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Planning, Execution and Monitoring of Physical Rehabilitation Therapies with a Robotic Architecture

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Abstract. Traditional methods of rehabilitation require continuous attention of therapists during the therapy sessions. This is a hard and expensive task in terms of time and effort. In many cases, the therapeutic objectives cannot be achieved due to the overwork or the difficulty for therapists to plan accurate sessions according to the medical criteria. For this purpose, a wide range of studies is opened in order to research new ways of rehabilitation, as in the field of social robotics. This work presents the current state of the THERAPIST project [1]. Our main goal is to develop a cognitive architecture which provides a robot with enough autonomy to carry out an upper-limb rehabilitation therapy for patients with physical impairments, such as Cerebral Palsy and Obstetric Brachial Plexus Palsy.

Keywords. Rehabilitation, Robotics, Computer-Assisted Therapy, Cerebral Palsy, Brachial Plexus Neuropathies, Clinical Decision Support Systems.

Introduction

The goal of neurorehabilitation therapies is the recovery of damaged neuronal areas and muscles by the repetitive practice of certain motor or cognitive activities. The therapy schedule, as a set of sessions, must maximise the engagement of the patient to the therapy, which should result in a better and faster achievement of some therapeutic objectives. Each rehabilitation session consists on monotonous exercise repetitions, which usually makes the patient feel unmotivated, especially when dealing with children. Social robots are demonstrating to be a powerful tool to direct these rehabilitation sessions [2]: the therapeutic interaction provided by a social robot will help patients to get more committed to the rehabilitation treatment program. In addition, Artificial Intelligence, specifically Automated Planning [3], could provide support to therapists when planning the whole therapy [4], whose definition and execution may follow the procedure described in Figure 1. In this procedure, the physician performs a primary evaluation of the patient, from which the therapeutic objectives are defined

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taking into account the expectations of the patient. Such objectives, together with other constraints (time, resources, etc.) are taken by the therapist to plan the different sessions: step A in Figure 1. The sessions are performed in a loop involving its execution, patient's progress and therapy update: step B in Figure 1. The goal of this work is to describe a framework that supports both the definition and execution (steps A and B) of neurorehabilitation therapies using social humanoid robots. Next section describes the architecture proposed, while the following describes some initial results.

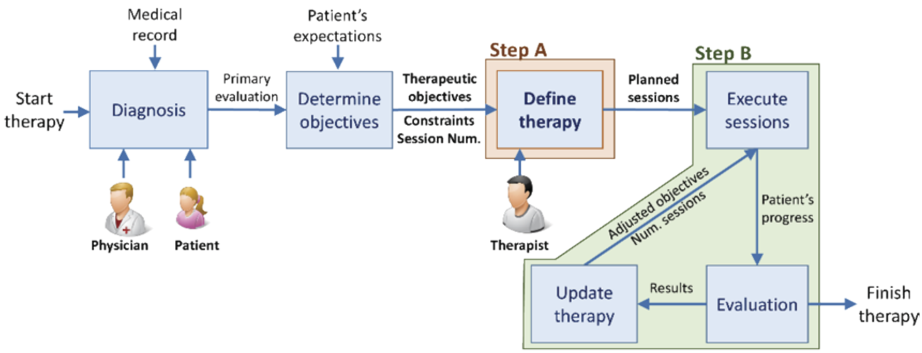

Figure 1. Rehabilitation procedure of Hospital Virgen del Rocío, Seville (Spain).

1. Methods

NAOTherapist is an early-stage architecture based on Automated Planning and Learning which aims to control a humanoid robot, specifically a NAO robot, to execute and supervise physical rehabilitation sessions. Figure 2 shows the NAOTherapist architecture schema. It comprises three levels of planning: high, medium and low. In order to provide a flexible platform, language-independent interfaces are included to ease the use of different robots and planning languages. This also improves the portability of this architecture into other systems with similar requirements.

