Motor Function Assessment Using Wearable Inertial Sensors

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***Abstract*— We present an approach to wearable sensor-based assessment of motor function in individuals post stroke. We make use of one on-body inertial measurement unit (IMU) to automate the functional ability (FA) scoring of the Wolf Motor Function Test (WMFT). WMFT is an assessment instrument used to determine the functional motor capabilities of individuals post stroke. It is comprised of 17 tasks, 15 of which are rated according to performance time and quality of motion. We present signal processing and machine learning tools to estimate the WMFT FA scores of the 15 tasks using IMU data. We treat this as a classification problem in multidimensional feature space and use a supervised learning approach.**

I. INTRODUCTION

Regaining functional ability after stroke is necessary for continued independent living. In this context, accurate assessment of motor function is needed in order to determine appropriate rehabilitative interventions and to document outcomes of employed rehabilitation programs. Assessment is based on the observations of the participants' motor behavior using standardized clinical rating scales and is labor intensive, usually necessitating one-on-one interaction with the therapist. However, the number of trained therapists is being outpaced by the number of individuals who suffer from stroke. Thus there is a large and increasing gap between the rehabilitative interventions that are needed and the amount being provided.

Furthermore, it has been noted that a substantial fraction of stroke patients perform or try to perform assessment tasks in the clinic better than they do at home [1]. Thus, laboratory motor tests do not fully provide the needed assessment information because of the disassociation between performance in the clinic/laboratory and in the home.

Thus, there is a need for an in-home upper extremity motor functionality assessment system that does not require the presence of a physical therapist during testing.

The above provides the motivation for the automated tool we have developed to augment long term monitoring and assessment of post-stroke individuals' functional ability in the home. In this paper, we present a methodology for estimating the functional ability score for 15 of the Wolf Motor Function Test tasks using on-body inertial measurement unit data. We compare the estimated scores with those assigned by the physical therapist for one post-stroke participant.

This study builds on our previous work [4] to validate our hypothesis that the timing and functional scores can be accurately obtained in real world settings.

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II. STANDARDIZED TOOLS FOR MOTOR FUNCTIONALITY ASSESSMENT

To evaluate upper extremity (UE) motor capabilities in stroke patients and set a proper rehabilitation exercise regimen, a number of direct-observation standardized functional assessment instruments have been devised. Some of the standard assessment tools, such as the Action Research Arm Test, Chedokee McMaster (CM), Fugl Meyer Assessment (FMA), Frenchay Arm Test, Jebsen Taylor Test, TEMPA assessment, and Wolf Motor Function Test (WMFT), have been discussed in [11]. The WMFT is preferable to the commonly used UE performance tests because it covers a wide range of functional tasks (i.e., from simple to complex, from proximal to distal) and explores performance time, quality of movement, and strength [2]. Although specific equipment is needed for test administration, most of the items used in conducting the WFMT are commonly available and inexpensive. This, combined with its reliability, consistency, and validity, makes the WMFT valuable for research purposes [3].

III. WOLF MOTOR FUNCTION TEST

The Wolf Motor Function Test is an assessment performed under the supervision of a physical therapist [2], [3]. It requires the participant to perform 17 tasks (Table III), 15 of which are rated on the basis of performance time and a functional ability (FA) scale for quality of motion; the remaining two tasks are strength-based. The WMFT quantifies upper extremity movement ability through these functional tasks. The WMFT is conducted in a standardized setting (Figures 1, 2); this includes a table, camera positions, and a template (taped on the table surface) which specifies the location of objects and start and end points for each task. The WMFT starts with simple items such as placing the hand on a table top and swiping the hand, and progresses to more challenging fine motor tasks such as stacking checkers, picking up paper clips, and folding a towel. Each task starts when the physical therapist says "Go" and ends when the participant has met the required conditions for the completion of the task (e.g. checkers are stack, or the thumb has passed a specific line on the template). A physical therapist rates the performance for each task on a scale of $0-5$. The guidelines for FA scoring are shown in Table I .

