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Adaptive rehabilitation games

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ABSTRACT

In conventional neuromuscular rehabilitation, patients are required to perform biomechanical exercises to recover their neuromotor abilities. These physiotherapeutic tasks are defined by the physiotherapist, according to his estimate of the patient's pathologic neuromotor function. The definition of the task is mainly qualitative and it is often merely demonstrated to the patient as a gesture to reproduce. Success of the treatment relies then on the accuracy and repetition of the motor training.

We propose a novel approach to neuromotor training by combining the advantages of a virtual reality platform with biofeedback information on the training subject from biometric equipment and with the computational power of artificial neural networks. In a calibration stage, the subject performs motor training on a known task to train the network. Once trained, the tuned network generates a new patient-specific task, based on the definition of the subject's expected performance dictated by the therapist. The system was tested for upper limb rehabilitation on healthy subjects. We measured a 33% improvement in the triceps performance ($p = 0.027$). The novelty of the proposed approach lies in its use of learning systems to the estimation of biological models.

1. Introduction

1.1. Motivation

Rehabilitation consists in the execution of motor tasks designed to help the patient recover maximal movement and organ functionality. The design of these tasks by the physiotherapist is made according to the patient's state and pathology. However, the patient's needs may vary along the rehabilitation sessions and the physiotherapist must adapt his tasks accordingly. This adaptive physiotherapy is very difficult to perform online and relies on the trainer's qualitative interpretation of the subject's performance.

Accurate repetitions of these biomechanical exercises are key points for successful physiotherapeutic treatment. These physical tasks are often strenuous to the patient and the therapy's efficiency largely relies on the subject's motivation, in particular with children who often lack the patience and perseverance necessary for their treatment.

Performing motor training in virtual reality (VR) offers several advantages. The training task can be continuously demonstrated to the subject and act as a virtual teacher. Moreover, the subject can receive in virtual environments (VEs) and with adequate biometric equipment immediate biofeedback on his performance during training. Furthermore, rehabilitation can be performed in the form of interactive games greatly stimulating the subject's motivation during training. This kind of system can additionally provide the physiotherapist with quantitative data on the training session for further investigation. Finally, virtual systems can be augmented with computational models and artificial intelligence.

1.2. Literature review

In the last decades, the use of VR has bloomed in the field of physiotherapy and, at the present time, studies associating VR with rehabilitation are countless. Since the beginning of the 1990's, studies showed scientific evidence that motor skills could be learned in VE (e.g. Goldberg, 1994; Theasby, 1992), replicated into the real world (Rose et al., 1998), and even generalized to certain untrained tasks in the real world (Holden et al., 1999; Holden and Dyar, 2002).

Success of rehabilitation resides in three key concepts: feedback, repetition and motivation (Holden and Dyar, 2002). VE are likely to amend each of these concepts. The technological advancements in both VR and biosensory instrumentation offer the opportunity to provide augmented feedback in real time about one's motor performance. VR systems generally involve specially written software which grants entire control on the provided feedback.

Scientific evidence suggests that learning by imitation leads to the neurophysiologic changes linked to motor rehabilitation (Nudo and Milliken, 1996). VR offers the possibility of producing a *virtual teacher* (Holden et al., 1999), tireless and always available, who may tutor a patient over and over. VR systems can teach and

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correct a subject during practice with real time feedback and, by such, can significantly improve the accuracy of his performance.

Motivation plainly affects performance during rehabilitation (MacLean et al., 2000). With the advancements of graphic hardware and software tools, real-time programs can be shaped as virtual games, in which the measured biomechanical data provide interactive control to the user. Recent examples for this kind of system in the field of entertainment are the Nintendo Wii and Microsoft's Kinect. With this new aspect, motor rehabilitation can be made much more attractive for patients than conventional neuromotor rehabilitation, often repetitive and annoying (e.g. Bryanton et al., 2006).

In summary, VR provides unique tools for rehabilitation that have often been verified to overcome the conventional methods in rehabilitative therapy (Holden, 2005). With the use of VR, the physiotherapist benefits from enhanced control on the rehabilitation session, and the performance and experience of the patient are significantly improved.

The study of human motion and motor control has been the source for the development of dynamic, kinetic and mechanical models used in medicine, motion capture (Stanney et al., 1999), robotics (Krakauer, 2006) and neuroscience (Wren and Pentland, 1998). The existence of internal models (neural processes that simulate the response of the motor system to estimate the outcome of a motor command) for motor control and trajectory planning has also been investigated during the last years with respect to cognitive science and neurophysiology, and they have been applied to motor system identification (Pollard et al., 2002). Nevertheless, in our study we adopted an approach radically different from the methods commonly found in the literature: instead of elaborating a sophisticated model of the patient, we relied on the ability of artificial neural networks to estimate unknown models from known inputs and outputs.

