Upper-Extremity Stroke Therapy Task Discrimination Using Motion Sensors and Electromyography

Joseph P. Giuffrida, *Member, IEEE*, Alan Lerner, Richard Steiner, and Janis Daly

***Abstract*—Brain injury resulting from stroke often causes upper-extremity motor deficits that limit activities of daily living. Several therapies being developed for motor rehabilitation after stroke focus on increasing time spent using the extremity to promote motor relearning. Providing a novel system for user-worn therapy may increase the amount and rate of functional motor recovery. A user-worn system comprising accelerometers, gyroscopes, and electromyography amplifiers was used to wirelessly transmit motion and muscle activity from normal and stroke subjects to a computer as they completed five upper-extremity rehabilitation tasks. An algorithm was developed to automatically detect the therapy task a subject performed based on the gyroscope and electromyography data. The system classified which task a subject was attempting to perform with greater than 80% accuracy despite the fact that those with severe impairment produced movements that did not resemble the goal tasks and were visually indistinguishable from different tasks. This developed system could potentially be used for home-therapy compliance monitoring, real-time patient feedback and to control therapy interventions.**

***Index Terms*—Accelerometers, electromyography, gyroscopes, rehabilitation, stroke.**

I. Introduction

STROKE refers to sudden onset of weakness or other neurological symptoms as a result of injury to a blood vessel in the brain [1]. Two types of cerebral vascular accident are hemorrhagic and ischemic. The overall effect is dependent upon brain side damaged, infarct location, infarct size, character of blood vessels and collateral circulation, and recovery of tissue involved. Stroke is a leading cause of serious long-term disability in the United States [2]. Prevalence is about 5 700 000 with about 700 000 people suffering a new or recurrent stroke each year. More than 1 100 000 American stroke survivors have functional limitations and difficulty with activities of daily living. Young stroke survivors may expect to live a long life and elderly patients have survived for longer than seven or eight years after a stroke. This illustrates the need for effective motor therapy techniques after stroke.

Almost every patient that experiences a cerebral or brain stem stroke develops a physical disability that affects activities of daily living including eating, dressing, and personal hygiene [1]. Limiting these tasks greatly reduces independence, societal participation, and quality of life. Cerebral hemisphere strokes generally affect motor function with a common impairment being loss of motor control of the contralateral upper extremity. Upper extremity motor deficits may include paralysis or weakness, abnormal muscle tone, abnormal posture, abnormal movement synergies, and coordination loss [3]. As time progresses, patients can regain some motor function originally lost. It was thought that dynamic recovery only occurred up to six months poststroke, but new therapies are illustrating that motor recovery can continue after that [4]–[6].

One stroke rehabilitation method is compensation techniques using nonparetic limbs to complete functional tasks. While this can improve some independence measures, it can also lead to learned disuse of the paretic limb and limit functional recovery. The adult cerebral cortex is capable of significant functional plasticity and postinjury behavioral experience modulates neurophysiologic and neuroanatomical changes in undamaged tissue [3], [7]. Occupational and physical therapy contribute to functional recovery of patients suffering from central paresis of the upper-extremity [8]. Motor rehabilitation after stoke has been shown to be efficacious in both acute and chronic stages. Previous research indicates that repetitive motor activity provides the basis for motor learning and functional recovery [8]. Repetitive, volitionally executed movement, or repetitive sensorimotor training is of great benefit in terms of functional outcomes for centrally paretic arm and hand [9], [10]. Methods that rehabilitation therapists effectively use to stimulate functional plasticity and motor recovery include active and passive range-of-motion, bilateral training, forced use, robotic-assisted therapy, and constraint induced therapy [11]–[15].

Repetitive training of both simple, isolated, single joint movements, and complex tasks have been shown to improve upper-extremity motor recovery after stroke [10], [16], [17]. Grip strength, an important variable for activities of daily living [18], can also be significantly improved by this type of training. The repetitive execution of complex motor movements accelerates the time course and supports functional recovery. Relationships have been demonstrated between the amount of time a patient practices use with the paretic limb and the amount of motor recovery he or she achieves. Increasing the amount of time as well as using task specific methods to encourage motor learning helps improve function and can reduce long-term disability [17], [19], [20]–[22].

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J. P. Giuffrida is with the Division of Movement Disorders of Cleveland Medical Devices Inc., Cleveland, OH, 44103 USA (e-mail: jgiuffrida@clevemed.com).

A. Lerner is with Department of Neurology, Case Western Reserve University, Cleveland, OH 44106 USA.

R. Steiner is with the Department of Statistics, the University of Akron, Akron, OH 44325 USA.

J. Daly is with the Louis Stokes Cleveland Department of Veterans Affairs Medical Center, Cleveland, OH 44106 USA, and with the Department of Neurology at Case Western Reserve University School of Medicine, Cleveland, OH 44106 USA.

