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Computational architecture of a robot coach for physical exercises in kinaesthetic rehabilitation

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***Abstract*— The rising number of the elderly incurs growing concern about healthcare, and in particular rehabilitation healthcare. Assistive technology and and assistive robotics in particular may help to improve this process. We develop a robot coach capable of demonstrating rehabilitation exercises to patients, watch a patient carry out the exercises and give him feedback so as to improve his performance and encourage him. We propose a general software architecture for our robot coach, which is based on imitation learning techniques using Gaussian Mixture Models. Our system is thus easily programmable by medical experts without specific robotics knowledge, as well as capable of personalised audio feedback to patients indicating useful information to improve on their physical rehabilitation exercise.**

I. Robot Coach for Physical Rehabilitation

A. Motivation

Low back pain is identified as one of the major musculoskeletal condition of the millennium, according to [1]. 50 to 80% of the world population suffers at a given moment from back pain which makes it in the lead in terms of health problems occurrence frequency [2]. It is also a main cause of sickness absence in industrial countries. The prevalence of chronic low back pain is about 23% and 11% of the population is disabled by it [3]. It is the third cause of disabling condition in the 45-65 years old population. Low back pain particularly affects the elderly whose proportion in European societies keeps rising, incurring growing concern about healthcare, as medical professionals soon will not be able to face this steadily increasing demand.

Assistive technology in general and assistive robotics in particular may help to address the increasing need for healthcare. Chronic low back pain has been associated with reduced physical activity, abnormal movement patterns [4], and psychological factors such as fear avoidance [5]. For these reasons active rehabilitation (physical rehabilitation classes with cognitive-behavioural principles) is considered as more effective than usual care [6].

In this context, we propose to develop a robot coach for physical rehabilitation exercises. The goal is to increase the time patients spend exercising, by alleviating the lack of time a physiotherapist can spend monitoring a patient. With this perspective, we aim to develop a robot coach capable of first, understanding the requirements of a rehabilitation exercise from the medical expert. Then, it should be capable of demonstrating rehabilitation exercises to patients, watch a patient carry out the exercise and give him feedback so as to improve his performance.

To tackle this growing problem, we develop an assistive robot that instructs, evaluates and encourages patients. We aim at scenarios where our system can :

— Let a physiologist select an exercise for the robot to coach
— Show a demonstration of the exercise to the patient
— Monitor the patient while he carries out his exercise
— Give a feedback to the patient to improve his performance and encourage him

Thus the patient and the robot will work together on a rehabilitation exercise assigned by the physiologist. Their interaction will rely on the advanced perception and action capabilities of the system, which enables the robot to show demonstrations of the exercise as well as monitor the movements of the patients and give him feedback on his mistakes.

B. Use of Robots in Medical Rehabilitation

From the point of view of medical practitioners, rehabilitation robotics has been mainly concentrated on helping the patient to do exercises in virtual environments (as in upper limb rehabilitation with InMotion2 or ArmeoSpring robots) or even without any stimulating environment as in many robotic devices dedicated to gait rehabilitation. More recently, [7] studied an intelligent tutoring system for a gait rehabilitation robotic system by automatically learning from the therapist. These robots are usually very expensive and only dedicated to rehabilitation units in hospitals.

But many rehabilitation programs are realised in private physiotherapist offices particularly for rheumatologic problems. These kinds of programs are usually based on active movements that are carried out in autonomy by the patient under the supervision of the physiotherapist. Unfortunately physiotherapists usually can spend only little time for this time-consuming supervision, and leave most of the time patients to carry out the exercises on their own. We aim at transferring this supervision to a robot so that patients gain better supervision and feedback.

Within this perspective, virtual reality has also contributed to the field of rehabilitation either through training programs for low back pain [8] or home based programs in elderly (VERA project San Diego). These programs have been demonstrated to improve the number of repetitions of movement compared to classic home based rehabilitation programs [9]. However, virtual reality agents evolve in their own world and lack social and physical connection with the user's world. On the contrary, robots have been considered as

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social mediators in different categories of clinical conditions like children with special needs or the elderly [10], [11]. Robot mediated physical exercises may improve the acceptance and adherence to active rehabilitation program and enhance the involvement in physical activities. Robots also assist the physiotherapist.