In this research, we introduce a novel approach able to improve neuromuscular training in VR by means of artificial intelligence systems. Artificial neural networks (ANNs) are trained to learn from observation of the patient's performance and subsequently produce new patient-specific virtual physiotherapeutic tasks. During a training session, the subject is exposed via a head-mounted display unit to these virtual tasks which demonstrate to him the movements to perform. By means of a 3D motion capture system and electromyographic (EMG) sensors, the system constantly tracks the kinematics of the subject and his muscles activation. From these data, an ANN is trained to respond to the subject's biofeedback information, having the desired muscles activation and motions as references. Once trained, the network generates a new trajectory as a biomechanical exercise, according to the previous performance of the subject.

This system allows the physiotherapist to plan the expected neuromuscular performance instead of designing the physiotherapeutic exercise leading to it. He may decide which muscles to focus on and which functional pattern is expected to be executed. Since the system is tuned per patient and per session, the generated exercise is specific to the patient's pathology and to the stage he is at within his rehabilitation program.

2. Methods

The purpose of the system is to generate a virtual rehabilitation task adaptively to one's current motor performance and to the desired motor performance prescribed by the physiotherapist. The system should thus receive a performance to produce an adequate exercise. Conversely, a subject performing motor training can be seen as producing a motor performance on a given exercise. This automated task generator is thus actually based on the estimation of the inverse model of the subject (Fig. 1).

We hypothesize that the inverse model of a patient can be estimated with a neural network specifically trained and tuned to the patient's performance. Furthermore, we hypothesize that executing a patient-specific physiotherapeutic exercise will result in a better kinematic and electromyographic performance.

2.1. Experimental setup

Subject kinematics was recorded with Vicon™ motion capture system, which tracks anatomical landmarks marked by reflectors. In parallel, we used a wireless Aurion™ surface EMG ZeroWire system to collect electrical signals of the subject's target muscles. Both kinematics and EMG data were simultaneously collected by the Vicon system. The markers were placed on the limb to reeducate and on the head-mounted display unit in order to track the subject's head movements and accordingly modify the display of the virtual environment (Fig. 2). The processing and analysis of the data was performed in real time in the custom C++ application running on the workstation. In addition to the input data preprocessing, the software agent manages the graphic user interface, the estimation of the inverse model of the subject and the rehabilitation task generation. The subject was equipped with an eMagin™ 3DVisor Z800 head-mounted display from which he received the audiovisual feedback.

The kinematic recordings allow reproducing in the virtual environment a replica of the subject's hand. In each of the developed platforms (Fig. 3), the rehabilitative task was encoded in an interactive game controlled by the subject's arm. The user received in real time augmented feedback on his performance during training. For instance, in the virtual ball tracking application (Fig. 3), the user was constantly notified on the distance to the target with the color of a second ball on the virtual arm, a varying musical background volume and shadows on the ground.

2.2. Experiment workflow

In a first step, the subjects practiced motor training on a known exercise displayed as the trajectory of a virtual ball which he must follow with his pointing finger. At this stage, the subject is instructed to find a standing spot from where the entire exercise can be executed and to keep his feet steady during the training session. This exercise has been designed such that most of the reeducation workspace, in front of the patient and at the reach of his hand, is covered. This exercise, along with the corresponding performance of the subject, composes the training set on which the network is taught and customized to the subject. Once the network converges, we obtain an estimation of the inverse model of the subject. In parallel, the physiotherapist conceives, based on his

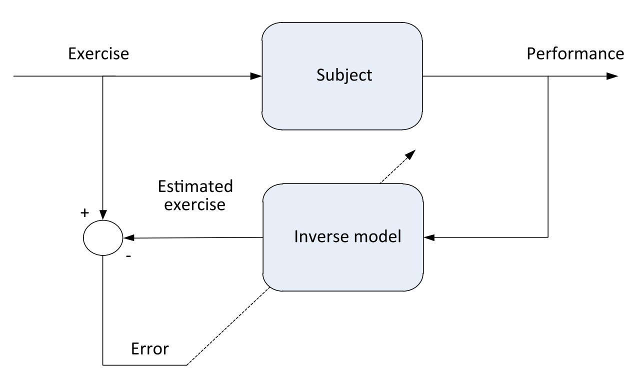


Fig. 1. Estimation of the subject's inverse model.

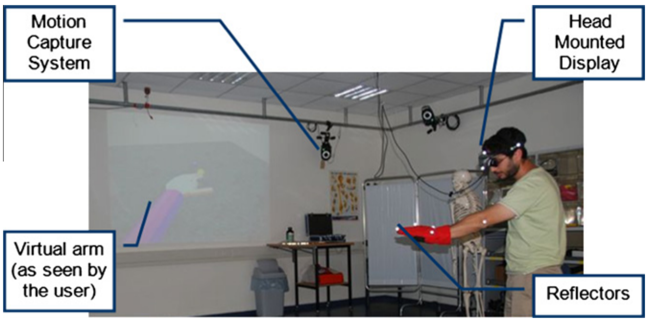


Fig. 2. Experimental setup.

diagnosis and professional knowledge, a desired performance involving the kinematics of the limb and the activation of specific muscles. The desired performance is then given as input to the tuned network that produces the appropriate patient-specific exercise. Theoretically, if the neural network estimates the inverse model closely enough, the performance of the subject during execution of the new exercise should be similar to the desired performance (Fig. 4).

