The subject was asked to perform the following:

1. Sit (Fig. 2)
    a. Sit in an arbitrary comfortable posture
    b. Sit with both legs on the ground
    c. Sit with crossed legs
    d. Sit while reaching forward
    e. Sit with one foot on a knee
2. Stand (Fig. 3(a))
    a. Stand comfortably
    b. Stand while reaching forward
    c. Stand while reaching to the left
    d. Stand while reaching to the right
3. Walk (Fig. 3(b))
    a. Walk at a self-selected comfortable pace
    b. Walk as fast as possible
4. Descend a flight of stairs
5. Ascend a flight of stairs

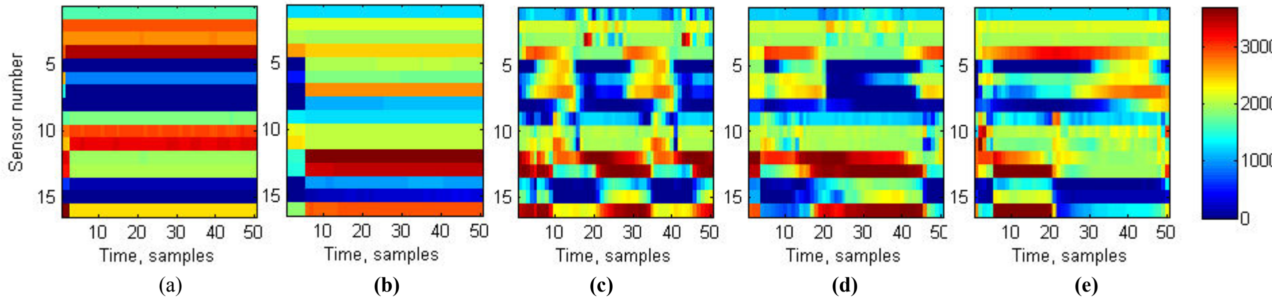


Fig. 4. Two-dimensional representation of feature vectors for each posture/activity before normalization: sitting (a), standing (b), walking (c), ascending stairs (d) and descending stairs (e). Each feature vector represents a 2-second time interval. The color scale is in ADC units.

The data from the shoe sensors was recorded. A total of 116 segments of 15 to 25 second duration were captured resulting in approximately half an hour of data equally distributed by listed postures and activities.

C. Data Preprocessing

Captured sensor data were processed to form feature vectors for the classifier. Each 800-element lagged feature vector represents pressure and acceleration histories from both shoes for the past two seconds (2 shoes x 8 sensors x 25 samples per second x 2 seconds = 800 samples). Thus, all predictions are made for non-overlapping 2-second epochs. Fig. 4 shows a two-dimensional representation of the lagged feature vectors. The X-axis shows time progression and Y-axis shows color-coded reading from the sensors in ADC units. First 8 sensors (top half of each image) correspond to the left shoe and next 8 sensors (bottom half of each image) correspond to the right shoe. As Fig. 4 shows, each posture and activity creates distinct features that can be used by the classifier. Each feature was normalized on the scale of [0,1].

D. The Classifier

The lagged feature vectors were presented to a supervised classification algorithm for training and validation. The selected classifier was a variation of Support Vector Machine (SVM) implemented as a Matlab package (libSVM, [9]). The choice of the classifier was defined by the consideration of the generalization ability.

The maximum margin classifier implemented by an SVM is less prone to overfitting compared to other available methods. For the target application of automatic classification of postures and activities the ability to generalize effectively is extremely important. As an example, motion of the lower extremities during ambulation is not perfectly repeatable. Similar variation in sensor data is expected from other postures and activities. In addition, some of the recorded data segments may contain transitions between similar postures and activities introducing the data, which cannot be perfectly labeled as one the classes. Thus the classifier is posed with a difficult task of learning a decision boundary, which should provide the best generalization from expectedly imperfect data.

The training and validation subsets were produced by repeated random sub-sampling where the randomly selected 50% of the collected dataset were used for training and the remaining 50% for validation (reporting of the results). Each posture/activity was represented in the same proportion both in training and validation sets. A total of 10 randomized experiments was used for reporting.

Each lagged feature vector was assigned a label representing a distinct class {1-sitting, 2-standing, 3-walking, 4-ascending stairs, 5-descending stairs}. The feature vectors and corresponding labels from the training set were presented to a multi-class SVM [10].

Two different versions of the SVM classifier were used: a classifier with a linear ($\boldsymbol{u}' * \boldsymbol{v}$) kernel and a classifier with a Gaussian ($\exp(-\gamma * (\boldsymbol{u} - \boldsymbol{v})^2)$ kernel. The expectation was that the linear kernel classifier may perform on the par with the non-linear Gaussian kernel classifier due to the high dimensionality of the lagged feature vectors.

