Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Identification of Tasks Performed by Stroke Patients Using a Mobility Assistive Device

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Abstract - **Many stroke patients are prescribed canes or other mobility assistive devices. Once taken home, these mobility assistive devices are often abandoned or misused. A means for assessing the use of the cane in the home and community settings is required to assist clinicians in the prescription of these devices. In this study, we propose the use of wearable sensors to identify tasks performed by stroke patients with a mobility assistive device. Subjects performed ten tasks with a three-axis accelerometer attached to their ankle and a neural network was trained to identify the task being performed. Results from 15 stroke patients indicated that these motor tasks can be reliably identified with a median sensitivity of 90% at a median specificity of 95%. These results indicate that it is possible to use a single module with a three-axis accelerometer attached to the ankle to reliably identify motor tasks associated with the use of a cane. Therefore, we envision that the methodology presented in this paper could be used to evaluate the use of a cane in the context of the task being performed.**

I. Introduction

APPROXIMATELY 700,000 Americans are affected by stroke every year and around 275,000 Americans die from stroke every year [1]. Stroke affects a person's language, perceptual, sensory, cognitive, and motor abilities [2]. More than 1,100,000 Americans have reported difficulties with functional limitations following stroke [3]. Recovery from stroke is a long process that continues beyond the hospital stay and into the home and community settings. Many stroke patients are prescribed mobility assistive devices to improve balance and function.

Mobility assistive devices can improve mobility and allow independent performance of motor tasks [4]. In addition to improving balance, canes can prevent injuries related to falls and negative behaviors resulting from fear of falling [5]. Despite their acknowledged qualities, mobility assistive devices are often misused or abandoned once they are taken home [6]. A study of elders who had been discharged from rehabilitation found that 38% of them seldom or never used their mobility assistive device [7].

In this study, we use wearable sensors to identify the task being performed by a stroke patient using a mobility assistive device. Our interest for the identification of motor tasks performed by stroke patients is motivated by the observation that once the task has been identified on the basis of the sensor data, the use of the cane could be analyzed in the context of the task being performed using a combination of sensors on the subject and the cane.

II. Methods

A. Data Collection

Fifteen subjects that used a mobility assistive device following stroke were recruited in the study. Figure 1 shows the setup utilized for data collection. A three-axis accelerometer module was attached to the subjects' right ankle. Analog signals (n=3) from the sensors were digitized and sampled on a PDA at a rate of 100 Hz. A cane was equipped with a load cell and two accelerometers parallel to the ground. Analog signals from these sensors were sampled and wirelessly transmitted using a dedicated RF transceiver. Data from the PDA was transmitted to a PC through an 802.11b TCP/IP link and synchronized with the signals from the cane.

All subjects were tested at the Research Center on Aging at the University of Sherbrooke, Canada. Test procedures were approved by the internal review board. Each subject performed the following set of motor tasks: level walking, walking carrying an object, walking on an uneven surface, walking up a ramp, walking down a ramp, walking up a flight of stairs, walking down a flight of stairs, walking over an object, pivoting, and opening a door. Depending on the duration of the task, subjects performed 10 to 30 repetitions of each task. The tasks were performed over the course of 2-3 recording sessions to avoid excessive fatigue.

Manuscript received April 24, 2006. This work was supported in part by the Canadian Institutes of Health Research under the grant entitled "*Ecological momentary assessment (EMA) of mobility assistive device use in balance impaired individuals.*"

