Self-managed Patient-Game interaction using the Barrett WAM Arm for Motion Analysis

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ABSTRACT

In this paper, we present a framework for physical rehabilitation, that uses a combination of video gaming and robotic technology to allow the monitoring and progress tracking of a person during physical therapy. The system, called MAGNI, uses the advanced control capabilities of the Barrett WAM Arm robot and a custom-made video game. The MAGNI system helps the patient to complete a rehabilitation session through a user-system, game-based interaction program, involving exercises prescribed by a therapist. The system can control and supervise the rehabilitation sessions to ensure compliance and safe exercising. It uses motion analysis to provide an evaluation of the patient's progress over time. The MAGNI system records the position of the subject's hand during game interaction with the robotic arm and analyzes this data using pattern matching and machine learning algorithms, in order to guide self-managed physical therapy. Our experiments show that we can accurately classify user motion activity between a set of different exercises, and measure user compliance with the prescribed regimens.

Categories and Subject Descriptors

I.5.1 [**Pattern Recognition**]: Statistical; I.2.8 [**Problem Solving/Control Methods and Search**]: Control Theory—*Robotics*

General Terms

Human-robot interaction, Algorithms, Usability and HCI issues, Tele-rehabilitation, Experimentation

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Keywords

Therapy Games and Rehabilitation, Motion analysis, Human-robot interaction, Machine learning for decision making, Haptics

1. INTRODUCTION

A traffic accident, a battlefield injury, or a stroke can lead to brain, musculoskeletal, or neuromuscular injuries that impact motor and cognitive functions and drastically change a person's life. In such situations, rehabilitation plays a critical role in the ability of the patient to partly or fully regain motor function. Occupational therapy is a crucial part of the rehabilitation process during recovery from an injury that has resulted in hand motor function loss. Emerging sensor technologies are enhancing traditional occupational therapy with tools and systems that complement the expert's work and by enabling rich data collection and accurate analysis. In recent years, a number of different approaches have been proposed, aiming to assist and support, not replace, the expert by complementing the patient-therapist interaction with assistive technologies, such as therapy-oriented computer games, virtual reality, and robot-aided rehabilitation systems. In this paper we focus on human robot interaction used in tele-rehabilitation.

If a robot is to react properly to human gestures or movements in tele-rehabilitation therapy, tracking and understanding human motion is important. In this paper we analyze the trajectories of a robotic arm's end-effector as the subject plays a virtual game in order to use a performance-based impedance control algorithm to define the levels of robot assistance in the future. In our system, the robotic arm identifies the hand motion trajectories, as the patient exercises using the robotic arm, and classifies them in order to extract the patient's upper limb limitations (Figure 1). In parallel, the system evaluates how accurately each exercise is performed, compared to what was prescribed by the therapist, and dynamically adjusts resistance or assistance, in order to help the patient stay within the acceptable limits of deviation as we propose in our previous work [19].

MAGNI is a self-managed, game-based human-robot tele-rehabilitation system that can be operated without a contin-