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A current trend in therapy relies less on one-to-one activities and instead makes use of technological advances including interactive computerized systems that increase time spent in active practice [23]. Therefore, the development of a system that a person who suffered a stroke can easily and effectively utilize at home to continue upper-extremity therapy outside the clinic should provide benefit. To be effective, a user-worn system should provide real-time feedback to encourage the subject as well as document and report progress and compliance to a clinician. Therefore, as a first step, a home-therapy system should integrate hardware and software to automatically detect the therapy tasks a stroke patient is performing. One potential method is to monitor upper-extremity motion and electromyography (EMG) during patient therapy activities. A candidate for this system would need a minimum of grade 2/5 strength (Medical Research Council) in shoulder flexion and abduction. However, the system could also be effective in patients ranging to strong shoulder and elbow control, but limited hand function. Essentially, there must be at least a few upper-extremity or shoulder muscles retaining enough function to generate motion or EMG.

Specific patterns and coordination of muscle activity have been demonstrated [24], [25]. As a subject who suffered a stroke attempts to perform repetitive movement tasks with their paretic limb, we aimed to classify the task he or she was attempting based on arm motion and/or EMG recordings from nonparalyzed muscles even though for severe impairment the produced motion may not closely approximate the goal task. Neural networks employing upper-extremity and shoulder EMG have successfully detected shoulder and elbow angles [26] and classified movement types [27]–[29]. EMG features have been input to standard backpropagation neural networks, clustering algorithms, and self-organizing maps to classify movement. EMG features used include discrete time intervals of integral absolute value, difference absolute mean, variance, and autoregressive model coefficients [27], [29]. EMG can also provide real-time feedback to patients which has been useful when combined in a comprehensive treatment program to regain arm function after stroke [28]–[31]. Kinetic sensors have also been used extensively to quantify and classify motion in movement disorders [32]–[35]. Current micro-electrical-mechanical (MEMS) technology provides miniaturized accelerometers and gyroscopes to measure motion.

The aim of this study was to design, implement, and evaluate a prototype hardware system and algorithm to input motion and EMG data from a stroke subject during therapy and correctly discriminate the upper-extremity task attempted or performed. Subjects were instrumented with motion and EMG data collection instrumentation while they performed a subset of their normal in clinic therapy tasks. Data was collected, processed, and used to develop and test algorithms for upper-extremity stroke therapy task discrimination.

II. Methods

A. Subject Selection

Clinical trials were completed either at CleveMed or at a subject's home. The study was conducted under an approved Institutional Review Board protocol and each subject provided informed consent. Clinical trials were completed with 13 subjects including eight persons without neurological impairments (N) and five persons diagnosed with stroke (S). A clinician screened potential subjects diagnosed with a stroke to ensure no cognitive impairments would prohibit understanding instructions and that subjects could effectively communicate to indicate they understood upper extremity task instructions required for the clinical study. Ensuring task comprehension was important since a major study goal was to detect a particular upper extremity task a subject was attempting even if the arm motion did not match the goal.

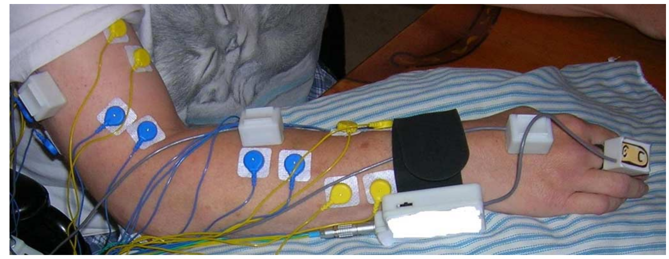

Fig. 1. Each subject was setup with six KinetiSense motion and EMG capture systems consisting of a sensor unit and command module connected by a thin cable.

All subjects diagnosed as having a stroke had some upper-extremity impairment. To document feasibility across a wide ranging degree of motor impairment, we recruited five subjects diagnosed as having had a stroke with varying degrees of upper extremity motor impairment. S1 was six months poststroke with good shoulder control, good elbow control, good wrist, but lacked fine finger control. S2 was two years poststroke with limited shoulder, limited elbow, limited wrist, and no hand control. S3 was one year poststroke with good shoulder, limited elbow, limited wrist, and no hand control. S4 was one year poststroke with limited shoulder, no elbow, no wrist, and no hand control. Finally, S5 was two years poststroke with good shoulder, limited elbow, limited wrist, and no hand control. We evaluated one arm in each subject. For stroke subjects, the affected side was evaluated. For subjects without neurological impairment, the side was randomly selected.

B. Experimental Setup

A 3-D motion and EMG sensing unit (KinetiSense, CleveMed, Cleveland, OH) was used to obtain data from each subject. Each unit consisted of two parts including a sensor unit and command module. The sensor unit consisted of a small, lightweight plastic enclosure that housed a flex circuit with three orthogonal MEMS accelerometers and three orthogonal MEMS gyroscopes. The sensor module was connected to a command module with a thin cable. The command module supplied power, transmitted data via a wireless link, and amplified and acquired two EMG channels. An embedded Bluetooth radio wirelessly transmitted data to a base station computer approximately 20 ft away.