2.3. Inverse model estimation – kinematic input

Whereas the exercise consists of a simple spatial trajectory, the performance may be defined arbitrarily to include kinematic data, information on the muscles activation, kinetic recordings, etc. The same model could be used for reaching tasks of different limbs or for analysis of the patient's neuromotor functions. In order to check the feasibility of estimating the inverse model of the subject in a simple case, the position and velocity of the subject's fingertip were first set as the goal performance.

We first designed a cyclic trajectory $\kappa(t)$ for the virtual exercise. We note by n the number of samples in a cycle. Then, a healthy subject is asked to perform several cycles of this exercise. The kinematic performance K_{raw} consists of the complete trajectory of his fingertip (while uncompleted cycles are truncated from the recorded set). The average over the m number of cycles of the subject's kinematic performance $K(t)$, combined with one single cycle of the trajectory of the virtual task, constitutes the training set for the neural network.

The velocities of the finger and of the virtual ball, computed from smooth derivation and respectively noted by V and υ, are added to the input and output neurons of the network, in order to define the kinematic state more accurately. We note by P the $6 \times n$ matrix composed of all the temporal samples of positions

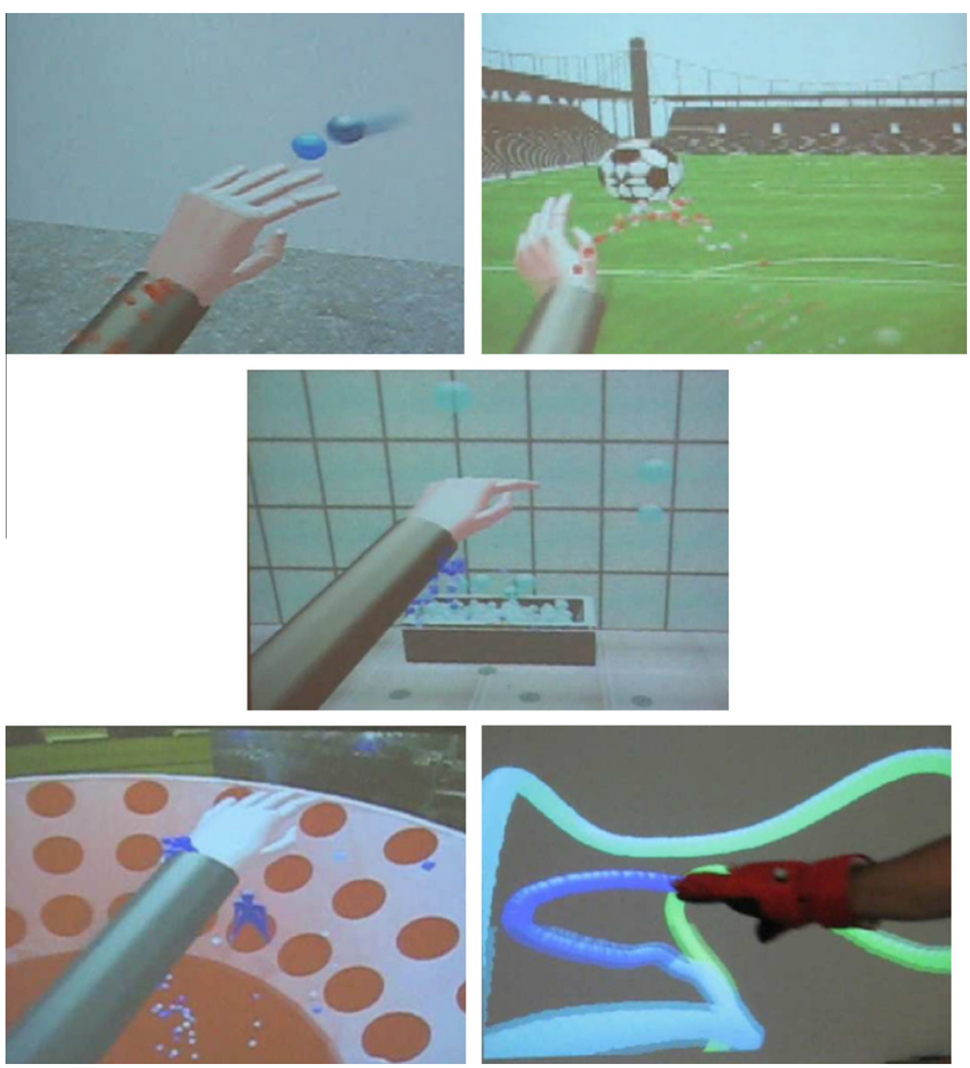


Fig. 3. Interactive rehabilitation games: (from left to right and from top to bottom) virtual ball tracking, goalkeeper, popping bubble, whack-a-mole, 3D drawing.