Our endeavour moves away from all the technologies usually developed in research projects around virtual reality or serious games or home assistance to training programs. Instead of relying on interfaces like haptic devices, such as in upper limb rehabilitation robots or sensors worn by the patient, such as in virtual reality caves or just in simple games like WII, we concentrate on a robot capable of helping the patient and the physiotherapist in their own environment.

C. Coaching Robots for Physical Exercises

Perhaps the robotic systems for physical exercises coaching most related to our system are [12], [13] and [14].

Fasola *et al.* in [12] presents a socially assistive robot (SAR) system designed to engage elderly users in physical exercise. They developed a system working on the user's intrinsic motivation and the personalisation of the human robot interaction to play on the user engagement. Goerer *et al.* [13] proposed a robotic fitness coach for elderly and explained the importance of verbal interaction with the subject. More recently, Takenori *et al* [14] developed a system of imitation learning for daily physical exercises. The robot could learn new exercises from the therapists and be an exercise demonstrator. However, it could not provide feedback or active guidance to the patient. The communication was performed by voice and gesture in order to engage elderly people in the exercise activity.

These examples of coaching robots have their own characteristics, but all coaching robots are built around an intelligent tutoring system.

II. INTELLIGENT TUTORING SYSTEM

An intelligent tutoring system (ITS) is an artificial system that aims to provide immediate and customised instruction or feedback to learners, usually without the intervention from a human teacher. The main advantage of a tutoring system is to be able to personalise education to the specific needs of each student. In particular in our application example of rehabilitation, personalisation is essential as patients can be of different ages, genders and global fitness. Therefore the system needs to give patients instructions adapted to their level of performance.

A. Tutoring System for Physical Exercises

Whereas mathematical exercises are easy to assess (right or wrong answer), assessing whether a re-habilitation movement is performed well is much more tricky. Thus, several ITS for mathematical exercises have been studied such as in [15], fewer have been developed for physical exercises.

For physical exercises, both learning a new exercise and assessing the performance of an imitation movement have led to state-of-the art methods. We develop algorithms for an Intelligent Tutoring System (ITS), that both can give meaningful feedback to the patient to help him improve his performance.

For instance, [12] proposed for the automatic evaluation of physical exercises to compute the distance between the user's current arm angles and the specified goal arm angles. This metric could be used in the simple setting where the patient can only move a few articulations, because their experimental setup required them to sit and only move the arms on the side.

B. Learning from the experts

Learning movements by robots has been tackled by robotics and given rise to imitation learning algorithms, also known as programming by demonstration (PbD) algorithms [16]. They cover methods by which a robot learns new skills through human guidance. PbD takes inspiration from the way humans learn new skills by imitation to develop methods by which new tasks can be transmitted to a robot. Indeed, behavioural psychology studies [17], [18] highlight the processes through which the behaviour of an individual β may come to be like α's, such as mimicry, stimulus enhancement, imitation or emulation. PbD targets an implicit means of training a machine, such that explicit and tedious programming of a task by a human user can be minimised. It is an intuitive medium of communication for humans, who already use demonstrations to teach other humans. It can in principle offer a natural means of teaching machines that would be accessible to non experts. For instance trajectory and keyframe demonstrations have been shown to be efficient and easy to use for non-roboticists [19].

It thus constitues a convenient method for therapists who are not roboticists to specify new exercises for the robot to coach. Without any understanding of how robots work and the algorithms behind, therapists can thus explain the exercises by simple demonstrations.

Whereas [14] have developed a neuro-genetic approach for imitation learning, [13] used direct visual input for angle transformation and optimisation of appearance. Besides, [12] does not describe a method for non-roboticists to specify exercises for the robot. More generally, PbD methods based on Hidden Markov Models and Gaussian Mixture Models (GMM) have proven successful for robots learning by observation of demonstrations such as in [20]. The Gaussian Mixture Model thus learned after a few demonstrations constitute a probabilistic description of the ideal movement, which is robust to noise and small errors in the training data. The robot can make exercise demonstrations by applying the Gaussian Mixture Regression (GMR) algorithm on the GMM model such detailed in [16], [20].

C. Assessing an imitation performance

Assessing the patient's performance to provide him adequate and personalised support such as performance feedback to help him correct his errors are also essential for an intelligent tutoring system. [14] only focuses on the algorithms for learning from experts and does not tackle the assessment of an imitation attempt. [13] and [12] based their automatic evaluation on the distance measure between the user's current arm angles and the specified goal arm angles. This metric could be used in the simple setting where the patient can only move a few articulations, because their experimental setup required them to sit and only move the arms on the side. However, this technique does not take into account the speed of execution or the dynamics of the movement. Moreover, it is ill adapted to complex full-body exercises that can involve several parts of the body but not necessarily all parts of the body. The assessment algorithm should be able to understand which parts are important, and what are the ranges of freedom that are acceptable.