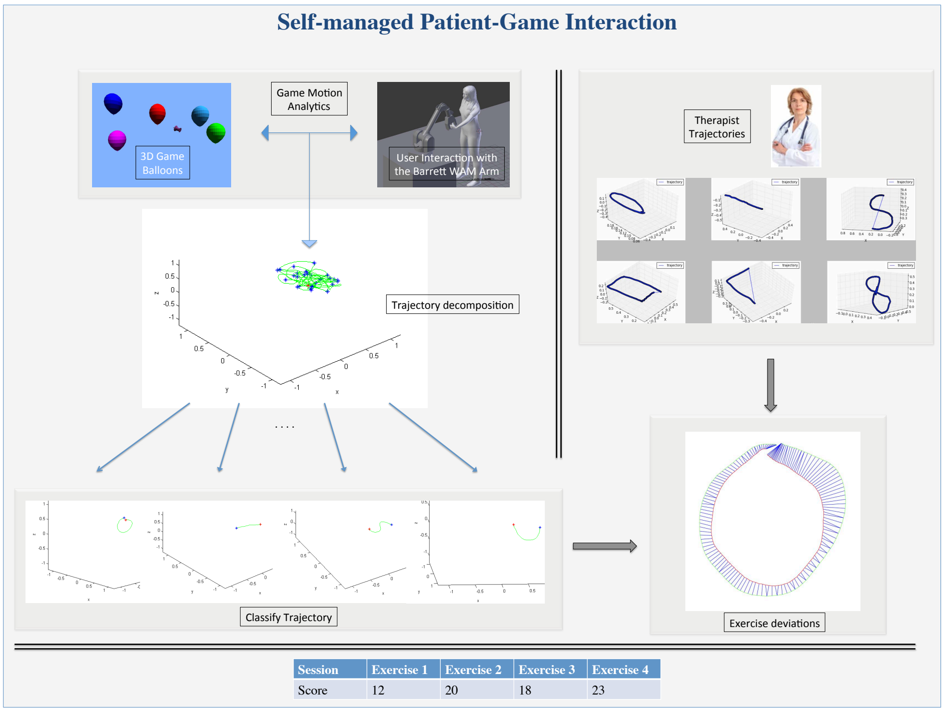

Figure 1: The proposed system scheme that classifies and evaluates the user performance and activity scores.

uous supervision by the therapist, and for each patient, there are specific types of motion associated with their rehabilitation regimen. We have implemented a 3D video game that was designed to help the patient complete the exercise regimen by providing entertainment incentives. Data collected include, the user's hand position over time, game performance, abrupt changes, reaction time or delays and overall score. A performance activity score (PAS) is generated for each session and visualized in a way that allows the therapist to control and supervise the session remotely. The therapist, using a back-end database, can also perform a comparative analysis to compare a particular patient's progress to other similar cases.

There rest of this paper is organized as follows. Section 2 provides a brief overview of previous related work in the area. In Section 3 we introduce the physical rehabilitation system. In Section 4, we present our approach for trajectory classification. Section 5 explains our motion analysis strategy. In Section 6, we show results and the evaluation mechanism. Finally, section 7 concludes with observations and future directions.

2. RELATED WORK

An automated robot-aided rehabilitation system is very task-specific, typically consisting of a robot waiting for the onset of the patients voluntary motion and then guiding the patient to accomplish predefined analytical movements [18]. Exercise motions controlled by robotic devices have been shown to help stroke patients reduce impairment and increase motor power [23]. Patients with early sensorimotor robotic training after stroke, were compared to patients with standard post-stroke rehabilitation and were found to show greater improvements in functional abilities [13, 12]. Recent research has led to the development of a tele-rehabilitation system for home-based therapy. Matarić et al. [14], proposed in-home robot-interaction-based therapy and further examined upper limb recovery after hemiparesis, combining the intensity of task-specific training and the engagement and self-management of goal-directed actions. Another mechanical orthosis device, SaeboFlex [3] supports the weakened wrist, hand, and fingers of patients. A haptic robot, Wrist-RoboHab [2], utilized hand movement therapy for treatment and evaluation of forearm, wrist ulnar, and radial motor disabilities. Additionally, in [9], the authors describe the design and modes of operation of a robot-based neurorehabilitation framework that enables artificial support of the sensorimotor feedback loop for patients with severe motor impairment due to cerebrovascular brain damage (e.g., stroke) and other neurological conditions.

The use of robots to enhance rehabilitation has been previously reported in the literature [13, 23, 24]. Robots have been used to test how the nervous system models its external dynamic environment as the nervous system builds internal models and uses them in combination with feedback control strategies. Robots are being used for repetitive movement exercises after a brain injury and can haptically assess sensorimotor performance, quantify training, thus eventually enhancing motor learning and rehabilitation beyond the levels possible with conventional training [20]. A strong motivator for the use of robotic devices in rehabilitation is that they record and measure the kinematics and kinetics of human movements (speed, position and force) with high resolution, and that they facilitate clinical assessment. In [17], a closed-loop, position-tracking controller is presented to drive the robot stably and smoothly stretch the impaired limb of the patient along a predefined trajectory with a supervisory controller for patients suffering stroke or spinal cord injury (SCI). Current tele-rehabilitation systems generally lack au-

Area of the Body	Muscles
Anterior and Posterior Trunk	Deltoid, Infraspinatus, Latissimus Dorsi, Levator Scapulae, Pectorals, Rhomboids, Subscapularis Supraspinatus, Teres Major and Minor, Trapezius
Upper Arm	Biceps Brachii, Brachialis, Triceps
Forearm and hand	Brachioradialis, Extensor Carpis, Extensor Digitorums, Flexor Carpis, Flexor Digitorums, Palmaris Longus, Pronator Teres

Table 1: Muscles that affect the Shoulder and Arm.

tomated real-time system adaptation of tasks and feedback in response to participants performance and evolution.

