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ARhT: A Portable Hand Therapy System

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***Abstract*—We introduce ARhT (Automated Relearning hand Therapy), a portable hand therapy system that enables a user to perform physical therapy at the comfort of their own home. This reduces rehabilitation time, enhances the user experience, reduces cost and provides accountability to physical therapy sessions. ARhT complements traditional therapy methods by interacting with the user in real time and providing the patient user friendly instructions, feedback, and progress tracking. The therapist pre-selects the hand gestures that comprise every workout and can view session information on a patient to patient basis within a standalone web application. ARhT incorporates a data acquisition subsystem which houses EMG sensors and a custom computation and communication board. The sensor data is transmitted to an Android smartphone that determines the user performance and interacts with the user through a graphical user interface. Our results show that our system recognizes hand therapy gestures with over 95% accuracy.**

I. INTRODUCTION

AUTOMATED Relearning hand Therapy (ARhT) is a system that combines sensors placed on the forearm with an Android phone to track and monitor hand and finger gestures. Our solution involves instructing a hand therapy patient to perform a specific movement, monitoring how well the patient performed the instructed movement, and displaying the session's results on the screen of the Android device. The system stores these results in a database which allows the therapist to track a patient's progress.

For people who suffer injuries to their hands and arms, a significant amount of physical therapy may be required to regain strength and flexibility. This is usually done by a mixture of therapy appointments and at home exercises. In order for physical therapy to be effective, patients need to have multiple appointments a week over a course of a few months. Each session with a therapist is expensive and can cost up to $50 per visit [1]. However, if the home exercises are performed incorrectly, or not done at all, the therapy is less effective.

Three main technologies are being studied to assist hand therapists with treatment: Grip Measurement Devices [2], Electromechanical Orthotics [3], and Gloves [4]. Grip Dynamometer (MAP) is one type of electronic grip measurement device [2]. Electromechanical orthotics, such as the Mentor™ [3] incorporates EMG sensors and robotic components to provide strength and flexibility training. The Mentor™ combines resistance to wrist movements and monitors progress through a tracking system. The glove reported in [4] is used to measure grasp aperture, or how well a person can open and close their hand, by calculating the distance between the thumb and the index finger.

These systems are expensive, bulky, and do not allow the patient to perform their therapy at home. This means that progress tracking must be done during the limited visits a patient has with a therapist. Additionally, each one of these systems is designed to target only one aspect of hand motion or one exercise.

In contrast, ARhT enables portability by harnessing the processing power of an Android device. While current systems require the patient to be in a therapy center, ARhT encourages the patient to perform exercises at any location and at any time. Our system tracks patient results with every use, thus providing a comprehensive collection of user statistics. The application instructs the patient to perform a hand therapy gesture, virtualizing the therapy session. Finally, ARhT is used for multiple gestures and measures more than one aspect of the motion. In summary, ARhT is a standalone system, without many of the constraints found in current physical therapy technologies.

To get maximum benefit out of physical therapy, therapists require patients to exercise at home, but without any evidence of the exercises, there is no guarantee of patient compliance. An issue arises because health insurance providers are increasingly holding patients accountable for their own recovery [5]. ARhT addresses this problem by collecting information about each repetition of a gesture during a session and storing it in a database. With our system, a therapist has proof that patients have been following instructions.

The paper is organized as follows. In the next section we introduce ARhT system overview. The hand/arm device is described in Section III and gesture recognition algorithms are introduced in Section IV. Section V describes the experiments and results and Section VI concludes the paper.

II. ARHT SYSTEM OVERVIEW

ARhT includes three parts (see Figure 1):

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1. Hand/Arm Device: A collection of circuits worn by the patient that provides filtering and amplification to the signal obtained by electrodes placed on the skin.
2. Android device: Custom software processes signals received from the Hand/Arm device, performs gesture recognition, interacts with the patient through a graphical user interface, stores the results locally for short term progress tracking, and transmits the results to a remote server for long term progress tracking. The Android device interfaces with the Hand/Arm Device through an IOIO [6].
3. Server: Custom software receives and stores the information generated by the Android device and provides a content management system and visual analytics to the therapist.