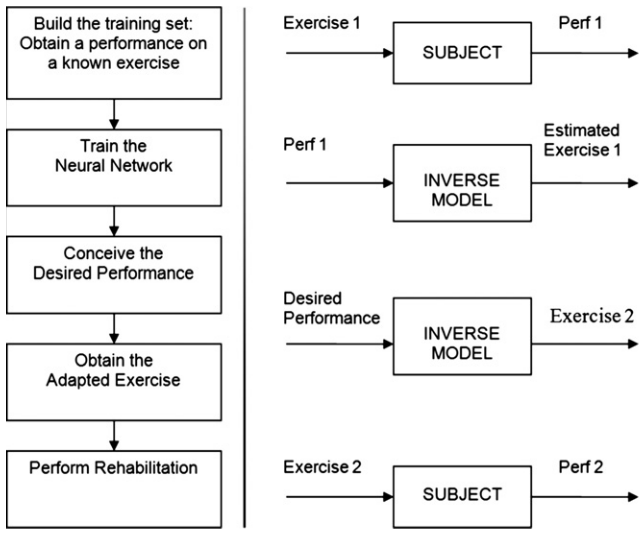


Fig. 4. Experimental workflow. The desired performance should be designed by the physiotherapist based on his expectation of the kinematic and muscular performance of the patient.

and velocities relative to the performance of the subject, by T the $6 \times n$ matrix relative to the target of the network, and by $Y(P)$ the $6 \times n$ matrix corresponding to the output of the neural network on the input set P (Fig. 5). Since the network's mapping is applied discretely for each instant state, we consider $Y(P)$ as the moving average of the raw output of the network, in order to generate a smooth exercise that the subject may easily interpret and reproduce.

After testing iteratively different network characteristics (by varying the number of hidden neurons, the activation function or the number of epochs), we choose the architecture of the network providing the best results for different patients and exercises (the methods have been detailed in Barzilay and Wolf (2009)). The search for the neural network's optimal configuration is performed only once from experimental sessions. In this way, we find an ANN architecture for inverse model estimation while the performance is defined as the kinematic data only, whereas patient-specificity is attained only after teaching the neural network on the training set produced by one's motor performance. We use seven neurons in the hidden layer, in order to obtain a good performance together with an acceptable runtime, fifty epochs and the hyperbolic tangent as the hidden layer's activation function.

2.4. Inverse model estimation–kinematic and EMG inputs

In a second phase and after having obtained satisfactory results from the estimation of the inverse model according to kinematic input only (Section 3.1), we included electromyographic signals into the definition of the performance of the subject. From a physiotherapeutic perspective, it is more meaningful to inspect the muscular information rather than giving emphasis to how close the subject motion is to a specific trajectory.

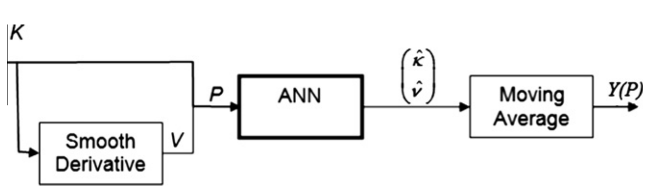


Fig. 5. Exercise production module.

The same kind of training was requested from the subject, although this time we placed electromyograph electrodes on his biceps and triceps which are stimulated by the movements executed during the exercise. The processed envelopes of the corresponding EMG signals were then added to the network's input layer (Fig. 6). To reduce the computing time spent on the EMG digital signal processing (DSP), we have developed an accelerated method for the computation of linear envelopes for several signals in real time (Barzilay and Wolf, 2011).

The neural network's configuration was determined in a similar way to (Section 2.3). We used a feed-forward network with eight input neurons corresponding to the position and velocity of the subject's pointing finger and the EMG signal envelopes of his biceps and triceps. The network contains six output neurons and one hidden layer with seventeen neurons with the hyperbolic tangent as activation function (Barzilay and Wolf, 2009). The error back-propagation is performed by Levenberg–Marquardt's scheme and the weights are initialized according to Nguyen–Widrow's method.

2.5. System evaluation

As a feasibility check, the case of kinematic input only was mainly qualitatively evaluated. We investigated the results obtained with this simplified definition of the motor performance of a subject and looked for observable facts on the detection of motor (or other) patterns in the estimated subject model. We additionally compared the performance of the subjects on new exercises with the desired performance.