In this work we evaluate the users metrics using prescribed therapist exercises and the Barrett WAM Arm to capture the users interaction with the robotic arm, while playing a custom-made video game. The purpose of this assessment tool is to encourage and engage the user in performing the exercises using a 3D balloon popping game. The general idea of our system is to learn the patients weaknesses and his arm limitations when he interacts with the game and to adapt the game level of difficulty in the next sessions. The balloons have random positions at the beginning of the game, but as the patients interact with the game the balloons positions are targeted to force the user to reach out farther for some of them and to help improve their capabilities. The interaction of the user with the game provides us with motion trajectories which can be analyzed and interpreted to assess the patient's arm limitations and weaknesses. Since the game requires the user to pop the balloons that appear in the game, the range of motion and forces that the user places upon the Barrett WAM Arm's end-effector can be decomposed to primary and basic exercise movements, and force feedback is applied for their arm rehabilitation.

3. REHABILITATION SYSTEM

The automated, 3D, upper-limb, robot-aided, adaptive therapy, rehabilitation system that we have developed consists of three main components: the rehabilitation exercises, the robotic system, and the patient-game interaction. While the user performs reaching exercises in the game environment with the use of the robotic device as a manipulator (joystick control), the system records his motions, forces, and decomposed movement sub-trajectories (exercises) according to the game's stages. Our system then uses pre-trained statistical models to identify the shape of the user's exercises and count the repetitions of each exercise, thereby evaluating its score using deviation analysis algorithms.

3.1 The physical exercises

We have developed a system that can guide a handicapped patient performing physical therapy exercises, which focuses mainly on moving and controlling their arm and shoulders. The muscles that apply to these constraints are shown in Table 1, sorted by the area of the body [1].

All the above muscles can be triggered using our patient-game rehabilitation instrument in combination with a specialist who can control and supervise the rehab sessions as well as create a comparative analysis. The initial therapists job in this system is to perform the desired exercises using the robotic device, thereby programming by demonstration the algorithms for the prescribed exercise trajectories that the patient should do for his arm disability. Figure 2 shows how newly introduced technologies can enhance the traditional physical therapy by complementing the expert's work and by providing rich data collection and analysis (Top gray images have been captured from the American Journal of Sport Medicine papers ([7] and [11]). The colored bottom image demonstrates the use of Barrett WAM arm in our system. More details about its specifications can be found in our previous work [19].). The usage of robot-assisted rehabilitation instruments could enable the therapists to emulate and apply the same dynamics and kinematics as traditional elastic resistance. The advantages of this system is that it can adapt to user's weaknesses and limitations and apply selective active resistances when the arm is used as a haptic device.

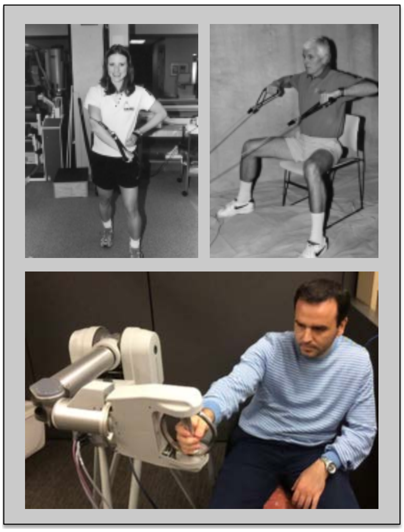

Figure 2: Robot-based rehabilitation system (bottom) to enhance the traditional rehabilitation paradigm (top).

3.2 Game

The main purpose of the game side of this system is to attract the patient's attention and to keep them engaged during the whole exercise session. Research has shown that playing games can have positive effects on the emotional and physical well-being of impaired and elderly persons, and can motivate them to maintain a basic level of activity [4]. The game was built using the Unity 3D game engine [22]. The virtual space within the game initially consists of a model of a thumbtack and a balloon spawning object (Figure 3). Once the game begins, the balloon spawner creates a selection of balloons in varying colors and at varying positions that fit the needs of the current session. It should be noted that these balloons are spawned slightly farther away from the player's viewpoint than the pin to keep the pin from accidentally popping balloons.