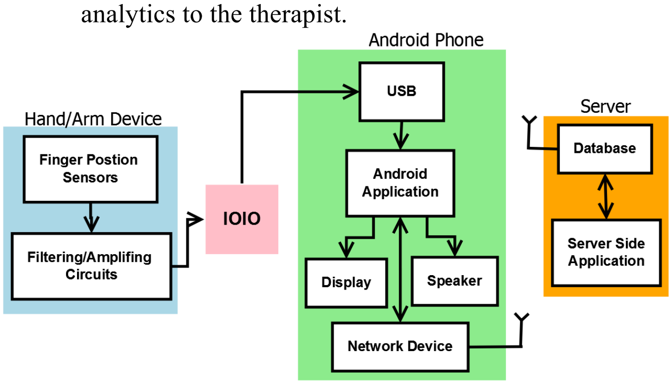


Figure 1. ARhT System Block Diagram

III. Hand/Arm Device

The Hand/Arm Device processes electric signals generated in muscles during movements such as finger bending or wrist flexion, known as electromyography (EMG) signals. EMG signals are captured by placing electrodes on the surface of the skin that pick up the electric potentials produced as a muscle contracts. Electric potentials are on the order of 100mV within a muscle and are attenuated by body tissues to the order of 1 mV at the surface of the skin; such potentials have different time and frequency footprints depending on what muscle is being contracted and the duration of the contraction [7]. Given these characteristics, time and frequency domain representations are used to create multiple gesture classifiers. A total of two sets of sensors are used in project ARhT. The patient places one set of electrodes on the Brachioradialis, a muscle that flexes the wrist located on the bottom of the forearm, approximately two centimeters apart. Another set of electrodes is placed on the extensors, muscles that move your wrist located on the top of the forearm, to capture any flexion movements.

The Hand/Arm Device consists of a filtering/amplifying circuit (see Figure 2) and a power indicator circuit. The main block of the filtering/amplifying circuit is the instrumentation amplifier, which is used because it has a high common-mode rejection. Since the EMG signals are so small in amplitude, they easily get lost in electric noise contained within the human body. Since the electrodes are placed close together on the skin, the instrumentation amplifier rejects the common noise signal seen at both sensors. The instrumentation amplifier has a buffered input built from JFET-input op-amps, which keep the current drawn from the human body on the order of a 1 nA. It would take much more current to cause harm to a human being. The rest of the circuit formats the signals to be compatible with the rest of the system.

IV. Gesture Recognition

Gesture recognition is used to classify how well a user performs an exercise. First, our software samples the

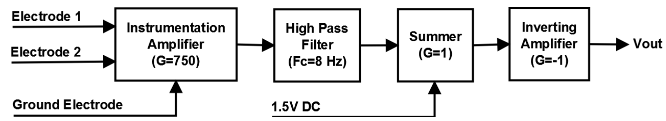


Figure 2. Block diagram of Filtering/Amplifying Circuits used for EMG signals.

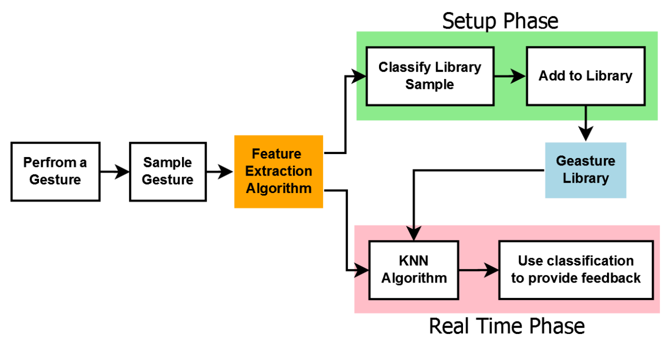


Figure 3. Gesture recognition flow

outgoing signals from the Hand/Arm Device and extracts its features. Then, these features can be used in the *Setup Phase* to or in the *Real Time Phase* (see Figure 3). In the *Setup Phase,* the sample is manually given a classification. In the *Real Time Phase* the sample is cross referenced to the library and classified by the software.