We develop a system for automatically assessing the movements of patients, to point out which parts of the movement need to be improved. More specifically we will use programming by demonstration algorithms to model for each movement the probability density of its sensorimotor and dynamics values. Programming by demonstration algorithms have been developed for robotics [16] . Programming by demonstration enable the robot to both demonstrate the exercise to the patient and to assess whether the movement of the patient is acceptable, taking into account the body postures but also the dynamics and the ranges of freedom of different parts of the body.

In particular, PbD methods based on Gaussian Mixture Models (GMM) provides the system with a probabilistic description of the ideal movement, and encapsulates the tolerated variance for each joint and timeframe, as detailed in [16], [20]. The robot coach thus has a more complex notion of acceptance of the imitation attempt, and can provide a more adequate evaluation.

We propose to build a coaching robot for physical exercises, built around an intelligent tutoring system that uses learning by imitation algorithms with Gaussian Mixture Models to learn from therapists new exercises and to be able to coach patients automatically.

III. Implementation

A. Description of our System

The system is composed with a low cost stereo vision camera (Microsoft© Kinect v2), an open source humanoid robot (Poppy) and a small computer board (Odroid board-XU4) located in the Poppy's head. Poppy is fully open-source and designed to be anthropomorphic [21].The humanoid robot is called Poppy and is an open-source platform based on 3D printing. This robot is 85cm high and has 25 degrees fo freedom (DOF) with a 5 DOFs articulated trunk. Given its unique capability of realising movements of the lumbar spine, this robot fits well with the objectives of rehabilitation programs dedicated to low back pain. We also chose the Kinect camera for its low-cost and ease of use both for the therapists and the patients. It is all the more advantageous than it does not need any preparation for the end-user to attach markers on their bodies.

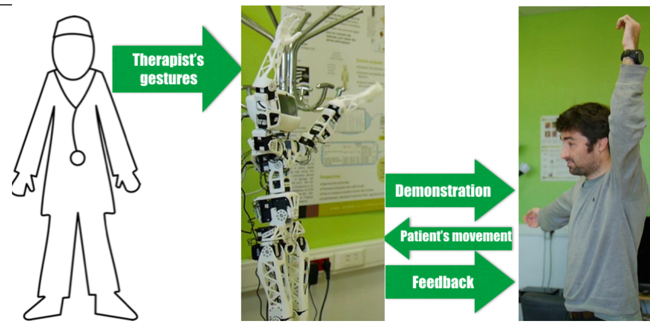

Fig. 1. Overview of the interactions between the therapist and the robot coach, and between the robot coach and the patient. The robot coach first learns the specifications of the exercise from the therapist. It then is capable of coaching by itself the patient, by making a demonstration of the specified exercise, assessing the patient's attempt and giving him his feedback.

B. The coaching scenario

After discussion with domain experts, the human interaction between professional and patient appears to be not well standardised. The patient relationship is adapted every time according to the situation and the patients' profiles to engage them in the therapy. However, we can distinguish three specific phases, as represented in Fig. 1 :

1) The *demonstration phase* where the exercise is presented and explained to the patient.
2) The *coaching phase* when the professional encourages a patient during the exercise or motivates him to maintain for instance a position during a hard task to execute.
3) The *debriefing phase* where the patient listens to all the instructions related to the execution of his movements. This feedback step is also related to coaching aspects because a specific vocabulary empowering the patient can be used.

C. The Computational Architecture

Figure 2 depicts the computational architecture with a humanoid robot during physical exercises in kinaesthetic rehabilitation. The schema combines two different phases : learning and exercise. The first step is realised by recording the therapist in front of the camera while carrying out several times the same exercise. Then the "ideal movement" can be generated in order to be reproduced by the robot. In the second step, the patient is in front of the camera and robot. The *Robot ideal gesture generator* component transforms all movements composing an exercise in order to fit with the robot capabilities. It includes a translator from the doctor's joint configurations to those of Poppy. This translator is robot specific but it can be easily replaced to match with another robot without changing the overall architecture.