Each subject was set up with six KinetiSense sensor units on the skin using double-sided tape (Fig. 1). Specifically, sensor units were placed on the dorsal aspect of the middle finger, the dorsal aspect of the hand, the dorsal aspect of the forearm, the

TABLE I
RECORDED UPPER EXTREMITY AND SHOULDER MUSCLES

Muscle	Chief Action
Biceps (BI)	Flexion and supination of forearm
Brachioradialis (BR)	Flexion of forearm
Anterior Deltoid (AD)	Flexion of the arm
Posterior Deltoid (PD)	Laterial shoulder rotation, arm extension
Middle Trapezius (MT)	Retraction of scapula
Flexor Digitorum Profundus (FD)	Elbow extension
Extensor Carpi Radialis (ECR)	Wrist extension and radial deviation
Extensor Carpi (Ulnaris (ECU)	Wrist extension and ulnar deviation
Flexor Digitorum Profundus (FD)	Finger flexion
Extensor Digitorum (ED)	Finger extension
Pronator Teres (PT)	Pronation
Palmaris Longus (PL)	Wrist flexion

lateral aspect of the upper arm, the top of the shoulder, and on the waist. The six corresponding command modules were clipped onto an elastic belt worn around the subject's waist. Twelve channels of EMG (Table I) were recorded using the two channel EMG input connector on each of the six command modules. A pair of surface recording electrodes (MVAP Electrode, Newbury Park, CA) with snap connectors was placed over each muscle [36] and a ground electrode over the elbow.

C. Data Collection

A subset of upper-extremity therapy exercises normally completed in the clinic and that could be completed by stroke subjects with a wide range of impairments was selected. A total of five tasks were selected and are described below. One data collection trial consisted of five repetitions of the selected task. For each of the tasks below, the requested initial orientation of the forearm was neutral. However, the initial relaxed forearm orientation of stroke subjects varied as a function of spasticity.

- Task A) *Finger and Wrist Extension*: The subject began with the hand and forearm in a relaxed position resting on a table in front of the body. The subject then attempted simultaneous fingers and wrist extension with as large an excursion as possible, maintained the posture for a few seconds, and then returned to the original position.
- Task B) *Wrist Extension and Finger Flexion*: The subject began with the hand and forearm in a relaxed position on a table in front of the body. The subject then attempted to extend the wrist and at the same time flex the fingers, maintain the position for a few seconds, and then return to a relaxed position.
- Task C) *Arm Sawing Motion*: This task was supported or unsupported depending upon subject impairment level.
  Supported: The subject began with the hand resting near the edge of a table in front the body. The subject then attempted to slide the hand in a straight line on the table away from the body as far as he or she could and then slide the hand back to the body along the same line.
  Unsupported: The subject began with the hand at chest height directly in front of the body. The subject then attempted to move the hand in a straight line through space away from the body as far as he or she could and then move the hand back to the body along the same line.
- Task D) *Forearm Supination and Wrist Deviation*: Forearm Supination and Wrist Deviation The subject began with the hand and forearm in a relaxed position on a table in front of the body. The subject then attempted to supinate the forearm and radially deviate the wrist with as large an excursion as possible, maintain it for a few seconds, and return to a relaxed position
- Task E) *Forearm Pronation and Wrist Deviation*: The subject began with the hand and forearm in a relaxed position on a table in front of the body. The subject then attempted to pronate the forearm and radially deviate the wrist with as large an excursion as possible, maintain it for a few seconds, and return to a relaxed position.

Subjects received verbal instructions and a visual demonstration of each of the five therapy tasks. The goal was to complete ten trials of each task. However, due to time constraints and subject comfort, a few subjects completed less than 50 trials with a minimum of five trials of each task. Therapy task order was randomized and subjects were not given a practice session. The first attempt of the task was included in data collected for analysis. Practice sessions were purposely excluded because one goal was to produce a system that could be quickly trained to recognize subject therapy exercises. Collecting data without practice sessions was expected to produce a worst-case scenario to validate algorithm development.

While subjects performed each task, the KinetiSense command modules sampled and digitized upper-extremity motion and EMG data. Kinetic data, including three channels of linear acceleration from accelerometers and three channels of angular velocity from gyroscopes from each sensor module, were sampled at 128 Hz. EMG was sampled at 2048 Hz, low pass filtered with a cutoff of 1024 Hz, and then root mean square (rms) processed in discrete bins of approximately 7.8 ms so that both the raw kinetic sensor and processed EMG data were collected at the same 128 Hz rate. The accelerometer, gyroscope and rms EMG were then transmitted in a data packet from the command modules over the wireless network to a USB Bluetooth adapter located on the base station computer. Data was stored on the base station computer for offline analysis.

