

Learning of Arm Exercise Behaviors: Assistive Therapy based on Therapist-Patient Observation

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Abstract- Machine learning techniques have currently been deployed in a number of real-world application areas – from casino surveillance to fingerprint matching. That fact, coupled with advances in computer vision and human-computer interfaces, positions systems that can learn from human observation at the point where they can realistically and reliably be deployed as functional components in autonomous control systems. Healthcare applications though pose a unique challenge in that, although autonomous capability might be available, it might not be desired. And yet, based on recent studies focused on assessment of the changing demographics of the world, there is a need for technology that can deal with the shortcomings envisioned in the workforce. Traditional roles for robotics have focused on repetitive, hazardous or dull tasks. If we take the same stance on healthcare applications, we find that some therapeutic activities fall under this traditional classification due to the long-repetitive nature of the therapist-patient interaction. As such, in this paper, we discuss techniques that can be used to model exercise behavior by observing the patient during therapist-patient interaction. The ultimate goal is to monitor patient performance on repetitive exercises, possibly over the course of multiple days between therapy sessions.

I. INTRODUCTION

Physical therapy is a very practitioner intensive process. When patients enter into the process they are often required/asked to perform exercises that they have been shown how to do when they are at home between visits. Proper compliance is strongly correlated with shorter time to recovery as well as reduction of pain in the long term [1]. During the time between therapy sessions there are many factors which affect patient compliance, including forgetfulness, lack of motivation, boredom, and lack of instant feedback. To deal with these issues, researchers have shown the positive use of robots in assistive therapy applications ranging from stroke rehabilitation [2] to motor development in children [3].

In many of these applications, if we can correctly identify and match patient exercise behavior based on characteristics learned during previous therapist-patient session, we can develop a monitoring mechanism to provide feedback for patient recovery. To enable this capability, we present two methods that utilize image-based observation as a means of gathering sensing information, and classification to identify subsequent patient behavior based on observations during the therapist-patient session.

II. ALGORITHM: LEARNING EXERCISE BEHAVIORS

A. Learning of Exercise Primitives through Observation

Learning of exercise primitives involves modeling an exercise scenario by sequencing a series of repetitive motion behaviors together. A motion behavior is used to represent an interpretation of the basic movements of an arm exercise. It is not designed to compute specific motion vectors (such as specific arm joint trajectories), but rather to provide information about general movements. We define a motion vector

$$\mathbf{M}_v = (d, v) \quad (1)$$

where d represents the direction of motion and v represents the velocity of motion. In addition, the possible values associated with d and v are discretized based on pre-defined linguistic classes, as depicted in Table I. As such, there is a finite number of motion vectors that exist for defining a low-level motion behavior. We define this finite set of possible motion vectors as the motion class κ_{motion} .

Table I. Motion behavior definition structure

Motion Parameter	Linguistic Values
Direction (d)	Left, Right, Up, Down
Velocity (v)	Slow, Fast

The direction parameter represents the absolute direction of a hand with respect to a world coordinate system. The following direction vectors are used to classify this motion parameter:

$$LEFT = \begin{bmatrix} -1 \\ 0 \end{bmatrix}, RIGHT = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, UP = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, DOWN = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

The velocity of the motion behavior, v , is measured as follows:

$$v = \frac{\Delta p}{\Delta t} \text{ (px/s)} \quad (2)$$

Δp is defined, with respect to an observation, as the distance between the location of the hand when a motion initiates and terminates. Δt is measured by counting the frame numbers during a motion and dividing it by the average frame rate of the camera. Since the velocity required in this study need not be precise, it is reclassified as a speed: SLOW/FAST. If a motion is faster than the overall

sequence speed average, it is defined as FAST, and as SLOW otherwise. As an illustrative example, Table III shows the association between low-level motion behaviors and the resulting motion vectors.

Table II. Association - motion behaviors and vectors

Illustrative Description of Motion Behavior	Motion Vector
Human quickly lifts hand up	(Up, Fast)
Human shakes hand to the right	(Right, Fast)

The goal of the motion behavior analysis process is to populate instances of the motion vector based on observation of a human exercise action (such as depicted in Figure 1). This process is executed by computing a motion gradient during human exercise and fitting the motion gradient to the pre-defined motion class. The motion behavior analysis process is further described in [4]. Once motion behaviors are identified, the sequence of motion behaviors associated with an exercise scenario are stored and labeled (by the therapist). After therapist-patient interaction, the system is to match the stored therapy exercise information to the patient during subsequent exercises using the same motion behavior analysis process.



Figure 1. Sequence of images captured during observation (top) 180° left shoulder abduction (middle) 90° left shoulder abduction (bottom) right shoulder rotation

B. Learning Exercise Behaviors through Observation

In the previous approach, image-based methods were used to construct an exercise scenario from a sequence of identified motion behaviors. In the next approach, we utilize a method that classifies the entire exercise scenario using a single representation. Based on imaging the patient during a therapy session, a texture based feature vector is first generated for each image (frame) and stored in a database. This database is then used to train an adaptive classifier to classify the elements in the dataset, using the approach as described in [5]. During subsequent exercise, the method presented in [6] is used to extract period and frequency

information for the captured data in order to generate a mapping between observed state and its position in the exercise cycle. In this step, we assume only one exercise is exhibited in the captured data sequence. After therapist-patient interaction, a measure of similarity using the 2D Kolomogorov Smirnov test [7] is calculated to determine the statistical goodness of fit between pairs of exercise behaviors. This test is used to determine which of the stored therapy exercises the patient is performing during subsequent exercises.

III. INTERACTION BETWEEN USER AND ROBOT

In the subsequent section, we outlined two complimentary methods to correctly identify and match patient exercise behavior with information captured during therapist-patient interaction. Since exercise motions depend on individual capability (and can vary both between individual subjects as well as between the same subject during different exercise scenarios), the role of the therapist during these scenarios is 1) to correctly position the robot such that important body features are in view of the robot, and 2) to correct the labeling of the behaviors during subsequent sessions with the patient. In theory, to allow for development of a monitoring mechanism to provide feedback for patient recovery, the therapist must interactively work with the robot to correct learned knowledge.

IV. EXPERIMENTAL SETUP

To generate data akin to that expected with a therapy patient, the exercises, as shown in Table III, were first performed during a simulated therapist-patient session, and then subsequently, in random order, repeated with varying rates of execution (Figure 1).

Table III. Exercise Cases Considered

Shoulder Abduction Seated (right, left, 90°, 180°)
Shoulder Rotation Seated (right, left)
Shoulder Abduction Standing (right, left, 90°, 180°)

The goal in implementing the two different methodologies is to assess the capability of the system to correctly identify the patient exercise and determine the system characteristics that contribute to success of each approach. Preliminary analysis show that the recognition methods can uniquely identify patient behaviors as long as the following assumptions hold: 1) there is no significant change in the activity performed during subsequent sessions, 2) the therapist correctly shows the patient how to perform the exercises safely, and the patient is able to comply, 3) the patient's appearance remains relatively consistent during subsequent sessions, and 4) the robot can position its camera as appropriate to capture the execution of each exercise.

V. CONCLUSIONS

In this paper, we present two methods that enable learning of therapy exercises performed during a therapist-patient session. The approach uses vision as a means of observing the user during task execution. The stored exercise sequence can then be utilized by the system to match subsequent patient behavior. Future work involves developing approaches to extract specific performance metrics (i.e. speed and frequency) to provide feedback to the therapist for enhancing patient recovery.

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