Finally, during the exercise all movement done by the patient are recorded and analysed. In this study, we make the hypothesis that the exercise is based on joint angles and not on the positions of parts of the body. Then, the configurations of the doctor and patient are the same, and joint angles can be directly compared for analysis. At this

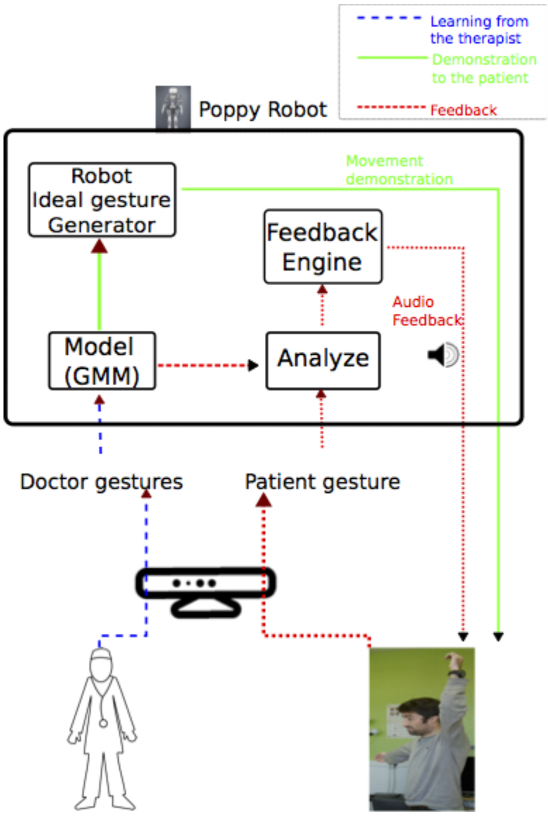

Fig. 2. Overview of the computational architecture for the robot to learn a model of the exercise from the doctor's gestures, then to make demonstrations from the model, and to give feedback to the patient

stage the robot plays role of a verbal coach to help the patient to perform the best movement for his rehabilitation. This part is realised with the *Feedback Engine* and *Analyse* component. Moreover, during the exercise, according to user outcomes, the agent can propose a new demonstration with adapted feedback to improve the learning phase of each exercises.

D. The Intelligent Tutoring : Corrective Feedback

1) Model: We encode the movement point positions as a Gaussian Mixture Model (GMM) of 16 components $\theta = [t, x]$ where t is the timestamp and x the joints positions.

$$p(\theta) = \sum_{i=1}^{K} \phi_i \mathcal{N}(\mu_i, \Sigma_i) \tag{1}$$

where the i^{th} vector component is characterised by normal distributions with weights ϕ_i, means μ_i and covariance matrices Σ_i. Each Gaussian of the mixture is thus defined by :

$$\mu_i = \begin{bmatrix} \mu_i^t \\ \mu_i^x \end{bmatrix}, \Sigma_i = \begin{bmatrix} \Sigma_i^t & \Sigma_i^{xt} \\ \Sigma_i^{xt} & \Sigma_i^x \end{bmatrix} \tag{2}$$

where the indices ^{t} and ^{x} refer to respectively time and position.

The parameters ϕ_i, μ_i, Σ_i are learned from the skeleton data of the movements captured by the Kinect. They are obtained by Expectation-Maximisation.

2) Robot Ideal gesture Generator: For movements demonstrations, we reconstruct a general form for the signals by applying Gaussian Mixture Regression (GMR). Consecutive temporal values t are used as query points and the corresponding spatial values $\hat{x}$ are estimated through regression. The conditional expectation and covariance of x given t are :

$$\hat{x} = \sum_{i=1}^{K} \beta_k(\mu_i^x + \Sigma_i^{xt}(\Sigma_i^t)^{-1}(t - \mu_i^t)) \tag{3}$$

$$\hat{\Sigma}_i^x = \sum_{i=1}^{K} \beta_k^2(\Sigma_x, i - \Sigma_{xt}^i(\Sigma_i^t)^{-1}\Sigma_i^{xt}) \tag{4}$$

By evaluating $\hat{x}$ at different time steps, a generalised form of the motion are produced. These joint positions are then sent to a transformed into joint angle commands using the kinematics model of the robot.

3) Analyze: A metric of imitation allows the robot to assess the movement of a patient automatically :

$$H = \delta^T W \delta \tag{5}$$

where $\delta = x - \hat{x}$ is the difference between the observed attempt x and the generalised motion $\hat{x}$ (obtained by GMR).