The best set of parameters for each classifier was found by a grid search procedure. For the linear kernel classifier the value of the cost parameter C was varied as $C = 10^x$, $x = \{-3, \dots, 4\}$. For the Gaussian kernel classifier the value of the cost parameter C was varied as $C = 10^x$, $x = \{-1, \dots, 4\}$ and value of the kernel parameter γ was varied as $\gamma = 2^y$, $y = \{-7, \dots, -1\}$.

Finally, the data from the validation set were presented to the trained classifier. Predicted labels were compared against expected and accuracy for each of the five classes computed.

III. Results

Fig. 5 shows confusion matrices obtained by training and validation for the linear and non-linear classifiers. In a confusion matrix the rows correspond to actual classes and columns correspond to predicted classes.

Two kinds of performance measures are computed to characterize the accuracy of classification. Class-specific recall is the proportion of a class instances that were correctly identified. It is defined as a ratio of the respective diagonal value to the sum of a row. Class-specific recall is sometimes called class-specific accuracy. Class-specific precision is the proportion of the predicted class cases that were correct. It is defined as a ratio of the corresponding diagonal value to the sum of a column. Finally, the total accuracy is computed as the ratio of correctly predicted class cases to the total number of cases. The total accuracy was 98.9% was the linear kernel classifier and 99.8% for the Gaussian kernel classifier.

IV. Discussion

The first observation that can be drawn from the results presented in Fig. 5 is that the suggested approach to posture and activity classification seems to be feasible and practically implementable. All five classes have been recognized with substantial accuracy that would be acceptable for practical applications. In a typical situation the postures and activities do not transition from one state to another and back on the time scale of seconds. Thus, occasional misclassifications of a two second epoch can be filtered out by a higher level algorithm that would smooth changes of states.

As expected, the linear kernel SVM came very close in the prediction accuracy to the Gaussian kernel classifier. The high dimensionality of the lagged feature vectors captures unique time patterns created by each posture and activity and thus enables linear separability of classes.

One notable difference is classification of ascending the stairs in which the linear kernel classifier did not perform as well as the Gaussian kernel classifier. However, the class of ascending the stairs is the most poorly represented class in the data set and recognition accuracy may be heavily dependent on the random selection of the samples during partitioning into the training and validation sets.

Both linear and Gaussian kernel SVM showed good generalization ability which is partially reflected by number of support vectors drawn from the training set. Both classifiers kept approximately 30%-40% of the training set as support vectors.

It should also be noted that the proposed approach is significantly less intrusive that any other device for identification of postures or activities. The most well-known device IDEEA (www.minisun.com) used in a study by Zhang et. al. [11] has a sensor box with sophisticated electronic controls is worn on a belt with several wired sensors connected to the box. Each sensor has to be individually attached to a limb of interest by adhesive tape.

Overall, the results of the presented experiments show that reliable and fully automatic recognition of postures and activities is feasible in individuals recovering after stroke. Such methodology can be employed in therapy and rehabilitation of recovering stroke patients.

V. Conclusion

In conclusion, the feasibility of using Support Vector Classification for automatic classification of postures and activities in people with stroke has been established by this study. The results suggest potential high accuracy of the suggested classification approach. Further research and development is necessary to test the sensor in the home and community and to incorporate into a comprehensive CIMT based therapy for the lower extremity.

Predicted class

Actual class	Sit	Stand	Walk	Ascend	Descend	Class-specific recall
Sit	1600	0	0	0	0	**1.00**
Stand	0	1120	0	0	0	**1.00**
Walk	13	0	857	0	0	**0.99**
Ascend	0	0	10	89	11	**0.81**
Descend	5	0	3	0	242	**0.97**
Class-specific precision	**0.99**	**1.00**	**0.99**	**1.00**	**0.96**	

(a)

Predicted class

Actual class	Sit	Stand	Walk	Ascend	Descend	Class-specific recall
Sit	1600	0	0	0	0	**1.00**
Stand	0	1120	0	0	0	**1.00**
Walk	0	0	870	0	0	**1.00**
Ascend	0	0	0	106	4	**0.96**
Descend	0	0	2	0	248	**0.99**
Class-specific precision	**1.00**	**1.00**	**1.00**	**1.00**	**0.98**	

(b)

Fig. 5. Confusion matrices for the linear kernel SVM classifier (a) and for the Gaussian kernel SVM classifier (b) over 10 randomized experiments.

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