We were more interested in the case where muscle activation was taken into consideration, for its significantly superior therapeutic value. We considered the definition of exercises in classic rehabilitation sessions. In conventional physiotherapeutic training, the physiotherapist demonstrates to the subject with his hand, for instance, the movement to reproduce. In this manner, the patient is shown the desired trajectory to perform, based on the physiotherapist's expectation about the induced activation of the subject's muscles. In our case, this comes to present the desired kinematic performance as the exercise to perform ($\kappa = K_{desired}$). We thus compared the results of the system to the results obtained in a conventional-like rehabilitative session. This consists in comparing, in the same training conditions, the subject's performance on the task created by the system with his performance when he is directly shown the desired kinematic performance as the exercise, unprocessed by the system. More precisely, we consider the deviation of each performance from the desired one and compare between the obtained errors. The desired EMG performance for a given exercise was measured as the average performance of a dozen healthy subjects. Although this definition of the desired performance as the averaged EMG envelope is likely to discard high-frequency features, it provided a baseline for the evaluation of the system's

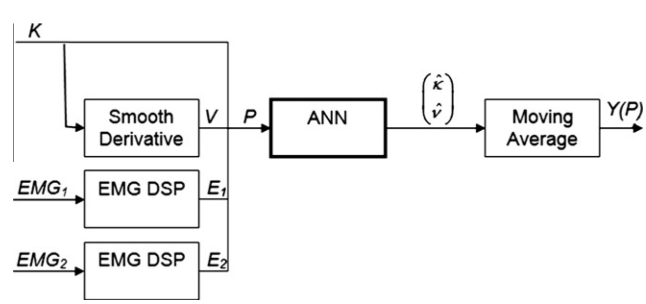


Fig. 6. Exercise production module (including EMGs). DSP stands for digital signal processing.

performance. Furthermore, the low-frequency components of the EMG power spectrum describe best the slow cyclic movements performed by the subjects during training. Eventually, it is expected that the desired performance will be determined by a trained physiotherapist. For physiotherapeutic significance, we put emphasis on the deviation in EMG performance more than the kinematic performance.

The system was evaluated on a study population of 15 healthy subjects (aged 19–35) that had not been screened for orthopedic limitations. The subjects performed motor tasks with their non-dominant hand such as to simulate some degree of neuromotor deficiency.

3. Results

3.1. Kinematic input

The neural network converged in most cases for every subject. In a first step and to start with a simple case, the exercise given to the subject was set as a planar trajectory. Fig. 7 demonstrates the averaged performance of a subject on a planar exercise and the smoothed network. Its proximity to the trajectory of the original exercise is manifest. The trajectory of the exercise designed by the network has an average deviation of 15 mm per point from the target trajectory. This average deviation is reduced to approximately 4 mm per point after smoothing.

We would like to point out a phenomenon which may occur during exercise, that is: a projection of the exercise as seen by the subject. The phenomenon can be observed in Fig. 7, in which it appears that, due to the relative location between the target and the subject's eye and to the fact that the exercise was displayed in two dimensions in the head-mounted display, the task might be interpreted by the subject as a projection on a plane normal to his line of sight. Nevertheless, the neural network system was able to learn the projection, although far from being a linear phenomenon. The trajectory of the exercise created by the network remained close to the original exercise's trajectory in spite of the significant offset between the exercise and the subject's performance. In Fig. 7b, one can see the subject's interpretation of the projected exercise.

Fig. 8 shows the exercise designed by a network trained on a three dimensional training set, the desired performance and the actual performance produced by the subject on the new exercise. One may notice on the left side of in Fig. 8b how the network was able to predict that, in order to position the subject's hand at the desired place (in black), the virtual ball had to be displayed a bit farther along the *Y* axis (corresponding approximately to the subject's line of sight). The subject's hand effectively deviated from the exercise in the expected direction. This fact suggests that the model edified by the network includes some of the subject's behavioral patterns. The recurrence of this phenomenon in several sessions and for different subjects brings additional support to this claim. One can observe in Fig. 8, that the prediction was effected twice on the same portion of the exercise trajectory, but with the hand coming from different directions.

The sample case presented above is representative for most of the sessions performed by the different subjects: when averaged over the total number of samples, the actual trajectory was approximately at midway between the exercise and the desired performance, but with occasional marked offsets towards either of them. These results were optimistic enough to encourage us to carry on this study with kinematics and EMG signals defined as the subject's performance.

3.2. Kinematic and EMG inputs

As expected, appendage of the EMG signals to the neural network's input increased the error relative to the kinematic performance. However, for physiotherapeutic significance, we focused our attention on minimizing the error in the EMG performance and the kinematics error was considered more moderately. We analyzed the EMG signals in the frequency domain, in order to overcome the issues of EMG calibration and phase shift due to the subject's response time. Furthermore, frequency domain analysis puts emphasis on the rhythmic patterns embedded in the signals, holding significant information on the behavioral patterns of