A. Gesture Features and Extraction

Throughout any given exercise, the voltage measured by the hand arm device varies dramatically in amplitude. An example of this can be seen in Figure 4. This signal is also composed of many different frequencies, making it difficult to classify a signal directly from the Hand/Arm Device. We developed an algorithm to extract certain features from both the time and frequency domain representations of the signal. We chose features that [8] found to work the best after post analysis.

In the time domain, the features are the *signal length*, *mean value, root mean squared value, number of vertices,* and *number of baseline crosses.* The signal length is the difference between the start of the signal and the end of the signal as shown in Figure 4. The start of the signal is defined by the first sample above a voltage threshold we define to be the *time domain threshold*. The end of the signal is defined by the last sample below the time domain threshold. Since the signal from the Hand/Arm Device oscillates from a positive to a negative value frequently within one continuous sample, it is necessary to check that many consecutive samples are below the time domain threshold to make sure part of the signal is not lost. We defined this number of samples as the *end of signal threshold*.

The following values are defined within the signal length. The *mean value* and *root mean square value* are their respective quantities. The *number of vertices* is the number of times there is a local minimum or maximum. The *number of baseline crosses* is the number of times the signal crosses the virtual zero called the baseline. The analog to digital convertor used in this system only accepts positive voltages. Since EMG signals can also be negative, a DC offset had to be added to the signal which is the baseline value.

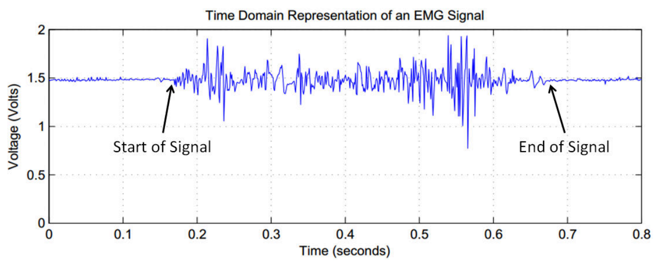


Figure 4. Time Domain representation of an EMG Signal from the Hand/Arm Device.

In the frequency domain, the features we use are *fundamental frequency, region length*, and *Fourier variance.* The *fundamental frequency* is the frequency with the greatest magnitude. The *region length* is the amount of frequencies above the mean magnitude. The *Fourier variance* is the variance of the magnitudes of the frequency domain components.

B. Setup Phase

The setup phase is used to build the gesture recognition library. The application allows a subject to perform any exercise, sample the signal, analyze the signal, and then assign a classification to that sample. After the signal analysis, the application displays the gesture features to confirm the classifications. Then the sample can be added to the gesture library, and stored on a server to be downloaded for use on the phone when needed.

C. Real Time Phase

The Real Time Phase is responsible for real-time gesture recognition. A K-th Nearest Neighbor (KNN) Algorithm is used and works by mapping the library in a space with a dimension for each gesture feature. For example, if six gesture features were used for gesture recognition, this would be a six dimensional space. When an unknown exercise is preformed, sampled, and has its gesture features extracted, the unknown sample is also mapped into this space. The algorithm then finds its K nearest neighbors based on Euclidean distance, where K is the desired number of neighbors for comparison. Finally, the algorithm takes a vote of the K nearest neighbors to find the most popular classification, which becomes the classification of the unknown sample.

KNN algorithms generally treat each set of gesture features as a vector and then normalize and scale the vectors to improve accuracy. For this project, the greatest accuracy was achieved using un-scaled values because all but one dimension was on the same order of magnitude. The Fourier variance was of magnitude higher than all others. Another criterion for classification using KNN algorithms is the weight given to each dimension in the voting process. There are many different ways to weight the distances, but after an empirical examination, weighing each vote by dividing by the squared value of the distance provided the highest accuracy for this project.