TABLE I: Functional Ability Scale

Score	Description
0	Does not attempt with involved arm.
1	Involved arm does not participate functionally; however, an attempt is made to use the arm. In unilateral tasks the uninvolved extremity may be used to move the involved extremity.
2	Arm does participate, but requires assistance of uninvolved extremity for minor readjustments or change of position, or requires more then two attempts to complete, or accomplishes very slowly. In bilateral tasks the involved extremity may serve only as a helper or stabilizer.
3	Arm does participate, but movement is influenced to some degree by synergy or is performed slowly and/or with effort.
4	Arm does participate; movement is close to normal*, but slightly slower; may lack precision, fine coordination or fluidity.
5	Arm participates; movement appears to be normal.*

* For the determination of normal, the uninvolved limb can be used as an available index for comparison, with premorbid limb dominance taken into consideration [2].

Fig. 1: Standardized WMFT setup, showing the camera positions, the testing table, and the template.

Automated administration of the WMFT tasks requires 1) automation of the time score and 2) automation of the FA score. In our previous study, we presented the sensor modalities and framework for automating the timing [4]. This paper builds on that previous work and presents signal processing and machine learning tools to quantitatively estimate the FA scores for functional tasks from wearable IMU data.

IV. PREVIOUS WORK

Researchers have investigated the automation of functional assessments and home-based healthcare analysis. Hester et al. and Knorr et al. explored the estimation of the WMFT FA score with statistical tools using wearable sensor modalities [5] [6]. Hester et al. correlated accelerometer data from the trunk and arms to FMA, CM, and WMFT scores using linear regression techniques. Knorr et al. used statistical features and regression analysis to estimate the FA score for 2 of the WMFT tasks from accelerometer data. However, use of

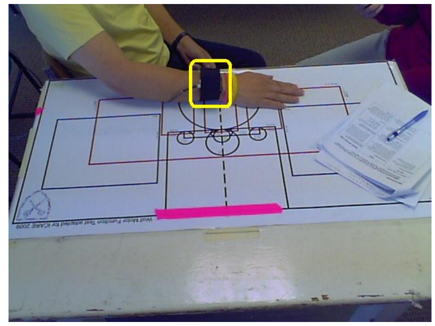

Fig. 2: Standard WMFT template and the participant with the wearable IMU (highlighted).

gyroscope (angular rate sensor) for post-stroke functional motion assessment has not been studied extensively. In this work, along with the accelerometer we utilize a gyroscope to estimate the functional scores of the 15 WMFT tasks.

An alternative approach to stroke assessment and rehabilitation involves robotic devices and exoskeletons. Examples of such technologies are presented in [7]. These devices measure force and torque (F/T) applied by the user and the resulting motion profiles while performing functional tasks. The F/T data is generally used to quantify the required amount of assistance, motion smoothness, and movement synergy in participants' motion. These methods have been primarily used for augmenting the rehabilitation process but can also be extended to assessment, as has been shown in the works by Krebs et al. [8]. Finally, Van Dijck et al. used posterior probability based models for estimating FMA scores by analysing the F/T profile [9].

Though the robotic systems have the capability to provide very accurate motion profiles and assessment results, the issues of cost, safety, and calibration of the setup make them unsuitable for in-home settings. We chose inertial sensing technology because it is inexpensive, robust, and can be easily integrated into preexisting functional environments like homes and workplaces.

V. HARDWARE

In our experimental setup, the participant wears one sensor on the wrist. The wearable sensor used in this study is an inertial measurement unit (IMU) developed in the Interaction Lab at the University of Southern California [10]. This device has been validated in previous studies with stroke survivors as well as with healthy users [4] [10]. The IMU contains a triaxial accelerometer, three single-axis rate gyros, and one single- and one dual-axis magnetometer.

We employ the Gumstix-Wifitix stack as the wearable central controller. Gumstix is a small and powerful Linux based computer which hosts a number of on-board hardware interfaces (http://www.gumstix.org). It supports common data transfer protocols and is capable of wireless communication over the local network using wifistix.