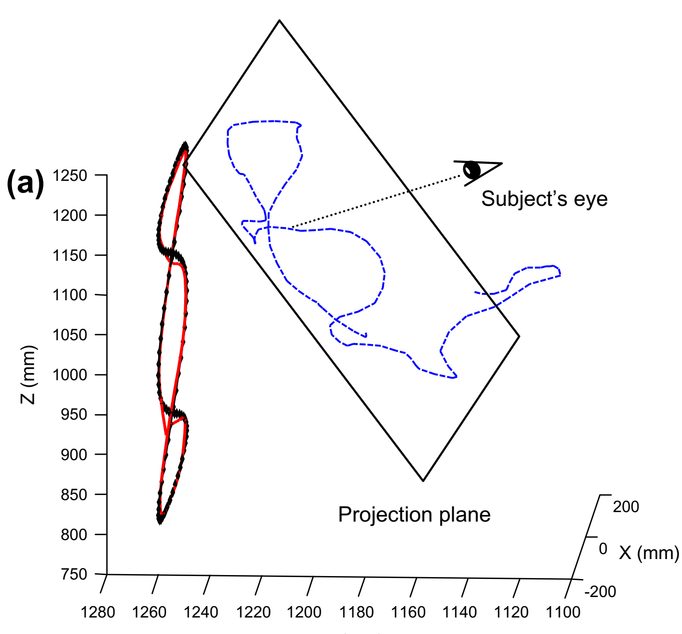


Fig. 7. The exercise projection: (a) side view and (b) subject's point of view.

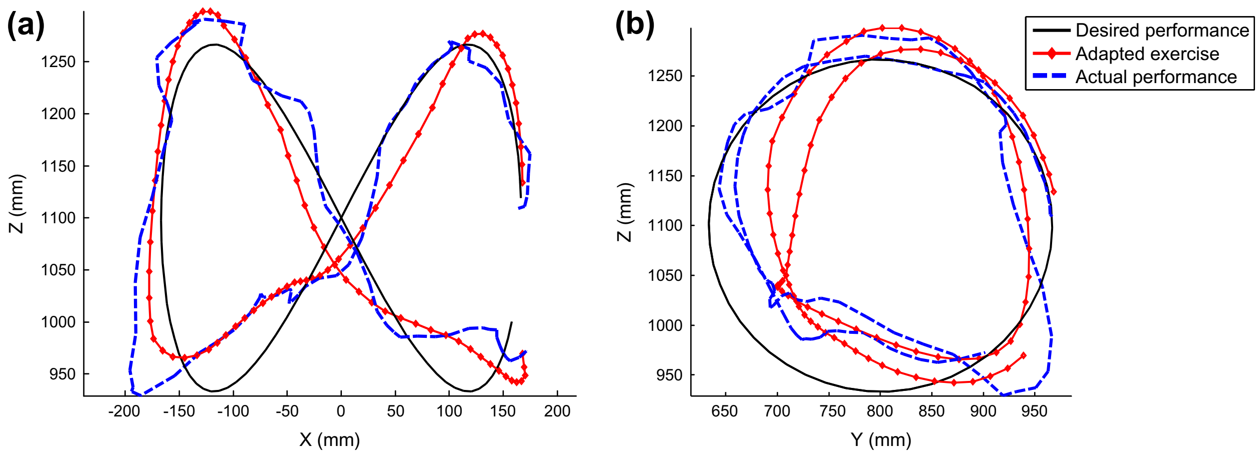


Fig. 8. Desired vs. actual performance: (a) front view and (b) right view.

the subject. Fig. 9 shows a sample EMG performance in the frequency domain (low frequencies).

Each participant ($n = 15$) performed motor training on two exercises: the patient-specific exercise produced by the neural network and the exercise having for trajectory the desired kinematic performance, simulating a conventional physiotherapeutic session. The deviations from the desired performance in each case are presented in Table 1. The primary criterion for the evaluation of the system was defined as the ratio of the errors obtained in the performances on both exercises (Table 1). This parameter quantifies the muscular performance relative to the expected performance of each subject for both the adapted exercise designed by the system and the conventional training exercise.

Most subjects ($n = 14$, 93.3%) benefitted from the system for at least one of the muscles, and almost half improved the accuracy of their muscular performance for both biceps and triceps ($n = 6$, 40%). The results indicate that the average muscular performance of the subjects was closer to the desired performance when the exercise was generated by our system, rather than set as the desired kinematic performance as in conventional physiotherapy. This is indicated by a 9% increase in the biceps performance and a 33% increase in the triceps performance.

A one-tail paired Student *T*-test conducted on the experiment data shows that the improvement in triceps performance was attained with statistical significance ($p = 0.027$). However, the improvement in biceps performance was lesser in magnitude and in statistical significance ($p = 0.40$). We believe this is due to the fact that the motor tasks involved the biceps in a smaller measure than the triceps or the shoulder muscles.

4. Discussion

In this study, we introduce a platform for motor and cognitive rehabilitation, able to model the subject's kinematics and to generate a subject-specific physiotherapeutic exercise. The system requires no prior knowledge of the patient or assumptions on his motor control or trajectory planning, but only a desired performance dictated by the physiotherapist and a training reference set recorded *in situ* from the patient's performance prior to rehabilitation. On this point, our system fundamentally contrasts with the systems reported in the literature, involving advanced kinematic and dynamic models of the subject's motor control. To date, and to the best of our knowledge, no study combining VR rehabilitation and learning algorithms for patient-specific training has been

