A Tool to Monitor and Support Physical Exercise Interventions for MCI and AD Patients

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ABSTRACT
This paper presents a tool to monitor and support the execution of common physical exercise interventions targeting people with Mild Cognitive Impairment (MCI), Alzheimer's Disease (AD) and elderly in general. Our tool aims (a) to stimulate and guide patients within physical exercise programs, (b) to monitor patient capacity to perform exercises suggested by clinicians and provide objective feedback and (c) to enable early diagnosis of significant changes in the physical capacity of users over time. Our tool incorporates a virtual 3D trainer, demonstrating prescribed exercises; currently, arms lifting, arms stretching, torso bending and torso twisting are supported. Utilizing a low-cost depth camera and markerless skeletal joint estimation, our tool monitors movement during exercise execution, evaluating patient performance with a set of metrics introduced herein. Through preliminary experimental analysis, our metrics were found of significant potential to discriminate among good and bad executions of the currently supported exercises.

Keywords
Physical Exercise Interventions, MCI, Motion Similarity Metrics, Exercise Performance Assessment, Patient Monitoring

1. INTRODUCTION
As the average age of the population in developed countries increases, medical conditions affecting the elderly, such as dementia and motor impairment, pose a significant challenge for the decades to come. Of particular interest is the case of Mild Cognitive Impairment (MCI), which is often described as a preliminary stage of Alzheimer's Disease (AD).

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It has been observed that MCI patients begin to exhibit difficulties in carrying out everyday tasks [10, 2] which in itself threatens to compromise their ability to live independently. The patient's performance in the so called Instrumental Activities of Daily Living has been developed as an indicator of their cognitive state [6]. Furthermore, it has also been shown that a connection exists between MCI and motor dysfunction, which is related to the risk of development of AD [1].

For the above reasons, the continuous monitoring of patients with MCI is particularly important, as well as the prevention of decline of their cognitive state. However, continuous monitoring is not always possible, especially with elderly people living alone. On the other hand, medical interventions with the intention to prevent further decline may not always be successful and depend on the patient's willingness to participate in them. These issues call for the development of new and effective methods of continuous monitoring and prevention, that would engage the participation of the patient and provide up-to-date information of the patient's current state.

To this end, an increasingly promising direction is the use of physical exercise interventions to MCI patients. Several studies suggest that physical activity and exercise training are significant moderators of age-related cognitive decline and are known to help maintain cognitive function in healthy older adults. In longitudinal studies, older adults participating in physical activity showed less cognitive decline over two- to 10-year follow-up periods [4]. In nationally representative samples of non-institutionalized persons aged 50 years and older, Aichberger et al. [3] reported that individuals who participated in any type of regular physical activity showed less cognitive decline after 2.5 years, especially when they engaged in vigorous activities more than once per week. Recently, Smith et al. [9] suggested that participation in physical exercises shows cognitive improvement even in MCI patients. Further investigation of the potential of daily physical exercise interventions in the treatment of MCI and AD is thus deemed of particular importance.

With the above in mind, we present in this paper a computer-based tool for the support of physical exercise interventions targeted to MCI and AD patients. The tool is intended to both stimulate the patient to participate in daily physical exercise and—using the patient's exercise records—to automatically provide the patient's doctor with continuous

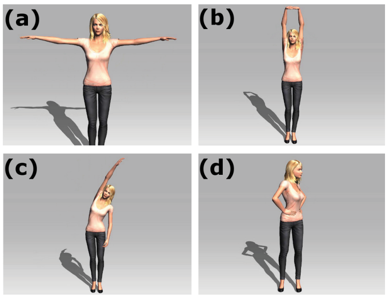

Figure 1: Exercises supported by the physical exercise companion tool: (a) arms lifting, (b) arms stretching, (c) torso bending, (d) torso twisting.