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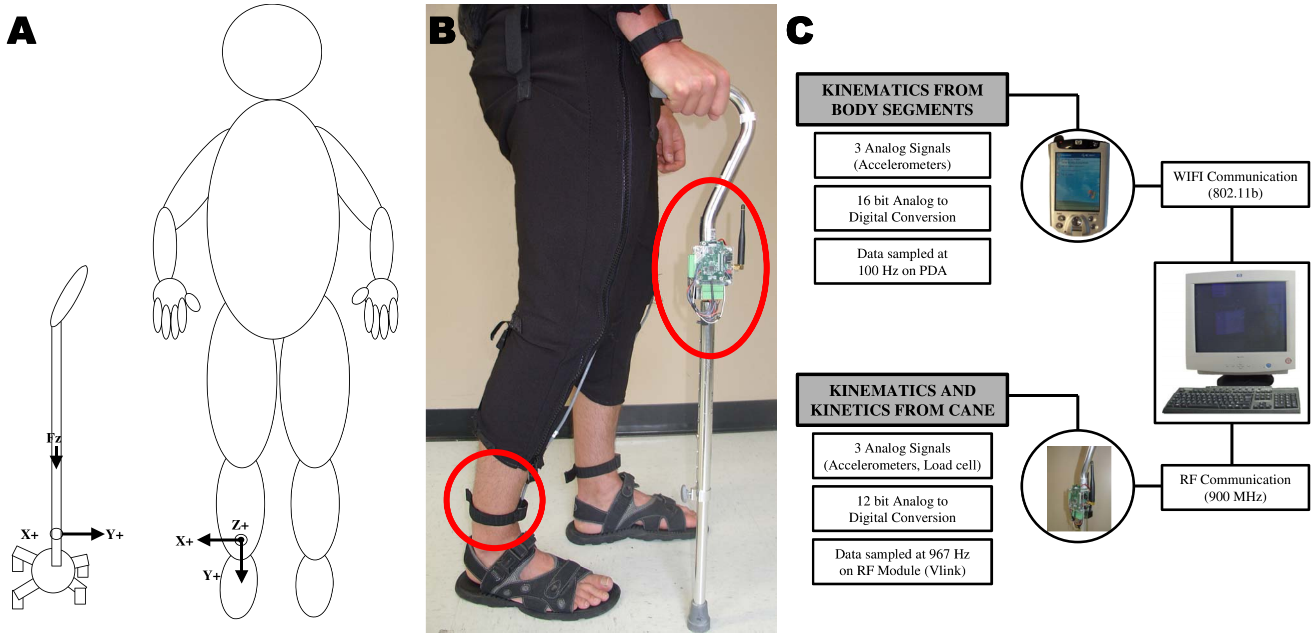

Fig. 1. Experimental setup: A) position and orientation of the sensors utilized to monitor motor tasks and use of a cane; B) picture of a subject using the hardware setup during level walking; and C) schematic representation of the data collection system.

B. Data Processing and Feature Extraction

The raw data from the wearable sensors were preprocessed before features were derived. First, data were digitally low-pass filtered with cut-off frequency of 15 Hz to attenuate high frequency noise. The three-axis accelerometer data were projected onto vertical and horizontal axes to prevent changes in the orientation of the sensors between testing sessions from negatively affecting the results. The mean of the data for the testing period was assumed to be the vertical axis output due to gravity and the horizontal projection was taken by subtracting the vertical projection from the total acceleration [8].

One hundred data segments were then randomly selected from recordings for each task. Windows from odd-numbered task repetitions were used for the training dataset and windows from even-numbered repetitions were used for the testing dataset. This was done to ensure that windows from the training and testing sets did not overlap. The following features were extracted from each window: the mean value, the dominant frequency, the ratio of the energy of the dominant frequency to the total energy of the data, the range of the autocovariance function of three accelerometer channels, and the root mean square values of the vertical and horizontal projections of the accelerometer data. In total, thirteen features were extracted from each data segment.

C. Task Identification

Features were fed into a neural network that was trained to identify the motor tasks of interest. The neural network was trained with an output neuron for each task, with only the output neuron of the correct task being activated. A threshold was used to determine whether the output pattern matched closely enough the target result to be counted.

Training of the neural network was done on a subject-by–subject basis. Optimal data segment length, neural network topology, and number of training iterations were determined via simulations. Window lengths from 2 to 8 s at half-second intervals were tested for a total of 13 window lengths. Six different network topologies with two hidden layers were tested with the number of neurons in each layer ranging from 20 to 40. All networks tested had an equal or smaller number of neurons in the second hidden layer than the first hidden layer. The number of training iterations tested ranged from 50 to 500 iterations at intervals of 50 iterations for a total of 10 different values. Every combination of these three parameters was tested by training neural networks for each subject on their training datasets and then testing the network on each subject's testing datasets. In total, 780 combinations of network parameters were tested. The optimal parameters were selected by choosing the parameters that provided the best sensitivity at the 95 % specificity level.

Following the selection of optimal network parameters, the performance of the network was also analyzed by looking at the sensitivity and specificity on a task-by-task basis. This was done to ensure that there no tasks that were being overwhelmingly misclassified or unclassified compared to other tasks.

III. Results

Figure 2 shows the average operating characteristics of the neural network for each window length with the network topology and number of training iterations set to their optimal values. Tests showed sensitivity ranging from

51.0 % to 84.1 % at the 95 % specificity level. An increase in sensitivity was demonstrated when the window length was varied between 2 s and 7 s and a slight decrease was demonstrated when the window length was further increased up to 8 s. Based on these results, a window length of 7 s was chosen because it provided the best sensitivity at the 95% specificity level.