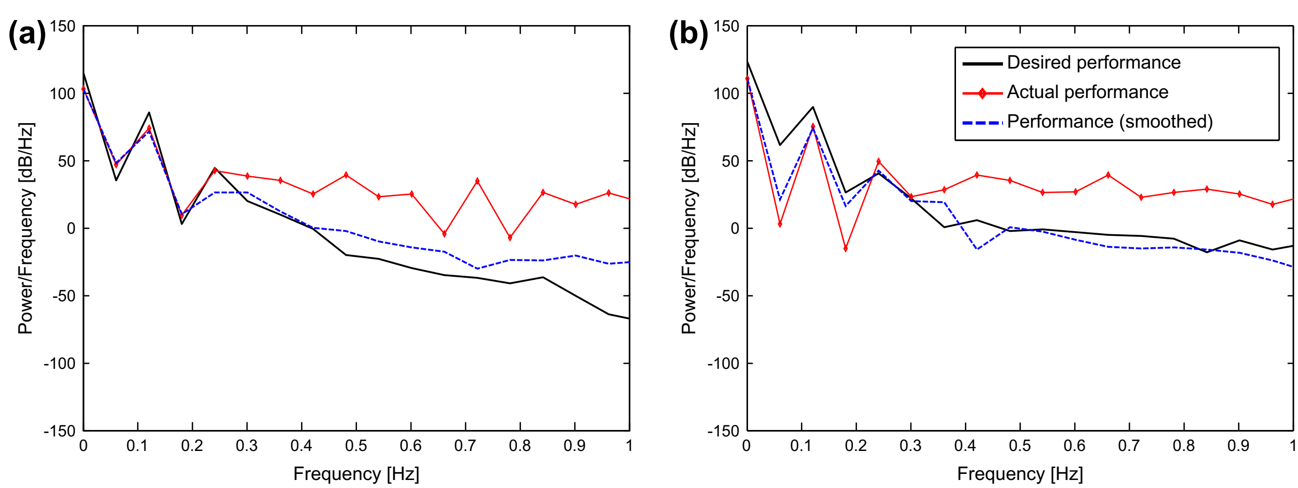


Fig. 9. Desired vs. actual EMG performance in the frequency domain: (a) biceps and (b) triceps. The blue dashed curves correspond to the subject's EMG performance after smoothing, to improve the consistency of the comparison with the averaged desired EMG performance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Error in the EMG Performance in the frequency domain.

Subject	Adapted training(dB/Hz)		Conventional training (dB/Hz)		Error ratio	
	Biceps	Triceps	Biceps	Triceps	Biceps	Triceps
#1	44.71	93.98	54.85	72.04	1.23	0.77
#2	36.25	85.10	76.95	79.76	2.12	0.94
#3	59.49	32.24	78.75	58.90	1.32	1.83
#4	85.00	85.64	40.44	92.74	0.48	1.08
#5	88.92	60.19	67.09	83.63	0.75	1.39
#6	63.85	97.61	56.58	84.20	0.89	0.86
#7	92.61	94.98	62.03	89.72	0.67	0.94
#8	62.94	39.51	18.53	68.19	0.29	1.73
#9	72.05	59.18	81.32	88.28	1.13	1.49
#10	74.67	42.19	148.20	58.98	1.98	1.40
#11	72.05	59.18	81.32	88.28	1.13	1.49
#12	65.00	29.28	74.27	86.06	1.14	2.94
#13	92.78	64.54	103.48	48.57	1.12	0.75
#14	56.12	55.39	71.95	69.94	1.28	1.26
#15	73.25	47.07	54.98	52.16	0.75	1.11
Mean	69.31	63.07	71.38	74.76	1.09	1.33
Std. dev.	16.56	23.30	29.08	14.65	0.50	0.56

reported. The application presented in this work was developed from the ground up and comprises approximately 17,000 non-blank lines of code.

Our approach leads to a generic architecture of network for a given definition of the subject's performance, while the specificity to the pathology of the patient is obtained once the network has been trained. It is then able to include into the estimated model some of the subject's behavioral patterns in response to the exercise, with respect to their trajectory planning and motor control, interpretation of the exercise, etc. It also appears that the stronger the patterns were, the easier it was for the network to simulate them (such as the projection described in Fig. 7). This leads us to believe that marked pathological patterns could be estimated accurately by the system, and that positive results might be obtained with impaired patients. Besides, amplification of the behavioral patterns provides the physiotherapist with additional information on the patient and may enrich his diagnosis.

The patient's motivation is greatly stimulated by the rehabilitative tasks presented as interactive virtual games. Most of the participants showed great enthusiasm while performing motor training in the virtual environments. We expect this new way of rehabilitation to ease the disagreeable effects associated with the therapy of pathological patients. With the improvements and low cost attained by recent motion capture systems such as Microsoft's Kinect, a lighter version of the system could be developed for home- or tele-rehabilitation. Several physiotherapists and medical doctors have expressed their interest in our system and envisaged its application to the rehabilitation of patients with acquired brain injury, children with cerebral palsy, dyslexia or other developmental coordination disorders.