By applying eq. 5 directly on the recorded motion, we obtain the overall quality of the observed attempt. The lower H, the better the imitation is.

Furthermore, we compute the contribution to this error by each joint by computing $H_j = \delta_j^T W \delta_j$ with δ_j as the projection of δ on the subplane of the j-th dimension (δ_j is δ where all values are zeroed except for the jth component).

We arbitrarily set a threshold Δ to get the list of outstanding errors $E = \{(j, \delta_j), if H_j > \Delta\}$. Indeed, this imitation metric has the advantage first of taking into account the covariance matrix, and thus highlighting only errors on data which have a high covariance, and ignoring unimportant errors when the initial dataset had high variability. The robot thus helps the patient focus on improving on his most noticeable errors, instead of confusing him with a list of all the minor errors. This list also is informative as it outputs the value of the error, so that the patient knows how to correct his movement and improve on his rehabilitation process.

This list of errors is sent as a dictionary in a json file to the Feedback Engine for audio feedback to translate this mathematical analysis into recommendation sentences for the Human-Patient Interaction.

E. The Patient-Robot Interaction

The system currently allows a one way interaction with the patient. The human robot interface is realised by the *Feedback Engine*. The system uses a text to speech server (MaryTTS) embedded in a Odroïd-XU4 board allowing to provide vocal user feedbacks. MaryTTS uses a client/server model. Moreover, we developed a specific API on the server side in order to generate a specific and adapted movement correction with the following parameters :

— lang : country language, e.g. "en" for English.

```
<?xml version="1.0" encoding="ISO-8859-1"?>
<resources>
<string name="arm-left-up">
Move your left arm higher
</string>
<string name="arm-left-down">
Move your left arm lower
</string>
<string name="arm-left-front">
Move your left arm more forward
</string>
...
```

Fig. 3. XML file example : user feedback sentences

- — part : body member, e.g. arm.
- — side : body side, e.g. left or right.
- — position : gesture or movement advice to improve the exercise, e.g. “higher".

Those parameters allows to address specific sentences previously defined in a XML file. As shown Figure 3 each sentences are defined by a unique key name, e.g. "arm-left-up" corresponding to “Move your left arm higher".

The feedback engine takes as input the relevant changes produced during the comparison step between the ideal movement and the current patient movement. Then it transforms the relevant changes in order to use the text to speech API previously described.

We perform a verbal interaction denoted as *Feedback Engine*. The system allows to load different language dictionaries in form of XML files.

An example video of our coaching robot can be seen in http ://nguyensmai.free.fr/roman2016.html.

IV. Results

A. Dataset

We set up with the Kinect a database for 2 different physical exercises, including 6 different recordings for each exercise. We obtained a model of exercise 1 using the 5 first recordings of exercise 1. We kept the 6th recording of exercise 1 for testing, as well as the recordings of exercise2.

For the assessment of the patients' motions, we set $\Delta = 100$.

B. Modeling and Generating

The GMM model obtained is represented in Fig. 4. This probabilistic representation is used to generate an ideal movement, which is then played by the robot to patients.

C. Assessing

We tested our assessment algorithm with the following test data, which consist of arms movements raised and lowered at different time patterns :

- — test1 : the first recording of exercise 1, which is in the training set.
- — test2 : test1 where we added an offset to the x position of the left shoulder
- — test3 : the 6th recording of exercise 1, which is not in the training set.
- — test4 : the 1st recording of exercise 2.

The analysis output the results shown in Fig 5. Our analysis outputs a general evaluation of the attempted imitation as a H value. The smaller H, the closer to the therapist's demonstrations the test attempt is. Here we arbitrarily consider that $H < \Delta$ is an acceptable attempt. As expected, we can observe that the error is acceptable for test1 and test3, which are movements of exercise 1. On the contrary the error is very high for test2 where an error has been artificially introduced, and test4 which is a recording of a different exercise.

Moreover, our analysis outputs a finer analysis to find out which joint positions are accountable for the errors and how much the error is. This analysis outputs a json file from where are extracted a few lines in Table 5. This output shows that the robot coach was satisfied for test1 and test2, that is when the patient repeats correctly exercise 1. In the case of test2, where we added an offset on the x position of the joint named "mShoulder", we can verify that it reported correctly this error, and did not report any other error. In the case of test4, as the patient was executing another exercise, our system reported several errors.