Once our system is run, a graphical user interface is shown to ease the therapy configuration to the physician according to the patient's diagnosis and to control the execution of the sessions with the robotic platform. Before starting the rehabilitation, the therapy needs to be planned in accordance with the therapeutic objectives and patient's requirements for all sessions. The therapy configuration is translated into an automated planning problem as the input for the Therapy Designer, which belongs to the high-level planning [4]. In this level, all available exercises in the knowledge base are considered, but only a set of them are included into a session. For each session, exercises must be distributed among three phases (warm-up, training and cool-down) according to their intensity and difficulty, following a Gaussian distribution. Therefore, softer exercises must be performed at the beginning and the end of a session and harder ones must be in the middle. Therapists can delegate this cumbersome task to the Therapy Designer which comprises an HTN algorithm (Hierarchical Task Network [5]) where the selection process of exercises is modelled. If there are no available exercises to be included, the model can suggest a new one whose attributes achieve the therapeutic objectives. This module is considered as a Clinical Decision Support System (CDDS) to plan therapies which fulfil the medical criteria.

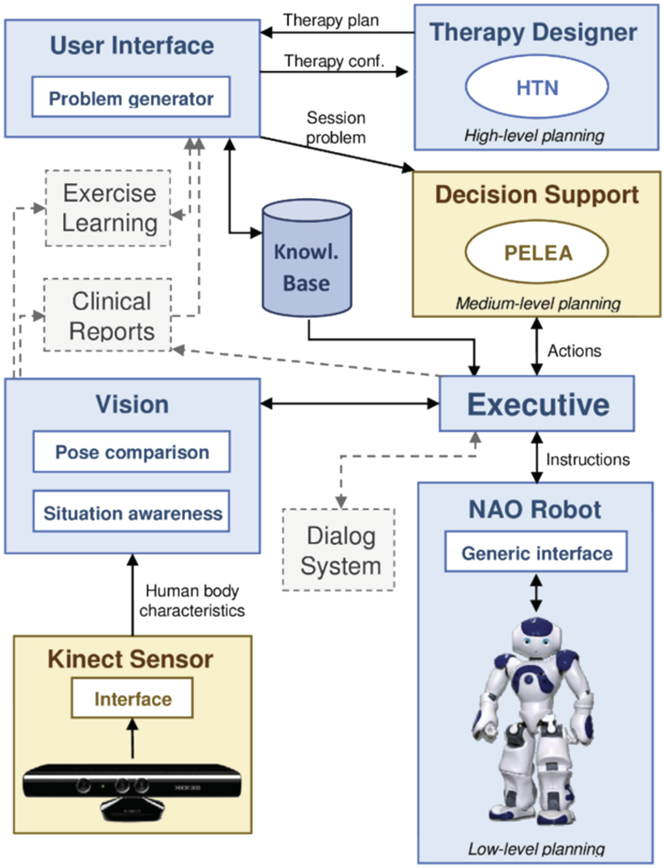

Figure 2. NAOTherapist architecture.

Attending to the state of the world provided by the sensors, the medium-level planning is in charge of planning and monitoring the execution of the exercises performed by the robot and the patient during a session. A replanning process can be triggered if the current state of the world differs from the expected one after the last action. The Decision Support component is governed by the PELEA architecture [6], which receives the planned exercises from the high-level to be executed during that session. This is modelled as a classical automated planning domain which considers the set of actions that the robot can perform in each session and possible unexpected situations. For instance, the robot starts a new session detecting and greeting the patient. Then, it introduces the exercises and shows the patient the required poses by performing them, while verifying that the patient is training correctly. It is possible that, suddenly, the patient sits down or loses his focus. If this situation is detected by the sensors, Decision Support has to generate a new plan to execute a proper action, e.g. to claim patient's attention.

To infer information about the pose or state of the patient, the Kinect Sensor and Vision components are used. Kinect Sensor returns human characteristics as body skeleton, hand positions and face feature points in real-time. This data is retrieved and processed by the Vision component, which is composed of two main elements:

- *Pose comparison* calculates the difference between the current pose of the exercise and the pose performed by the patient. This allows to determine a similarity level which can be used to suggest the patient how to correct the pose.
- *Situation awareness* is able to infer when the patient is in the training area, standing, sitting down or even distracted and the robot needs to claim his attention.