D. Task Discrimination Algorithm Development

Automated task discrimination algorithms for each subject were developed using different combinations of EMG, accelerometer, and/or gyroscope inputs. Several important system constraints were taken into account during development. First, one extremely important difference in subjects diagnosed with stroke compared to subjects without neurological impairment was that it was not only important to detect when they "were" performing a task, but also when they were "attempting" to perform a task. For example, someone who could not yet move their wrist joint may have produced repeatable patterns in elbow muscles as they were "attempting" to move their wrist. Second, different subjects diagnosed with stroke had different degrees of motor impairment and coordination patterns based on their specific injury. Therefore, large variations in coordinated muscle activity existed between subjects for the same therapy task as well as some variation within a single subject. It would not be reasonable to have assumed that a single hard coded algorithm could distinguish tasks among every potential

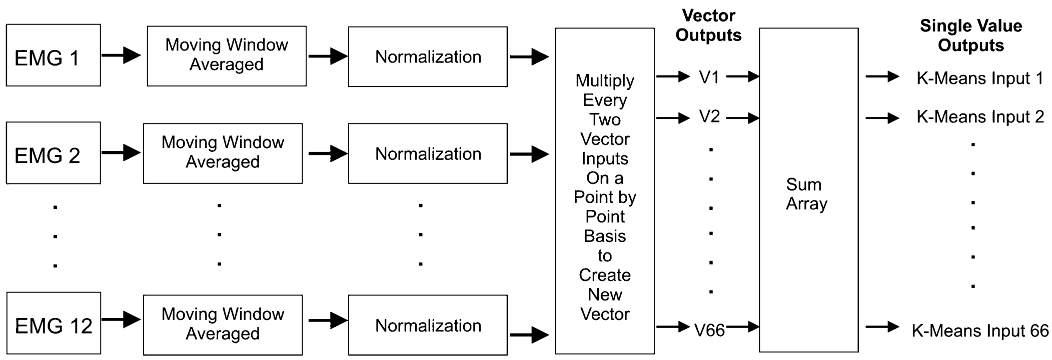

Fig. 2. Block diagram of the EMG signal processing algorithm to provide inputs for the K-means clustering algorithm.

subject. Because of this, the goal was to implement an algorithm structure that could be quickly trained in a clinician's office while the subject completes therapy tasks as part of their normal visit. Additionally, it is important to remember that a future goal is to improve motor control over time. Therefore, as a subject would use the system more and more, coordination patterns of motion and EMG should continue to change, albeit slowly. The algorithm structure should be capable of adaptive learning over time while the subject's motor function improves. Finally, the algorithm should take advantage of the fact that many therapy exercises are repetitive motions. These repetitive motions should produce specific patterns in a subset of the signals being recorded.

Based on these constraints, development began with a simple K-means clustering algorithm. The K-means algorithm provided many advantages including fast training and the ability to continue to add new data over time for adaptive learning. In general, the K-means algorithm defines a set of cluster centers of n-dimensions where n is the number of quantitative input features used to describe a task trial. Since five tasks were used in the therapy exercise set, the K-means algorithm included five cluster centers. Once the cluster centers were defined, the n quantitative features of a single trial were compared to each of the cluster centers. The Euclidean distance of all quantitative features was calculated to each cluster center. The task trial was then assigned to the cluster center with the closest Euclidean distance. That cluster center was then updated to reflect the additional value.

Therefore, quantitative input features were extracted for each task trial. These inputs were expected to capture repeatable patterns generated by subjects during tasks. More specifically, the input features were required to be a function of repeatable relationships that existed between the motion of different limb segments or EMG channels during a specific task. Additionally, relationships were not be penalized for being small, i.e., weak muscles or small amplitude movements. Furthermore, the algorithm was expected to produce good results regardless of task speed. Finally, the need to normalize EMG signals to a global maximum and minimum was removed to simplify setup and avoid calibration before each use. As described earlier, 48 channels of data at 128 Hz were collected for each trial. This included 12 channels of processed rms EMG, 18 channels of linear acceleration from accelerometers and 18 channels of angular velocity from gyroscopes. Based on the above criteria, the following quantitative feature inputs were extracted.

We first attempted to use only EMG for task discrimination, as this would minimize the requirements to power electromechanical transducers and reduce system cost and size. Each channel of rms EMG was moving window averaged using a window size of 30 data points and then independently normalized to a zero mean and standard deviation of one (Fig. 2). In other words, normalization for a particular data channel and trial depended only on that channel and trial. Next, every combination of 2 out of the 12 processed EMG channels was multiplied together on a point-by-point basis to create a new vector of the same length. That new vector was then summed to create a single value for the K-means input. Since there are a total of 66 combinations of 2 out of 12 EMGs, each trial had an input pattern vector of 66 dimensions. The same procedure was repeated for processing both the accelerometer and gyroscope data.

E. Task Discrimination Algorithm Testing

Separate cluster algorithms were trained and tested for each subject. We defined initial cluster centers for each task by calculating the average of the dimension pattern vectors for a randomly selected 80% of data collected for each task. This 80% was known as the training set. After the five cluster centers were calculated, we then reapplied each of the training set pattern vectors and calculated to which of the five clusters they were assigned based on Euclidean distance from the cluster centers. Additionally, we calculated to which cluster center the remaining 20% of the trials, or the generalization set, was assigned. A correct task classification means that the trial was assigned to the correct cluster center. The percentage of correct task classifications was calculated by dividing the number of correct cluster center assignments by the total number of trials. The percentage of correct task classifications for both the training and generalization sets was calculated for each subject.