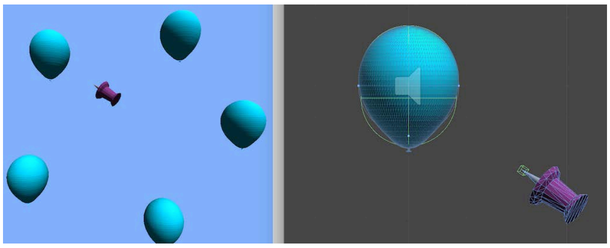

Figure 3: The 3D balloon game and the predefined trajectories

At this point, the player can begin popping balloons by touching the pointed end of the thumbtack to a balloon. To accomplish this, the 3D position of the player's hand in the physical space is mapped to the 3D position of the thumbtack in the game. The actual popping is completed through standard collision detection between the thumbtack and the balloons. An invisible cylinder surrounds each balloon and a small invisible cube is placed at the tip of the pointy end of the thumbtack.

Whenever the cube touches a cylinder, the matching balloon will "pop", disappearing with a loud noise. These invisible shapes are used as the math needed to check for collisions with simple shapes is drastically simplified compared to the math needed for collision detection with the actual shape of each model. An important factor in our game is that the balloons are in random positions at the beginning of each session. As the user interacts with the game through the robot arm, the number and position of the balloons is adjusted according to the therapists predefined trajectories and order of exercises. An instance of the human-robot interaction is shown in figure 4. Some experiments are presented in this link:
`https://www.youtube.com/watch?v=dbgkrlAevIk`

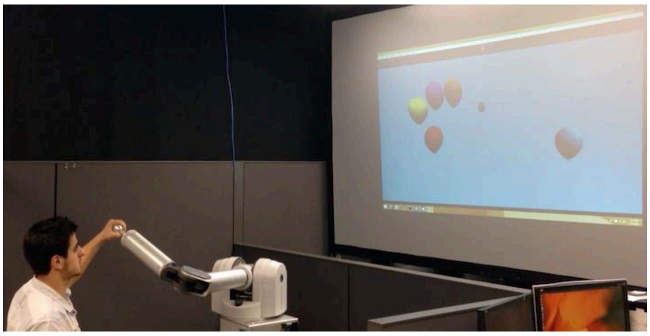

Figure 4: Human Robot and Game Interaction

3.3 Robotic platform

Our work takes advantage of the advanced capabilities of the Barrett WAM Arm for dynamic adaptation, force-feedback, and torque sensing in order to deliver a safe, computer-guided physical therapy regimen. The arm consists of a 3D haptic-force-field, a highly dexterous back-drivable manipulator with zero backlash and near-zero friction, and an isometric, nearly spherical workspace that makes it a useful tool for reaching movements for handicapped people.

3.4 Calibration

A calibration process is required every time a new patient interacts with the game. This routine enable the system to estimate the users range of motion and by extension their workspace in the 3D video game and in the real world.

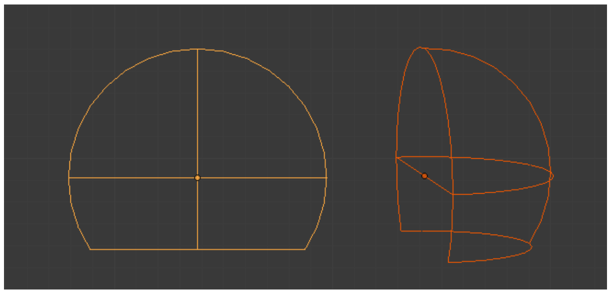

Figure 5: The calibration pattern

After the calibration process the system transfers the users raw data from the arm to the game in normalized Cartesian position coordinates $[x, y, z]$. Figure 5 shows the calibration path that a new user needs to perform, usually with the supervision of the therapist. Subsequent uses of the system by the same user, can load existing calibration profiles.