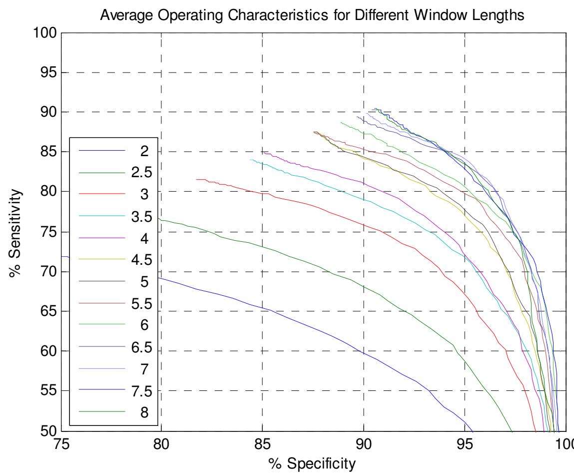

Fig. 2. Average operating characteristics for various window lengths.

Figure 3 shows the average operating characteristics of the neural network for each topology with the other parameters set to their optimal values. The sensitivity at the 95 % specificity level ranged from 78.4 % using a topology with 20 neurons in the first and second hidden layers to 84.1 % with a topology with 40 neurons in the first hidden layer and 30 neurons in the second hidden layer. The neural network that was selected had 13 input neurons for each feature, hidden layers with 40 and 30 neurons, and 10 neurons representing each task in the output layer.

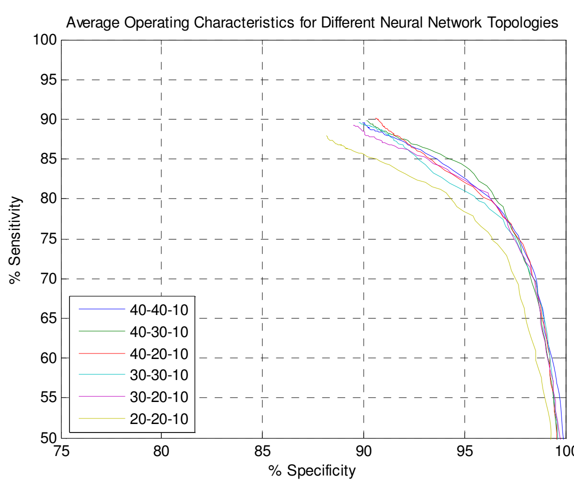

Fig. 3. Average operating characteristics for different neural network topologies.

Figure 4 shows the average operating characteristics of the classifier for each number of training iterations with the other parameters set to their optimal levels. The sensitivity at the 95 % specificity level was very low for 50 and 100 iterations and then changed very little from 150 to 500 training iterations. With 50 training iterations, the sensitivity at 95% specificity was 63.5 %. Sensitivity ranged from 82 % to 84 % for 150 to 500 iterations. Training with 250 iterations provided the best results with 84.1 % sensitivity at the 95 % specificity level.

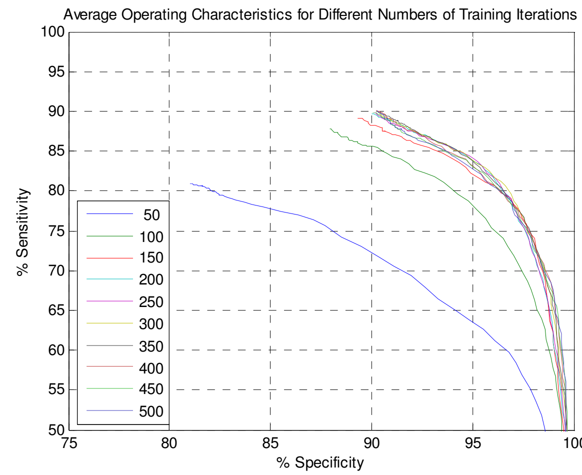

Fig. 4. Average operating characteristics for different numbers of training iterations.

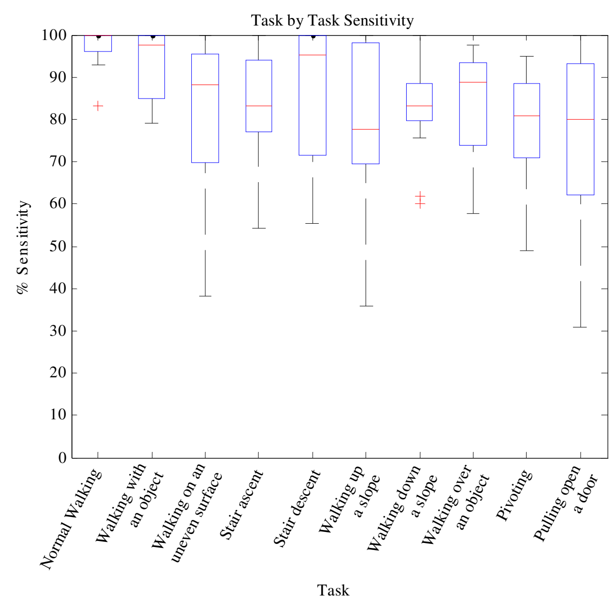

Fig. 5. Box plot of classifier sensitivity for each task.