Thus, our intelligent tutoring system reports correctly the errors seen in the attempted imitation. This output json file is then used by the Feedback Engine to translate this analysis into sentences for audio feedback.

V. Perspectives

In this paper, we have proposed the concept of a general framework of a robot coach for physical exercises of rehabilitation. the system. We have described a general software architecture and described a first intelligent tutoring algorithm. Our robot coach is capable of learning new exercises from demonstrations by the therapists. It can then demonstrate exercises to the patient, and assess the performance of the patient and provide him with corrective feedback. Our system has been designed to be a lightweight system using a light 3D printed humanoid robot. The algorithms behind enable therapists to easily specify exercises by means of demonstrations. It is also an easy-to-use system for the patients as it can be used on-the-go without any markers to setup beforehand.

However, these are only preliminary results as this system does not yet run online. In particular, we plan on developing an interface to be able to switch seamlessly from the 'learning from the therapist' mode to the 'assessing the patient mode'. Moreover, in our tests the same person has acted as the therapist and the patient. We will need to address the correspondance problems when we face several users with different sizes and kinematic models. Most of all, our tutoring system provides us only with feedback about which body parts need to be corrected, but does not provide any information on the timing of these errors. We should develop our works to be able to inform the patient when these errors occurred (in the beginning or the end of the exercise). Furthermore, as we have presented a general architecture for an intelligent tutoring robot, we aim at improving in future works the different components of this architecture. For instance, it should be interesting to add

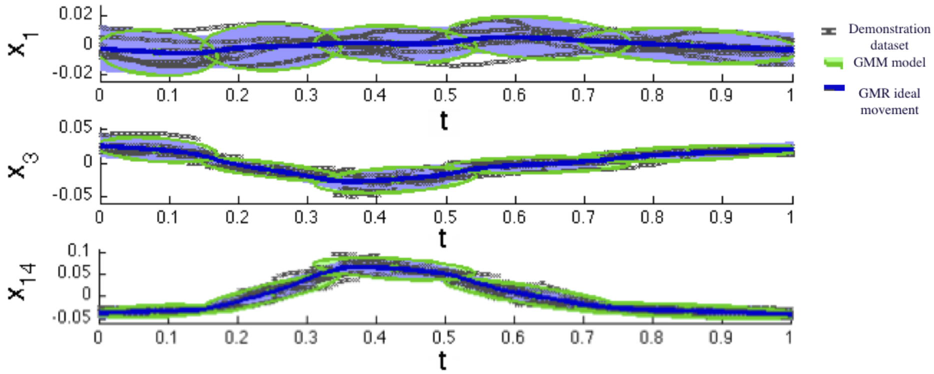

Fig. 4. Modelling the demonstrations with GMM and generating an ideal movement with GMR. Here we represent the results for 3 joint positions with respect to time. The values of the positions have been normalised beforehand. The green ellipses plot a representation of the components (means and covariance matrices) of the Gaussian Mixture Model (GMM). A sequence of temporal values is used as query points to retrieve a sequence of expected spatial distribution through Gaussian Mixture Regression (GMR) represented with the thick blue line.

	test1	test2	test3	test4
H	11.0891	8.338e3	13.98	1.4933e3
E	"mShoulder" : [0,-0,-0] "lElbow" : [0,-0,-0] "rElbow" : [0,0,-0]	"mShoulder" : [0.400003,-0,-0] "lElbow" : [0,-0,-0] "rElbow" : [0,0,-0]	"mShoulder" : [0,-0,-0] "lElbow" : [0,-0,-0] "rElbow" : [0,0,-0]	"mShoulder" : [0,-0,-0] "lElbow" : [0,-0.00103,-0.002] "rElbow" : [0,0,-0.002]

Fig. 5. Output of the analysis of test movements compared to the learned movement model. The analysis outputs both a global evaluation of the test movements, as well as a list of the outstanding errors for each joint position as a finer analysis. This output is then interpreted to give an audio feedback

non-verbal behavior to improve the human robot interaction. Moreover, it would be interesting to incorporate an ability to analyze the temporal improvement of each patient. During the exercise, according to the user profile and knowledge, new demonstration with adapted feedback could be proposed, with adjustments of the demonstration movement and a way of giving feedback. For instance we could modify the ideal movement to make it easier to be accomplished by the patient so as to enhance progress.

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