4. THEORETICAL BACKGROUND

Support Vector Machines (SVM) have demonstrated good classification performance and have widespread successful use in many pattern recognition problems. These classifiers rely mainly on the hyper plane optimization that maximizes the margin, or the distance between the separating hyper plane and the training examples nearest to the hyper plane [5]. In our paper, we rely on Multi-Class Support Vector Machines to classify the patient exercises and movements when they interact with the 3D Balloon game. The training feature-set used by multi-SVM is the direction and the curvature obtained from the hand motion trajectories during exercise. In our system each trajectory passes a prepossessing step that divides it in equal-distance sub-trajectories before it is incorporated into the classification model, with high importance for the shape modeling. Figure 6 shows the training and the classification phases of our system.

The Hidden Markov Models (HMM) approach belongs to supervised learning and statistical modelling methods for sequential data. It has been used prominently and successfully in speech recognition and, more recently, in handwriting recognition and visual recognition of sign language. The sample model is described as a graph with four internal and two marginal states connected by oriented transitions. Moreover, there are six associated output vectors, as seen in figure 7.

The trajectory classification is similar to the speech recognition tasks [5]. A trajectory is a continuous quantity that can be described analytically as the position of the object in time. An object trajectory O is a potentially infinite sequence of state vectors $o(t) = [x, y, z, dx, dy, dz]$, where the first three denotes the Cartesian position and the three last the direction.

The trajectory classification problem can be formulated as to identify the class $c_i (i = 1..N)$ to which belongs the trajec-

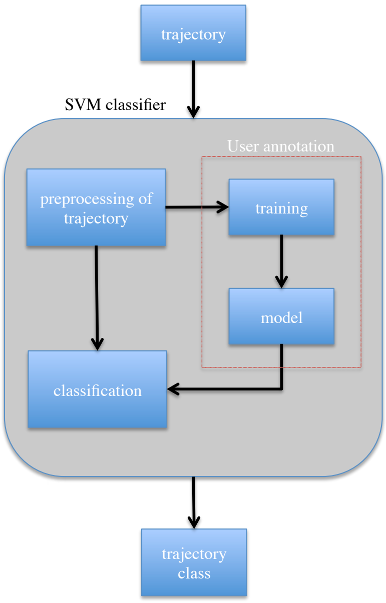

Figure 6: The procedure of the trajectory classification

tory state sequence. The basic formulation of the problem is given by maximization of a conditional probability:

$$i^* = \arg\max_i P(c_i|O) = \arg\max_i \frac{P(O|c_i)P(c_i)}{P(O)} \quad (1)$$

We use Bayes theorem in (1), because we cannot evaluate $P(c_i|O)$ directly. Assuming we know prior probabilities $P(c_i)$ and $P(O)$, we are about to compute the likelihood $P(O|c_i)$; the probability of the sequence O knowing the class c_i. To compute this, we should have a model M for class c_i. The model is a finite state automaton with K states generating sequence O. There are transition probabilities $a_{k,j}$ between the states. Except first and the last state, states are emitting or generating output probability density function $b_j(o(t))$. In the figure 7, there is a sample configuration of $A = [a_{k,j}](k, j = 1..K)$, the transition matrix, which defines the probability of transition to the next state for each combination of HMM states. The probability of passing an object O through a model M by a way X. is defined by equation 2.

$$P(O, X|M) = a_{x(o)x(1)} \prod_{t=1}^{T} b_{x(t)}(o_t)a_{x(t)x(t+1)}. \quad (2)$$

For the training and classifying procedure we have used the Hidden Markov Model (HMM) Toolbox for Matlab [16] with four mixtures of diagonal Gaussians. To classify a sequence into one of 6 classes (exercises), we trained up 6 HMMs, one per class, and then we computed the log-likelihood that each model gives to the test sequence; if the i_{th} model is the most likely, then declare the class of the sequence to be class i.

In this paper, we have a two-level exercise classification. The first level uses the SVM classifier which can define the

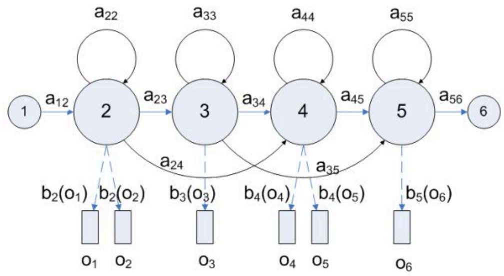

Figure 7: Hidden Markov Model configuration

shape of each exercise (3 or 6 base shapes of exercises) according to the curvature and the internal direction of each trajectory. In the second level we use the Hidden Markov Model to identify the direction of each exercise. For example if the multi-SVM classifier provides us with the information that an exercise belongs to a line-shape then the HMM can identify the direction of this line according to the training direction. The system incorporates the HMM inside the Motion Analysis of the user with the 3D video game so as to identify the position and the orientation of his movement. In other words, for each exercise that the system asks the user to perform, we have trained 6 different orientations for each of them in order to identify the portions that the user can accomplish successfully.