Using the classifier with the window length, neural network topology, and training iterations as specified above, the tasks were identified on the test dataset. The threshold was selected where the subjects averaged 95 % specificity. Although the selected threshold results in low sensitivity levels, it provides extremely high specificity and a very low rate of misclassifications. We were willing to give up some sensitivity to prevent misclassifications from affecting the evaluation of the use of the cane. Figures 5 and 6 show box plots of the sensitivity and specificity of the classifier for all tasks. The median sensitivity of the tasks ranged from 77.8 % on the task of walking up a slope to 100 % on normal walking with a mean value of 87.5 %. The mean sensitivity of the tasks ranged from 75.1 % to 97.4 % with a mean of 84.0 %. The median specificity of the tasks ranged from 92.9 % on the task of walking up a slope to 100 % on six tasks with a mean of 97.8 %. The mean specificity ranged from 91.3 % to 99.2 % with a mean of 95.1 %.

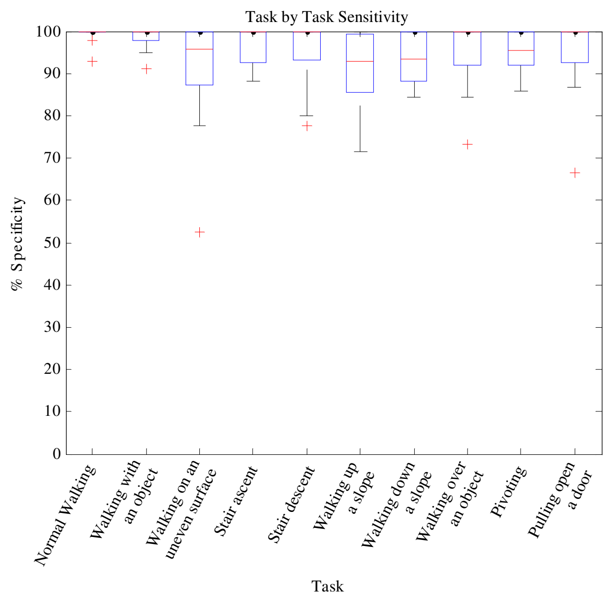

Fig. 6. Box plot of classifier specificity for each task.

IV. Conclusion

In our simulations to determine the optimal parameters for the classifier, we found that the window length had a much larger effect on the sensitivity of the classifier than either the network topology or the number of training iterations. The sensitivity covered a range of 33 % for the changes in window length, 22 % for the changes in the number of training iterations and 6 % for the changes in network topology. Based on the fact that changes in the window length had the largest effect on the results, it appears that the selection and extraction of features that are fed into the neural network are much more important to the results than the parameters of the neural network itself such as the network topology or the number of training iterations.

We were able to classify the tasks that patients performed with a cane to a mean accuracy of 95.1 % specificity and 84.0 % sensitivity using only a three-axis accelerometer on their right ankle. These results suggest that it is possible to analyze the use of the cane in the context of the tasks performed by stroke patients by relying on the classifier herein proposed. For analyzing the use of the cane, it is important to have high specificity to prevent misclassifications from affecting the analysis of the use of the cane in different tasks.

References

[1] American Heart Association, *Heart Disease and Stroke Statistics – 2005 Update*, American Heart Association, Dallas, TX, 2004.

[2] National Institute of Neurological Disorders and Stroke (NINDS), *Stroke: Hope Through Research*, NINDS, Washington, DC, 2004.

[3] Center for Disease Control (CDC), *Morbidity and Mortality Weekly Report*, CDC, Atlanta, GA, 2001.

[4] J. Mahoney, M. Sager, and M. Jalaludin, "Use of ambulation assistive device predicts functional decline associated with hospitalization", Journal of Gerontology, 1999, pp. M83-M88.

[5] S. Belhassen, A. Gastal, and V. Chauvineau, Aides à la déambulation, in Aide technique et matériel d'assistance en gériatrie, Masson, Paris, 2002, pp. 153-166.

[6] U. Sonn, H. Davegardh, A. Lindskog, and B. Stenn, "The use and effectiveness of assistive devices in an elderly urban population", Aging Clinical and Experimental Research, 1996, pp. 176-183.

[7] L. Gitlin, R. Levine, and C. Geiger, "Adaptive device use by older adults with mixed disabilities", Archive of Physical Medicine and Rehabilitation, 1993, pp. 149-152.

[8] D. Mizell, "Using Gravity to Estimate Accelerometer Orientation", Proceedings of the Seventh IEEE International Symposium on Wearable Computers, IEEE, 2003.