We use the Player/Stage robotics development software suite (http://www.playerstage.sourceforge.net). Player is an open source software suite that allows for the control and coordination of multiple devices using a server/client architecture. The gumstix connects to the IMU using the I^2C interface and streams the sampled IMU data at an average rate of 20 samples per second. The data is then transferred over the player interface from gumstix to the host machine for processing and analysis.

VI. EXPERIMENTS AND DATA ANALYSIS

For our FA scoring experiments, a trained clinician administered the WMFT with one post-stroke participant. This step was followed by data analysis and FA score estimation. Written informed consent was obtained from the participant before the start of the experiment. During these trials the participant wore the IMU on the arm on which the test was being administered. These trials were also video recorded, as shown in Figure 1. The purpose of the recordings is for post-experiment analysis of the performance of motor tasks by the therapist to assign the FA scores. The therapist was blinded to the IMU data processing and score estimation.

The first step in data analysis involved preprocessing the data stream by passing it through a low pass filter with cutoff frequency of 20 Hz and through a high pass filter with a cutoff frequency of 0.3 Hz. The low pass filter removed the high frequency noise, while the high pass filter removed the very low frequency device drift.

We approached the estimation of WMFT FA scores from the IMU data as a classification problem in multi-dimensional feature space. We extracted a number of statistical features, mentioned in Table II, from the filtered IMU data and used them in conjunction with a naive Bayes classifier for estimation. Naive Bayes classification is a simple and well-known method for classification. Given a feature vector f, the class variable C is given by the *maximum aposteriori* (MAP) decision rule as

$$C(f) = argmax_C \Big\{ p(C) \prod_{i=1}^{k} p(f_i|C) \Big\} \tag{1}$$

Here $p(C)$ is the class prior; $p(f_i|C)$ are the class conditional densities (conditional distribution over class variable C); and each member of the set C represents one of the 6 possible FA scores (Table I). The statistical features extracted from different axes of the IMU data were fed into the classifier, which estimated the most probable FA score class to which the motion profile belongs. The features were manually selected from a list of probable candidates by conducting extensive trials with the collected data. For training, we used IMU data from 5 tasks which were randomly picked (shown in Table III); the classifier estimated the scores for the 15 WMFT tasks.

In standard WMFT FA scoring, the unaffected arm gets a full score of 5 for all tasks. For rating the affected arm, corresponding affected arm gestures are compared with those of the unaffected arm. To take this into account, we normalized all feature values computed from affected arm data by dividing them with the corresponding values computed from unaffected arm. These normalized feature values were then used for classification.

TABLE II: List of features used for estimation of FA scores

	Features for classification
FAS	Kurtosis, Skewness, Mean, Variance Approximate Entropy, RMS of jerk, Power in $1.5-3$ Hz band, Power in $5-8$ Hz band, Time taken to perform the task

We also performed power spectrum analysis on the IMU data from the affected and unaffected arms. The results are presented in the next section.

VII. RESULTS AND DISCUSSION

The spectral analysis yielded some interesting observations. Figure 3 shows power spectral density (PSD) plots for the affected and unaffected arms. It is evident from the plot that both arms have major components in the frequency band centered at 2 Hz, which corresponds to the intended gesture motion. The difference between the two is evident at higher frequencies. The affected arm has more information content at higher frequencies as compared to the unaffected arm, which corresponds to the involuntary motion (tremor, jerk, etc.). We used average power content in the 2 Hz and 7 Hz bands as two of the features used in classification. Here, it should be noted that this PSD plot (Figure 3) is for one subject. We believe that the spectral density can also be a function of individual's motor capabilities. Hence the power content in different frequency bands might vary depending on the functional ability of the stroke patient.

