A humanoid robot for coaching patients for physical rehabilitation exercises

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1. Robot Coach for Physical Rehabilitation 1.1 Motivation

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 [1,2]. It is the third common cause of disabling condition in the 45-65 years old population, whose proportion in European societies keeps rising. This incurs growing concern, as medical professionals will not be able to face this increasing demand for healthcare.

1.2 A Robot Coach

Active rehabilitation is considered as more effective than usual care [3]. To enable rehabilitation to an increasing number of elderly patients, we propose a robot coach for physical rehabilitation exercises. The long-term goal of this project is to provide patients with a e-Health solution for personalised follow-up of long-term rehabilitation at home. We develop a robot coach capable of demonstrating physical exercises to patients, watch a patient carry out the exercises and give him feedback so as to improve his performance. Our system aims to be easily used by medical experts.

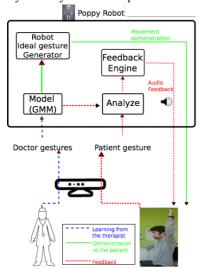


Fig. 1. Overview of the computational architecture for the robot to learn a model of the exercise from the doctor's gestures, then to make demonstrations from the model, and to give feedback to the patient

2. State of the art and challenges

Our approach for robotic systems coaching physical exercises is related to those presented in [4,5] and [6]. Takenori *et al* [6] 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. Fasola *et al.* in [4] and Goerer *et al.* [5] presented a socially assistive robot (SAR) to engage elderly users based on their intrinsic motivation or through HRI. They proposed an automatic evaluation of physical exercises by computing the distance between the user's current arm angles and the specified goal arm angles. However, it does not take into account the speed or the dynamics of the movement. It is ill-adapted to complex full-body exercises that can involve several parts of the body but not necessarily all parts.

We would like to focus on the intelligent tutoring system (ITS), and more specifically an algorithm capable of assessing which parts of the body are important to the exercise, and what are the acceptable ranges of freedom. More specifically we use probabilistic imitation learning algorithms to model each movement and detect errors.

3. Proposed system

3.1 The Hardware

The system is composed with a Microsoft Kinect v2 and an open source humanoid robot Poppy [7]. A demonstration video can be watched at http://nguyensmai.free.fr/roman2016.html.

3.2 The Computational Architecture

Figure 1 depicts the computational architecture with a humanoid robot during physical rehabilitation exercises. The schema combines three different phases: learning, demonstration and feedback. In the first step, the therapist records in front of the camera several movements of the same exercise. These therapist's gestures enable the robot to learn a Gaussian Mixture Model (GMM) with Expectation Maximization, as described in [8]. In the demonstration phase, the "ideal movement" can be generated in order to be reproduced by the robot, using Gaussian Mixture Regression (GMR).

Finally, during the exercise all movements done by the patient are recorded and analysed for vocal feedback by the robot. This part is realized with the *Feedback Engine* (section 3.3) and *Analyse* component.

For the Analyse component, a metric of imitation allows the robot to assess the movement of a patient for each joint j automatically:

$$H_{j} = \delta_{j}^{T} W \delta_{j}$$
 (1)

where W represents parameters of the GMM and $\delta = x - x^{\hat{}}$ is the difference between the observed attempt x and the generalised motion $x^{\hat{}}$ (obtained by GMR). The lower Hj, the better the imitation is. We arbitrarily set a

threshold Δ to get the list of outstanding errors Ej = {(j, δj), if Hj > Δ }.

3.3 The Patient-Robot Interaction

This list of errors is sent to the Feedback Engine for audio feedback to translate this mathematical analysis into recommendation sentences for the Human-Patient Interaction. The system currently allows a one-way interaction with the patient, using a text to speech server (MaryTTS) to provide vocal feedbacks.

4. Results

4.1 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.

4.2 Modelling and Generating

The GMM model obtained is represented in fig. 2. This probabilistic representation is then used to generate an ideal movement, to be played by the robot coach to patients.

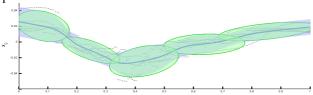


Fig. 2. Modelling the demonstrations with GMM and generating an ideal movement with GMR. Is represented a recorded joint position with respect to time (normalised values). The green ellipses plot a representation of the components of the GMM. The ideal trajectory (GMR) is represented with the thick blue line.

4.3 Assessing

We tested with the following data:

- d1 : a recording of exercise 1 (in the training set)
- d2 : d1 where we added an offset to the x position of the left shoulder
- d3 : a recording of exercise 1 (not in the training set)
- d4: a recording of exercise 2

The *Analysis* results are shown in Fig 3. Our analysis outputs a general evaluation of the attempted imitation as H. As expected, we can observe that the error is acceptable for d1 and d3, which are movements of exercise 1. On the contrary the error is very high for d2 where an error has been artificially introduced, and d4, which is a recording of a different exercise.

Moreover, our analysis finds out which joint positions are accountable for the errors. It shows that the robot was satisfied for d1 and d2. When the patient repeats correctly exercise 1. In the case of d2, where we added an offset on the x position of the joint named "rShoul", we can verify that it reported correctly this error. In the case of d4, as the patient was executing another exercise, our system reported several errors.

Thus, our ITS reports correctly the errors seen in the attempted imitations. This output is then used by the Feedback Engine to translate this analysis into sentences for audio feedback.

		d1	d2	d3	d4
	Н	11.0891	8.338e3	13.98	1.4933e3
E	rShoul.	[0,-0,-0]	[0.4,-0,-0]	[0,-0,-0]	[0,-0,-0]
	lElb.	[0,-0,-0]	[0,-0,-0]	[0,-0,-0]	[0,-4.5e-4,-2.0e-3]
	1Shoul.	[0,0,-0]	[0,0,-0]	[0,0,-0]	[0,-0,-0.00029]
Audio		Nothing	Move your	Nothing	Move your left
feedback			right shoulder		elbow lower,
			more to		move your left
			the right		elbow more
					forward move
					your left shoulder
					more forward

Fig. 3. Output of the analysis of test movements compared to the learned movement model (no units as the positions are normalised). The analysis outputs both a global evaluation of the test movements, and a list of the outstanding errors for each joint position. These figures are then interpreted by the robot to give an audio feedback.

4. Discussions

In this paper, we have presented a general software architecture for a robot coach for physical exercises of rehabilitation. Using programming by demonstration as a probabilistic imitation learning algorithm, our robot coach is capable of learning new exercises from demonstrations by the therapists, then demonstrate exercises to the patient, and assess the performance of the patient and provide him with corrective feedback.

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'. Second, we plan to adapt the threshold Δ to the patient. If it's too high, the robot will not correct movements that may be ineffective or even harmful, if too low, the patient will easily become frustrated. Furthermore, in our tests the same person has acted as the therapist and the patient. We will need to address the correspondence problems when we face several users with different sizes and kinematic models. We approach this problem by using joint angles instead of Cartesian positions.

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