In this study, we checked, on voluntary healthy subjects, the feasibility of integrating a basic learning agent into the rehabilitation stage. As a future development to this work, we intend to investigate better techniques for the subject's inverse model estimation (Karniel et al., 2001; Kawato, 1990), to perform clinical trials, and to extend the number of markers and EMGs in the performance definition. Additionally, different motions and muscles should be inspected.

Besides physiotherapy, this system could prove useful in sportive performance enhancement, in the development of new types of human-machine interfaces, in entertainment, and in the training of any kind of motor skill.

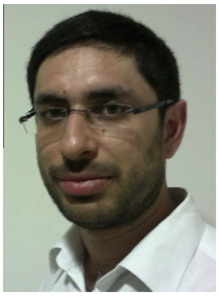
First to combine rehabilitation with machine learning of human models in virtual reality, this study provides optimistic results, promoting the use of biofeedback-based artificial intelligence for the modeling of human motor control and applications to therapy and diverse other areas.

5. Conflict of interest

The authors have no conflict of interest to declare or acknowledgment to state.

References

Barzilay O, Wolf A. An adaptive virtual system for neuromuscular rehabilitation. In: IFMBE Proc. world congress on medical physics and biomedical engineering, munich, Germany, vol. 25. no. 4; 2009. p. 1291–94.
Barzilay O, Wolf A. A fast implementation for EMG signal linear envelope computation. J Electromyogr Kinesiol 2011;21(4):678–82.
Bryanton C, Bossé J, Brien M, McLean J, McCormick A, Sveistrup H. Feasibility, motivation, and selective motor control: virtual reality compared to conventional home exercise in children with cerebral palsy. CyberPsychol Behav 2006;9:123–8.
Goldberg S. Training dismounted soldiers in a distributed interactive virtual environment. U.S. Army Research Institute Newsletter 1994;14:9–12.
Holden MK. Virtual environments for motor rehabilitation: review. CyberPsychol Behav 2005;8(3):187–211.
Holden MK, Dyar T. Virtual environment training: a new tool for neurorehabilitation. Neurol Rep 2002;26:62–71.
Holden MK, Todorov E, Callahan J, Bizzi E. Virtual environment training improves motor performance in two patients with stroke: case report. Neurol Rep 1999;23:57–67.
Karniel A, Meir R, Inbar GF. Best estimated inverse versus inverse of the best estimator. Neural Networks 2001;14:1153–9.
Kawato M. Computational schemes and neural network models for formulation and control of multijoint arm trajectories. In: Miller WT, Sutton RS, Werbos PJ, editors. Neural networks for control. MIT press; 1990.
Krakauer JW. Motor learning: its relevance to stroke recovery and neurorehabilitation. Curr Opin Neurobiol 2006;19:84–90.
Maclean N, Pound P, Wolfe C, Rudd A. A qualitative analysis of stroke patients' motivation for rehabilitation. BMJ 2000;321:1051–4.
Nudo R, Milliken GW. Reorganization of movement representations in primary motor cortex following focal ischemic infarcts in adult squirrel monkeys". J Neurophys 1996;75:2144–9.
Pollard N, Hodgins J, Riley M, Atkeson C. Adapting human motion for the control of a humanoid robot. In: IEEE proc. internat. conf. robotics and automation, Washington, DC, May; 2002. p. 1390–97.
Rose FD, Atree EA, Brooks BM, et al. Transfer of training from virtual to real environments. Presented at the 2nd European Conference on Disability, Virtual Reality and Associated Technologies, Skovde, Sweden; 1998.
Stanney KM, Kennedy RS, Drexler JM, Harm DL. Motion sickness and proprioceptive after effects following virtual environment exposure. Appl Ergon 1999;30: 27–38.
Theasby PJ. The virtues of virtual reality. GEC Rev 1992;1992(7):131–45.
Wren CR, Pentland AP. Dynamic models of human motion. In: Proc. internat. conf. automatic face and gesture recognition, Nara, Japan, 14–16; April 1998. p. 22–7.



Ouriel Barzilay was born in Caen, France in 1981. He received both his B.Sc. in 2007 and M.Sc. degrees in 2010 *cum laude* from the faculty of Mechanical Engineering at the Technion, Israel Institute of Technology. He is currently a Ph. D. candidate at the Biorobotics and Biomechanics Laboratory (BRML) at the Technion. His fields of interest include biorobotics, kinematics, artificial intelligence, and computer vision.

Alon Wolf, PhD, earned all his academic degrees from the Faculty of Mechanical Engineering at Technion-I.I.T. In 2002 he joined the Robotics Institute of Carnegie Mellon University and the Institute for Computer Assisted Orthopaedic Surgery as a member of the research faculty. He was also an adjunct Assistant Professor in the School of Medicine of the University of Pittsburgh. In 2006 Dr. Wolf joined the Faculty of Mechanical Engineering at Technion, where he founded the Biorobotics and Biomechanics Lab (BRML). The scope of work done in the BRML provides the framework for fundamental theories in kinematics, biomechanics and mechanism design, with applications in medical robotics, rehabilitation robotics, and biorobotics, such as snake robots.