All experiments were conducted on an Intel i7 machine with 8 Gigabytes of main memory, running MacOSX. Everything is implemented in Matlab. Additionally, LIBSVM [6] with a linear kernel is used to build a classifier, and the parameters of LIBSVM are set to the default values.

5. MOTION ANALYSIS

Each balloon, or each sequence of balloons, that the user tries to pop in the game, generates a 3D trajectory of the motion of the robotic arm's end-effector. This trajectory can be compared and tested with therapist's exercises' trajectories, used as gold-standards. In this work, we have developed a novel, two-level classification scheme to classify motion trajectories. In the first level we use the SVM classifier, which can identify the shape of each exercise according to the curvature and the internal direction of each trajectory, and in the next level we use the Hidden Markov Model to identify the direction of each exercise according to the centralized sub-trajectories points. The accuracy of the first level SVM classifier reaches 92% when the basic exercises are 6 (circles, line, u-shape, square, gamma and figure eight) and the second level Hidden Markov Model classifier provides us with 95-100% accuracy.

In this work, we have recorded 30 trajectories for each class. From this data, we used 20 trajectories of each class for training and 10 trajectories for testing. This means we have a total of 120 trajectories for training and 60 trajectories for testing. Also, we have split each trajectory in 20-70 sub-trajectories in order to obtain more information about their shape. The features that we have selected in order to classify the trajectories are:

- Curvature in sub-trajectories
- Direction of sub-trajectory

- The sub-trajectories are represented by their principal component analysis (PCA) coefficients.

In order to compute the curvature of each segment we have used the Hermann and R. Klette's formulas [10]. We projected each trajectory in the x-, y-, z- axis and we calculated the curvature in each 2D space. In figure 8: we have plotted the circle trajectory in each axis: x = red circle, y=green circle and z = yellow circle (figure 8).

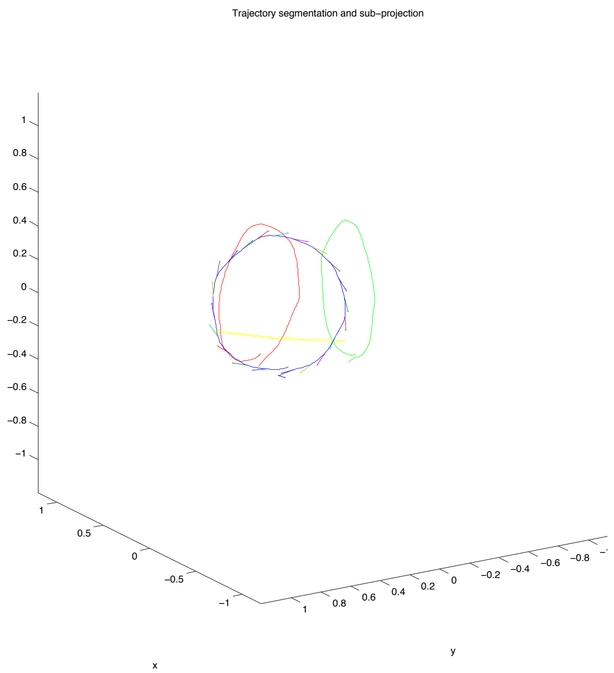

Figure 8: Projection in the 3 planes

Using the curvature analysis we extract the curvature of each segment in each dimension and create a vector of 3*30 segments = 90-dimensional curvatures for each trajectory. Then, for each segment we calculate the unit normal direction vector and we sum up all of them in order to generate the overall direction vector of the trajectory. This feature provides us with the direction information of each segment relative to the overall direction of the trajectory. Since, the new feature space for each trajectory is 120 dimensions, we use the PCA coefficients to decrease the dimensionality. In figure 8 we have selected the 3D line that is produced from the robotic arm's end-effector and we are generating the overall direction vector from all the segments.