The Executive component merges the information of sensory components (Vision and NAO Robot) to create an updated state of the world and to execute each action planned by Decision Support. When the robot has finished an action, the Executive module sends this state of the world to Decision Support, which returns the next planned action to be executed or generates another plan if something unexpected happens, e.g. the patient leaves the training area.

Then, the Executive component communicates with Vision and NAO Robot to execute the received action. A complex action like "execute pose" comprises: motion of the robot, checking the pose of the patient and certain human-robot interaction functions, like speaking and changing the eye colour in real-time depending on the accuracy of the current arm pose of the patient. The robot is controlled using a generic interface between NAO Robot and Execution which allows a robot-independent architecture. The movement interpolation between robot poses is performed in a low-level planner behind this generic interface. In the NAO robot this is controlled with an internal path planner which can also avoid auto-collisions.

There are three additional components in the NAOTherapist architecture, but not fully developed yet. Exercise Learning uses Vision to learn new exercises from the human therapist which were previously suggested by the Therapy Designer. The Clinical Reports component provides different clinical metrics to evaluate the progress of the patient, e.g. the GAS scale [7]. Finally, the Dialog System is an independent component of Execution to attain a more social and complex human-robot interaction.

2. Results

We have performed preliminary evaluations of both steps of the rehabilitation procedure shown in Figure 2: therapy definition and session execution. In order to evaluate the first step we consider a knowledge base with 72 exercises. This experiment is carried out with the following configuration: 30 sessions of 25-30 minutes, 20% of the total session time is assigned to the warm-up and cool-down phases each and the remaining 60% for the training phase. Exercises with intensity and difficulty values between 0 and 30 are considered soft exercises (for warm-up and cool-down phases), and those that exceed this limit are labelled as hard exercises (training phase). The effects in the distribution of the intensity and difficulty of the generated session plans are shown in Figure 3, where these two variables follow the desired Gaussian distribution among the three phases.

For the session execution, the human-robot interaction is evaluated in our first prototype with 10 healthy users and 3 manually generated sessions of 5 minutes each. Users pointed out the friendly appearance of the robot, the luminous coloured feedback of the pose comparison and the fluent interaction. There are online videos[3] of some of these preliminary experiments.

[3] http://www.youtube.com/user/NAOTherapist (accessed on 11th February, 2015).

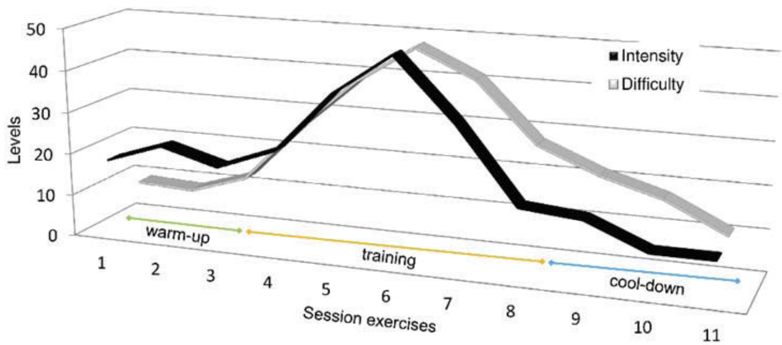

Figure 3. Average value of the intensity and difficulty of the exercises with 30 generated sessions.

3. Discussion

The combination of a robotic platform with our proposed Artificial Intelligence techniques allows the exploration of new ways of computer assisted medical procedures for rehabilitation. In this work we describe a novel approach to the automatic definition of neurorehabilitation therapies, as well as to its execution supported by a social humanoid robot able to monitor the patient and aiming to increase his commitment with the therapy. The initial evaluation shows an accurate definition of the therapies. This automated process saves professionals time and effort while guaranteeing the medical criteria. The user interaction with the NAO robot is carried out fluently, the response time is fast and the pose comparison has enough accuracy to complete the rehabilitation sessions. The participants of the system evaluation found the overall experience with the NAO robot pleasant and accepted being very motivated during the test session. In a near future, we expect to give a more complete evaluation with patients with upper-limb motor disorders.

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