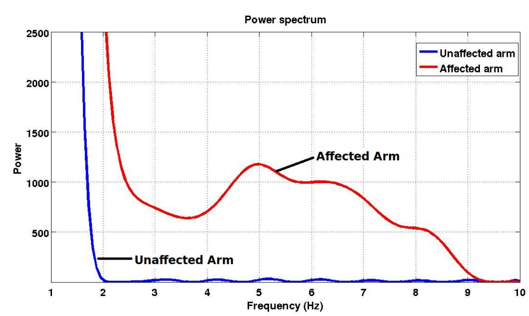

Fig. 3: PSD plot of affected and unaffected arm data

Figures 4 and 5 are two cluster plots showing the classification between affected and unaffected arm. The points in the cluster plots represent individual WMFT tasks. The classification is performed by the trained naive Bayes classifier using the features listed in Table II. These cluster plots are showing classification in 2 and 3 dimensional feature space respectively. The FA score estimation is performed in a similar way by classifying the IMU data in multidimensional feature space.

In Table III, we compare the functional scores assigned by the therapist with those estimated from the IMU data for each of the 15 tasks. The FA scores as rated by the therapist are labeled $FAS_{therapist}$ and the estimated scores

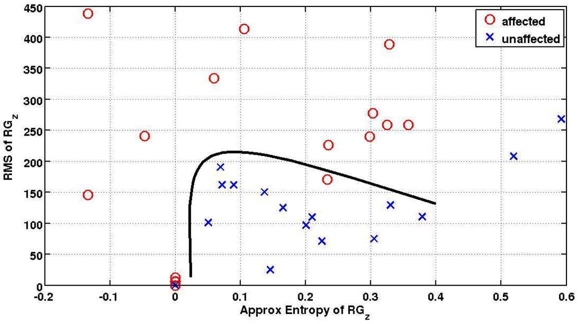

Fig. 4: Classification between affected and unaffected arm

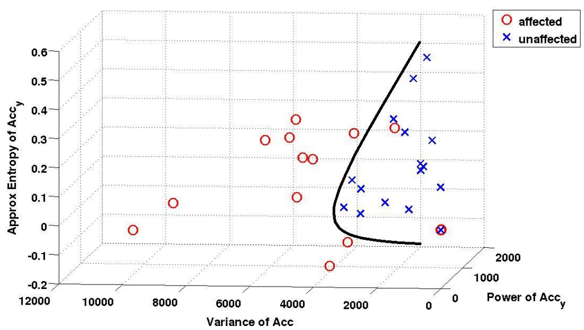

Fig. 5: Classification between affected and unaffected arm

from IMU data are labeled FAS_{auto}, respectively. It can be noted from Table III that the automated system is able to compute the FA score to a good level of accuracy. The distribution of error between $FAS_{therapist}$ and FAS_{auto} has mean = 0.0667; variance = 0.2095; and RMS value = 0.4472. This result strengthens our hypothesis that our automated system can perform accurate motor functionality assessment in a considerably short amount of time without involving a therapist.

The purpose of normalization of the feature values (before using them for classification) is to develop and train a generic classifier which is user independent. But this hypothesis of a generic estimation system must be validated across a larger stroke population and its performance compared with a *user-specific* classifier.

VIII. CONCLUSION

We have described a technique for automating the FA scoring of WMFT tasks. We have completed a feasibility study with one post-stroke participant and presented our sensor modality and the data processing techniques used in this framework. Our long term goal is to be able to automatically 1) quantify long term motor functionality changes in real world settings and 2) evaluate the rehabilitation methodologies. Towards that end, the reliability and validity of the described approach and system must be evaluated across a sufficiently large stroke participant population.

TABLE III: FAS of the affected arm as measured by the physical therapist and automated system

Task	$FAS_{therapist}$	FAS_{auto}
1. Forearm to table (side)†	4	4
2. Forearm to box (side)	3	3
3. Extend Elbow (side)	4	3
4. Extend Elbow,weight (side)	3	3
5. Hand to table (front)	4	4
6. Hand to box (front)†	4	4
7. Weight to box*	-	-
8. Reach and retrieve	3	3
9. Lift can	4	4
10. Lift pencil†	4	4
11. Lift paper clip	3	4
12. Stack checkers†	4	4
13. Flipping Cards	3	3
14. Grip strength*	-	-
15. Turn key in lock†	4	4
16. Fold towel	4	4
17. Lift basket	4	4

*Tasks 7 and 14 are not scored.
†Tasks used for training the classifier.

IX. ACKNOWLEDGMENTS

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