5.1 Deviation analysis

Exercises performed by patients are not always perfect, and they usually deviate from the optimal trajectory indicated by the therapist (gold-standard). The trajectory deviation is quantified as error in space (3- axes (x, y, z)) and in time. Figure 9 shows the differences in trajectories, in the three axes, of a therapist and a patient side. In our system, we accommodate the temporal deviations, and for that reason a more sophisticated method for trajectory alignment is required. Dynamic Time Warping (DTW) [15], has been successfully used in the past for the optimal alignment between two given (time-dependent) sequences.

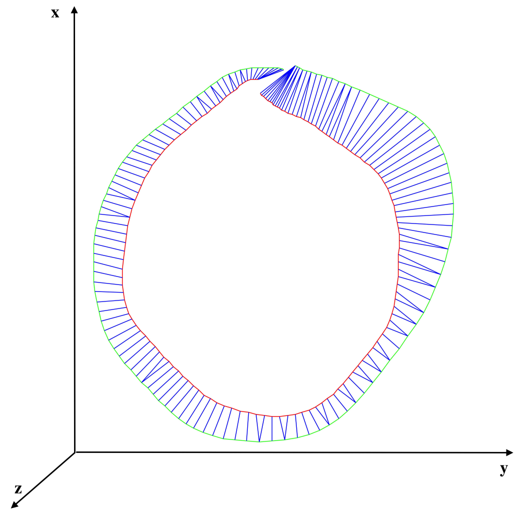

Figure 9: Temporal trajectory alignment on the 3 axes using the DTW algorithm. The green line represents the "gold-standard" trajectory, whereas the red line represents the trajectory of the motion performed by the patient.

The distance metrics that DTW algorithm provide us has been scaled and interpreted in a score value or in a performance activity score (PAS). For the score analysis of the motion deviations the system uses a parameter specified by the number of segments of a trajectory. The bigger the number of this parameter in the system, the bigger and more sensitive the error deviations are from the analysis. Afterwards, the system can choose the most appropriate game-exercise for the patient using thresholds that have been adjusted from therapist and specialists.

6. EXPERIMENTS

Before starting analysis and comparing the trajectories by using the DTW, as we did in our previous work, [19], we have to identify first their base shape and direction. For this reason, we classify each trajectory in 6 different classes in order to help us with the alignment phase using DTW and then estimate the error of each trajectory in each direction condition. The importance of our trajectory classification stage is that the system can adapt to the users range of motion. Since we have preprocessed the trajectories, it allows us to have a scale and time invariant classification phase. That property enables the system to calculate outcomes from different personalized human variations and compare directly the user shape-trajectory data.

In the below diagrams we have tested the accuracy of the trajectory classification according to the number of classes and the number of segments that we split each trajectory into. Figure 10 shows the accuracy of the classification algorithm when the number of classes increases. The more classes we insert in our Multi-Class SVM classifier, the less accurate it becomes. This is the obvious result when you have to deal with classification problems as the feature space limits the accuracy when the number of classes increases. In this experiment we have split each trajectory in 40 segments.

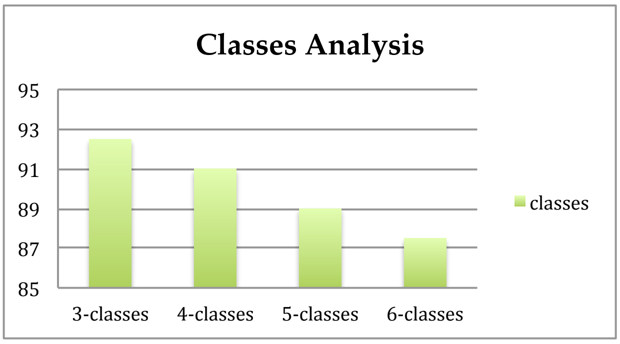

Figure 10: Accuracy estimation for different number of classes.

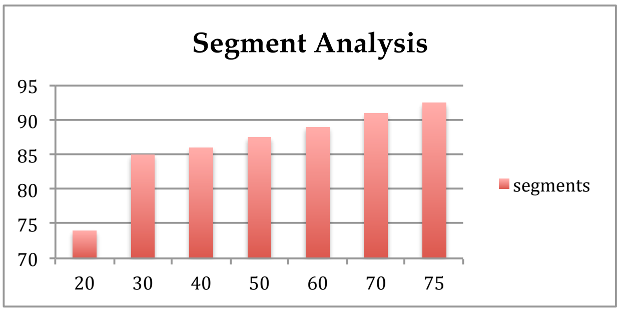

Figure 11: Accuracy estimation in comparison to the number of segments.