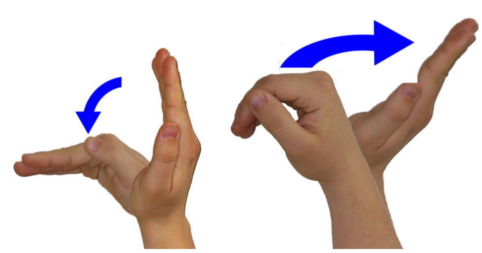
D. Classifications

Classifications are used to provide feedback to the subject on how well they are preforming their exercises. Feedback is important because it gives a subject a way to improve their performance of an exercise so they can get the most out of each repetition within a session. This project used three classifications for all of the gestures targeted by this project: *Good*, Abrupt, and *Slow.*

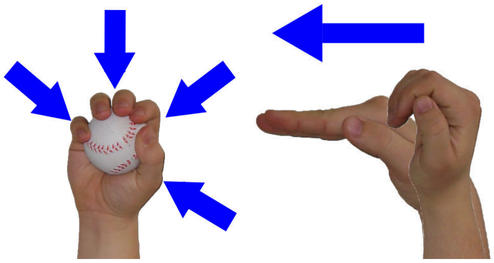
Good is used to classify a repetition of an exercise that was performed exactly as it should be. This means that the repetition was actively performed throughout the full range of motion of the exercise and with the correct pace as defined by the gesture library. “Actively performs” means the subject exerts effort through the whole motion of the exercise. For example, if the subject limply drops their hand during an exercise, they did not actively preform the exercise. Pace is the measure of how long it takes to perform the full range of motion of an exercise.

Abrupt is a classifier for when the repetition’s pace is quicker than the desired pace. This could be cause by an incomplete range of motion for a given gesture and/or performing the gesture too hastily.

Slow is a classifier for when the repetition is actively performed through the entire range of motion of the exercise, but at a pace significantly slower than the pace in the *Good* case. For example, if a gesture was performed through the full range of motion but at a pace of one second instead of the desired half a second as defined by the library, the exercise would be classified as *Slow.* This system then notifies the user that they need to perform their exercises at a faster pace.



(a) (b)



(c) (d)

Figure 5. Target exercises, (a) Wrist Flexion, (b) Wrist extension, (c) Finger Implement Squeeze, and (d) Finger Forward Flexor Tendon Gliding

V. RESULTS AND ANALYSIS

We tested ARhT with the following four exercises (see Figure 5): *Wrist Flexion*, *Wrist Extension*, *Finger Implement Squeeze*, and *Finger Forward Flexor Tendon Gliding*. These exercises which are given to wrist fracture patients halfway through the recovery process [9, 10] are ideal as a test case for our system because they work different combinations of muscle groups.

	Wrist Flexion	Wrist Extension	Finger Imp. Squeeze	Tendon Gliding
Good	100%	97.22%	100%	100%
Abrupt	92.11%	100%	90%	100%
Slow	100%	100%	100%	100%
Total	96.67%	98.68	96.15%	100%

Table 1. Classification results

Each of the four subjects is a 22 year old, right handed male, with similar life styles. In the *setup phase* (see Figure 3), we developed the library using the methods described in the following paragraph.

Each subject recorded 100 samples for each exercise, 20 of each classification mentioned above, in one sitting with the same set of electrodes. Classifications were assigned by the subject and then verified by a third party based on the gesture features of a sample. The same subjects came in at least one day later and recorded samples to be tested in the *Real Time Phase* against the previously built libraries. Table 1 displays the percentage of correct classifications by the gesture recognition algorithm compared to the class assigned by the subject to each exercise.

VI. SUMMARY AND CONCLUSION

Project ARhT provides an easy to use and low cost solution that complements hand physical therapy performed at a therapist's office. ARhT allows the patients to perform therapy exercises assigned by the therapist at any time and any place, while providing accountability.

ARhT's intuitive user interface allows the user to receive immediate feedback on how they are performing an exercise while storing that information into a database for long term tracking. The patient and therapist can review the patient's progress over time and make changes to the therapy sessions.

The results show that the system provides very high classification accuracy of over 95% in all cases.

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