By early visual inspection we determined that sensor modules located at the top of the shoulder and waist provided little added information. Therefore, they were removed from the analysis. Sensor modules on the finger, hand, forearm, and upper arm, and all EMG channels were included in the analysis. The above cluster algorithm analysis was completed with e ach of the seven combinations of sensor input types: 1) only EMG, 2) only accelerometers, 3) only gyroscopes, 4) accelerometers and gyroscopes, 5) EMG and gyroscopes, 6) EMG and accelerometers, and 7) EMG, accelerometers, and gyroscopes. The objective was to determine which sensor combination provided the best information. Using S-Plus 2000 statistical software, we completed an analysis of variance (ANOVA) using the dependent variable of percent correct classifications and the independent variables of subject population (stroke or normal), therapy task and sensor type combination.

III. Results

All subjects were able to elicit some type of movement pattern during the therapy tasks even if they did not match the goal therapy task and the movements were visually indistinguishable from attempts at different tasks. This provided motion and EMG inputs for the automated task discrimination algorithm. Two important questions were answered during algorithm development and testing. First, what was the minimum combination of sensor types required for accurate detection? Removing redundant or nonsignificant sensors would reduce size, power consumption, and cost. And second, what was the accuracy of therapy task classification that could be achieved using that combination of sensor inputs?

A. Subject Task Completion

All normal subjects were able to successfully complete the set of five therapy tasks. Stroke subjects had mixed results. Those that were less impaired were able to successfully complete all tasks. Those with greater impairment had less success completing the tasks. Nevertheless, all stroke subjects elicited motion and EMG from some part of the upper-extremity while attempting to complete the correct pattern of movement. Therefore, while the movement did not closely approximate the goal in some cases, motion and EMG were successfully recorded (Figs. 3–5).

B. Sensor Reduction Analysis

The trained algorithms structures allowed generalization of features to produce accurate task discrimination. When all collected data (EMG, accelerometers, and gyroscopes) was used in the ANOVA computation, sensor combination, subject population, and therapy task all were significant input variables. The grand means of task discrimination accuracy for population were 89.61% for normals and 82.27% for stroke indicating the algorithms worked slightly better for normals, which should be expected. The grand means for different sensor combinations are shown (Table II). While EMG alone produced the worst accuracy at 78.25%, it was important to retain EMG as in input parameter since it also reveals important information about motor recovery and is extremely useful as a real-time feedback mechanism to isolate single muscle activity. Therefore, at least one of the additional sensor types needed to be added to improve accuracy. Sensor combination was a significant variable ($p < 0.01$) when all sensor combination inputs were used in the ANOVA. However, when all trials using EMG alone were removed from the ANOVA, sensor combination was not a significant variable ($p = 0.28$). This revealed that task discrimination using only cEMG can be improved by adding at least one of the other sensor

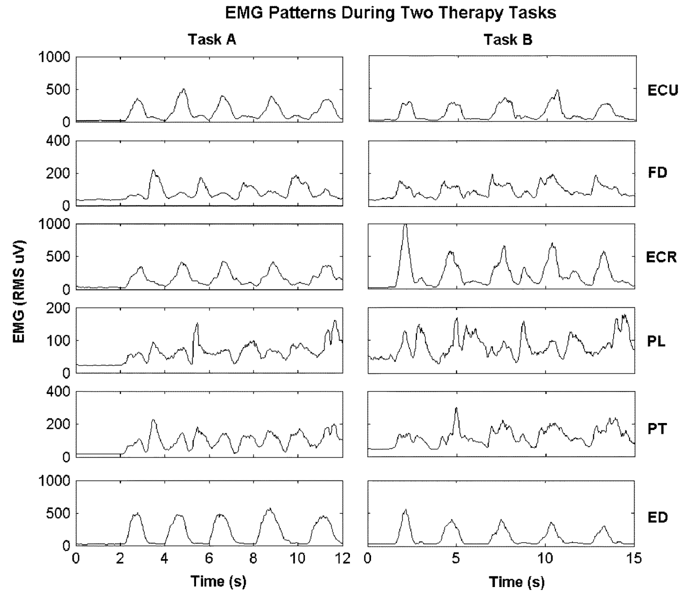

Fig. 3. The rms processed and moving window averaged EMG for subject N1 is shown for six channels including ECU, FD, ECR, palmaris longus (PL), pronator teres (PT), and extensor digitorum (ED). Two separate tasks are illustrated including Task A-Finger and wrist extension and Task B-Finger flexion with wrist extension.