Figure 11 depicts the accuracy of the classification relative to the number of segments in each trajectory. As we mentioned before the features that we have selected have been applied in the sub-trajectories, so this parameter (number of segments) plays an important role in the classification process in order to define the shape and the properties of each class. For these kind of experiments, we used 6-classes and tested the classification accuracy with different numbers of segments (20-70). Bigger number of segments increases computational cost, but achieves better classification accuracy. In figure 12 we provide a combined representation of results when the number of segments and the number of classes increases. Its obvious from the graph that the number of segments in the classification problems increases the accuracy.

The results obtained indicate the robustness of the proposed method. Although our framework, at this stage, does not evaluate the user's engagement and satisfaction, it can successfully manage to evaluate the user's physiological performance through a train-tested and well-defined exercise system.

7. CONCLUSION AND FUTURE WORK

In this work, we have presented an innovative physical rehabilitation system that uses video game technology to allow the monitoring and tracking of the handicapped patient progress using the advanced capabilities of the Barrett WAM Arm. The system is able to record the patient's exercise trajectories as he/she interacts with the game, to estimate the exercise score values regarding the range-of-motion, and to count the number of repetitions of each exercise. Even

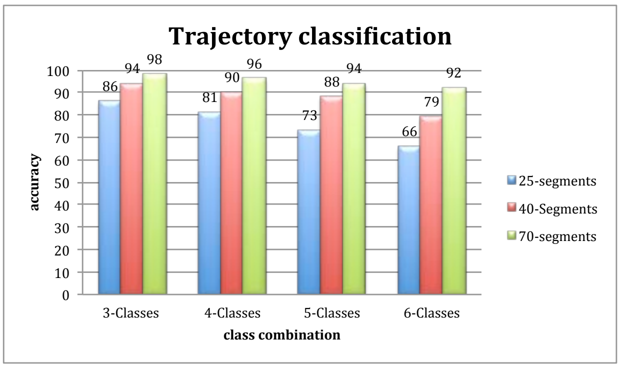

Figure 12: Trajectory classification accuracy. Comparison results for different number of classes and different number of segments for each trajectory.

though our current work lacks qualitative evaluation of the effects of the proposed system on the rehabilitation progress of real patients, the proposed methods have been successfully evaluated in our lab in experiments with healthy subjects. The system will be evaluated in clinical studies in the near future as part of a bigger system that incorporates multi-modal sensor data analysis in order to better assess the condition of the user at each moment and adapt accordingly.

The future goal of our project is to develop a front-end user interface for therapist and patients that can be used in real hospitals and a back-end motion analysis for the Patient-Game and Robot interaction. Also, our system will provide to the therapists the ability to track the patients performance evolution as well as the ability to update their therapy exercises. Additionally, therapists will receive data in real time from the patient sessions via a Graphical User Interface that we plan to design.

Other sensors that we want to incorporate in the rehabilitative therapy are Electromyography sensors (EMG). An EMG sensor shows the percent of maximum voluntary contraction (MVC) of the muscle that the sensor is placed on. In this work [8] the authors have identified which exercises target these muscles by analyzing the MVC of various muscles while a subject performed various exercises.

Using this type of exercises we will be able to correlate the maximum voluntary contraction of the muscle with the dynamics and kinematics that the Barrett WAM Arm facilitate in order to help us to evaluate better the electrical activities produced by the skeletal muscles during the exercise. The use of video game technology with the robotic arm manipulator provides us with the capability to apply some forces or use virtual elastic band forces during the game-robot interaction with specific arm joint links. The result of these active robotic forces is that we can measure the user's muscle strength during the rehabilitation session and its evolution.

Finally, we plan to employ an adaptation module, which will be responsible for the session personalization and adaptation. Each session consists of a certain amount of exercises as prescribed by the therapist. The system will be able to adapt the exercise type and difficulty based on the subject's performance and facial expressions (e.g pain). The subject's performance will be measured by the trajectory deviation between therapist and patient exercise trajectory. We will use Reinforcement Learning for the problem formulation and Dyna-Q algorithm [21] for the system training.

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