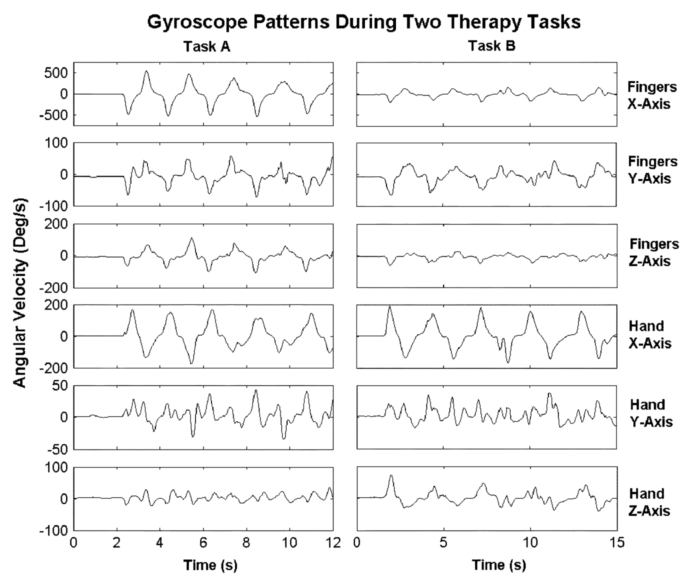

Fig. 4. Moving window averaged angular velocity for subject N1 is shown for each gyroscope axis of the sensor unit worn on the hand and finger. Two separate tasks are illustrated including Task A-Finger and wrist extension and Task B-Finger flexion with wrist extension.

options, accelerometers or gyroscopes. Adding both types of sensors to the task discrimination algorithm does not provide any further significance than only one. Gyroscopes were chosen over accelerometers since they act independently of gravity and can more easily be used to calculate angular range of motion and quantify other therapy parameters.

C. Task Discrimination Accuracy

The system accurately classified therapy tasks using the combination of 12 channels of EMG and 12 gyroscope inputs from

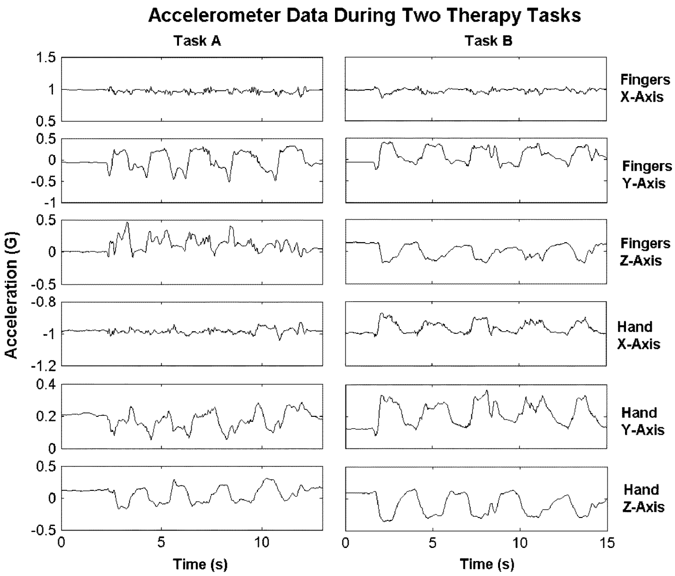

Fig. 5. Moving window averaged linear acceleration for subject N1 is shown for each accelerometer axis of the sensor unit worn on the hand and finger. Two separate tasks are illustrated including Task A-Finger and wrist extension and Task B-Finger flexion with wrist extension.

TABLE II
GRAND MEANS CALCULATED FOR ALL SENSOR INPUT COMBINATION TYPES DURING AN ANOVA

A	AG	E	EA	EAG	EG	G
86.19	88.99	78.25	87.06	89.41	88.22	87.76

E: EMG, A: Accelerometers, G: Gyroscopes

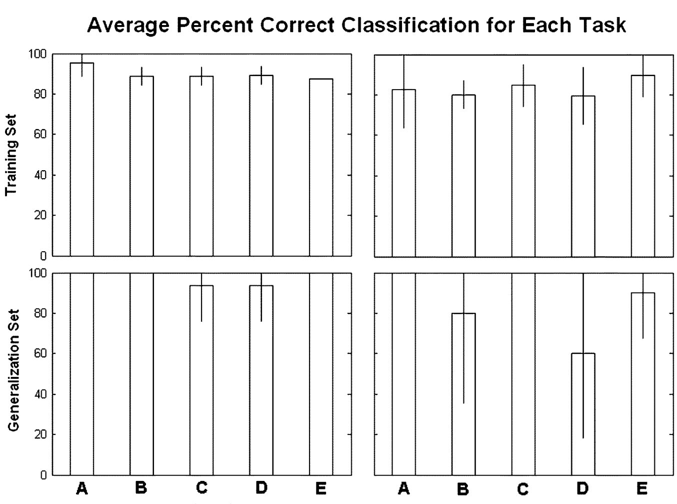

Fig. 6. Percent correct task classification for each task (A, B, C, D, E) is averaged over each subject. Data is separated by normals or stroke and training or generalization results.

four sensor units (each with three orthogonal gyroscopes) on the finger, hand, forearm, and upper arm. Results are shown for separate therapy tasks across all subjects (Fig. 6) and for separate subjects across all therapy tasks (Fig. 7). The trained algorithm structure accurately classified therapy task trials that were a part of the training set and also generalized to accurately classify the set of generalization data. All but one (Task D of the generalization set in stroke subjects) showed at least 80% accuracy. The large standard deviations in some of the generalization results are due to the limited number of trials. The system accurately classified which task a subject was attempting to perform despite the fact that those with severe impairment produced movements that did not resemble the goal tasks and were visually indistinguishable from other tasks.

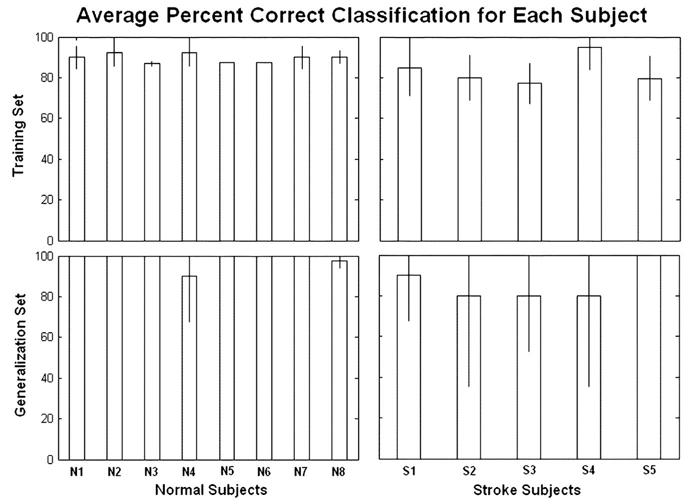

Fig. 7. Percent correct task classification for each subject is averaged over every task for that subject.

IV. DISCUSSION

A hardware technology platform consisting of accelerometers, gyroscopes, and electromyography was implemented to transmit data over a wireless network to a base station computer. Multiple motion sensor outputs and multichannel EMG data were collected from the upper-extremity as normal and stroke subjects completed a set of five upper-extremity stroke therapy tasks. The collected data was used to successfully train algorithms to accurately classify the therapy task being completed by the subject.

A. Task Discrimination Accuracy and Sensor Selection

The results represent an important first step in the development of a user-worn system for upper-extremity motor rehabilitation after stroke. The compact, wireless, prototype system accurately classified the therapy task not only when a normal or slightly impaired subject was "completing" the therapy task, but also when a stroke subject with severe impairment was only "attempting" to complete the goal task. The accuracy rates above 80% for all but one data point should be considered good in light of the fact that subjects were not allowed to practice tasks before data collection and the limited number of trials collected. Allowing a subject to practice and collecting more data should produce even more repeatable patterns and further improve accuracy results. Furthermore, it is important to note that during therapy sessions subjects should not continually produce abnormal movements or movements with other parts of the body such as the trunk to mimic the desired motion of the upper extremity. However, for subjects that are severely impaired, these may initially be the only signals available to indicate the actual task a subject is trying to complete. Once the desired task is detected, interventions such as functional electrical stimulation (FES) described below, may be incorporated into the system to reinforce correct motor patterns and assist with the task during therapy.

One important goal of this initial study was to determine the appropriate sensor types to use for correct classification and further system hardware development. Electromyography is an important parameter to monitor for home-therapy applications as it provides insight into individual muscle recovery and is an effective tool for real-time display feedback during therapy. Therefore, EMG was included as an input sensor. However, normalization is typically a problematic issue in EMG applications especially in the home environment. Normalizing each channel of data to a zero mean and standard deviation of one based only on the current trial solved this issue and did not penalize muscle activity for being of small amplitude compared to other stronger muscles. Additionally, it alleviated the need for a calibration routine. The combination of EMG and gyroscope data provided sufficient information to accurately detect the therapy task being completed. Gyroscopes were selected over accelerometers since simpler signal processing techniques can be applied to gyroscope data to determine parameters such as range-of-motion during the repetitive therapy tasks. The accelerometers did not add significant value to the task discrimination scheme and removing them will reduce size, cost, and power consumption.

Finally, the processing technique of multiplying each EMG channel by the other EMG channels and each angular velocity input vector by the other angular velocity vectors on a point by point basis to create a new vector related to the coordination patterns between EMG or angular velocity proved valuable. For example, Fig. 3 illustrates that extensor carpi ulnaris (ECU) and extensor carpi radialis (ECR) act as agonists in both Task A and Task B. However, ECU and flexor digitorum (FD) act differently depending on the Task. During Task A they act out of phase with each other while in Task B they act in phase with each other. The sum of this new vector created by multiplying different EMG or motion channels together described if muscles or limb segments acted agonistically or antagonistically during a therapy task. If muscles or limb segments acted as agonists it would produce very large positive numbers when the new vector was summed. If they were acting as antagonists, it would produce very large negative numbers. When there was little positive or negative correlation between the muscles it would produce numbers closer to zero. These single value inputs (Fig. 2) describing the coordination patterns between muscles or motion provided significant information for accurate task classification.

B. Sensor Reduction Analysis

A home-therapy system must be able to accurately classify the therapy task a subject is performing to provide feedback, monitor compliance, and allow the possibility for intervention. For example, correct classification allows effective real-time feedback to a subject to encourage them or provide information about repetitions and/or task time remaining as they complete therapy tasks. The system needs to have accurate task classification or a subject may become frustrated with incorrect feedback.

While we were able to accurately detect what task a subject was attempting, some stroke subjects could not accurately complete the requested tasks due to muscles weak or paralyzed from the stroke. Functional electrical stimulation (FES) can be used to integrate weak or paralyzed muscles into therapy. It has been established that repetitive motor activation of both simple and complex movements improves the rate and amount of functional recovery in stroke patients. Additionally, FES has been shown to improve functional outcomes during therapy. Therefore, since we have demonstrated the ability to accurately detect a task a subject is performing, we could potentially intervene with FES to the appropriate muscles to assist the therapy task. FES is advantageous compared to other stroke therapies since it is noninvasive with minimal side effects [37]–[46]. FES electrically stimulates muscles to create a contraction. Some post stroke patients have paralyzed muscles while others have weak muscles that are overpowered by spasticity of an opposing muscle group. Therefore, a muscle normally required for a therapy task, but inactive due to stroke could potentially be included during therapy using FES. By accurately detecting the task a subject is performing, FES could be applied to specific target muscles during their therapy task attempts to improve motor performance. Additionally, utilizing FES at the sensory level helps the user localize muscles they are trying to use for a particular therapy task. Sensory stimulation in conjunction with physiotherapy may improve motor skills. Providing feedback from the subject's own movements facilitates motor learning and may drive cortical reorganization.

Home rehabilitation has shown effectiveness in stroke patients [5], [47]–[49]. However, important factors that should be considered when developing a system for at home therapy include patient compliance time and ease of use. First, home rehabilitation should be provided with the same or greater intensity as inpatient treatment [50]. Therefore, a system designed for home use should encourage patients to complete therapy at home. A first step toward that end was achieved in this work by accurately classifying therapy tasks through EMG and motion sensors. The future envisioned system will use EMG, motion, and task classification to control graphical real-time feedback and video games to encourage patient use. Furthermore, the envisioned system will provide easy use by upgrading the hardware technology platform into an integrated sleeve-worn system easily donned by subjects at home. We plan to integrate the five KinetiSense systems and an FES device into a single unit to provide a complete, clinically deployable system for home therapy. Blanking will be an important feature in the next generation system to avoid stimulation artifact from contaminating the EMG. A sleeve-worn design should minimize problems with repeatable sensor and electrode placement that could cause cross talk from other muscles and produce errors in trained task recognition algorithms. Furthermore, a sleeve embedded with the motion sensors and labeled with appropriate pockets for electrode placement should simplify home setup for users and his or her caregivers. A system that allows subjects to continue therapy outside the clinic and monitors compliance should further improve functional recovery by increasing time spent in therapy. Providing multimodal inputs to the subject during therapy such as real-time visual feedback and sensory inputs from FES driven muscles actuated by muscle coordination patterns may help drive cortical reorganization, increase motor function and improve quality of life.

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Joseph P. Giuffrida (M’04) received the B.S., M.S., and Ph.D. degrees in biomedical engineering from Case Western Reserve University, Cleveland, OH, in 1999, 2000, and 2004 respectively.

He is currently the Director of the Division of Movement Disorders, Cleveland Medical Devices Inc., Cleveland, OH. His research interests include the development of clinically deployable devices to measure and rehabilitate movement disorders including Parkinson’s disease, stroke, spinal-cord injury, and cerebral palsy.

Alan Lerner received the B.S. degree in biology from the College of Agriculture and Life Sciences, Cornell University, in 1979, and the M.D. degree from Cornell University, in 1987.

He is currently Associate Professor of Neurology at Case Western Reserve University. Additionally, he is Director of the Memory and Cognition Center of the Neurological Institute at University Hospitals Case Medical Center, Cleveland, OH. His research interests include behavioral neurology, statistical approaches to behavior, and Alzheimer’s disease.

Dr. Lerner is a member of the American Academy of Neurology and Society for Neuroscience

Richard Steiner is with the Department of Statistics at the University of Akron, Akron, OH.

Janis Daly received the B.A. degree in biology from Oberlin College, the M.S. degree in physical therapy from Case Western Reserve University, Cleveland, OH, and the Ph.D. degree in psychology from University of Akron, Akron, OH.

She is currently a Research Career Scientist, Department of Veterans Affairs, Washington, D.C., the Director of Stroke Motor Control and Motor Learning, and Associate Director of the FES Center of Excellence in the Louis Stokes Cleveland Department of Veterans Affairs Medical Center, and Associate Professor in the Department of Neurology, Case Western Reserve University School of Medicine. Her research interests include the restoration of cognitive and motor processes required for the recovery of motor function after stroke or brain injury.