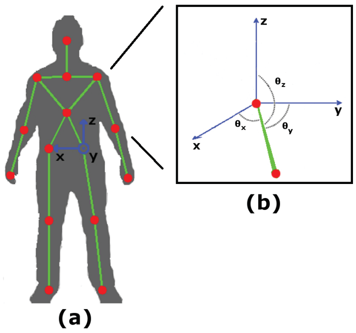

Figure 2: (a) Body joints (red), body parts (green) and orthonormal base vectors (x, y, z) monitored by the physical exercise companion tool, (b) Body part vector angles $(\theta_x, \theta_y, \theta_z)$

assessment of their state. At a higher level, it aspires to studying the connection between physical exercise participation and cognitive state and the possibility of the former serving as an indicator for effective cognitive assessment.

In the following, Section 2 describes how our developed tool guides and monitors exercises, introducing also our developed metrics for performance assessment. Section 3 presents preliminary experimental results on our tool's capability to assess physical exercise performance of MCI patients. Finally, section 4 concludes the paper.

2. THE PHYSICAL EXERCISE COMPANION TOOL

Our physical exercise companion tool is based on a virtual trainer, i.e. a virtual avatar, which demonstrates the execution of an exercise and invites the patient to perform the exercise along. Currently, the tool supports 4 exercises, which are specially designed for elderly patients in order to improve balance, muscle strength and joint flexibility. The exercises are: arms lifting, arms stretching, torso bending and torso twisting (Fig. 1).

In order to assess the patient's performance of the exercise, the system continuously monitors the execution of the exercise using a single low-cost Kinect depth sensor [12]. In particular, we use the method of markerless skeletal joint estimation [8] which is part of Kinect's standard software package in order to obtain real-time information about the 3D location of the patient's body joints. This way, for each video frame we record the position vector $\vec{p}_i = (x_i, y_i, z_i)$ for $M = 15$ joints, namely the head, the neck, the shoulders, the elbows, the hands, the torso, the hips, the knees and the feet. Since the above coordinates refer to the relative positions with respect to the camera, in order to render the method viewpoint invariant, we create a coordinate system local to the patient (composed of orthonormal base vectors $\hat{x}_0$, $\hat{y}_0$ and $\hat{z}_0$), using 3 body joints, namely the hips and the torso (Fig. 2a). These joints are selected as they are the most stationary and their relative position hardly changes, serving therefore ideally as a frame of reference. Let $\vec{p}_1$, $\vec{p}_2$ and $\vec{p}_3$ be the locations of the left hip, the right hip and the torso respectively. The base vectors are computed using the Gram-Schmidt orthonormalization process as in (1), using also $\hat{y}_0 = \hat{z}_0 \times \hat{x}_0$, where $\cdot$ and $\times$ denote the inner and cross vector product respectively.

$$\hat{x}_0 = \frac{\vec{p}_2 - \vec{p}_1}{\|\vec{p}_2 - \vec{p}_1\|}, \hat{z}_0 = \frac{(\vec{p}_3 - \vec{p}_1) - [(\vec{p}_3 - \vec{p}_1) \cdot \hat{x}_0]\,\hat{x}_0}{\|(\vec{p}_3 - \vec{p}_1) - [(\vec{p}_3 - \vec{p}_1) \cdot \hat{x}_0]\,\hat{x}_0\|} \quad (1)$$

Having defined the local base, our next step is to express the skeletal movement information in a systematic way. In particular, we are interested in the $N = 13$ body parts defined by the following couples of joints: head–neck, neck–shoulders, shoulders–elbows, elbows–hands, shoulders–torso, hips–knees and knees–feet. These can be easily expressed as 3D vectors $\vec{v}_i = \vec{p}_k - \vec{p}_l$, where $\vec{p}_k$ and $\vec{p}_l$ are the two joints that define them. In order to render the process anthropometric invariant, we only record the angles of each $\vec{v}_i$ relative to the base vectors $\hat{x}_0$, $\hat{y}_0$ and $\hat{z}_0$ so as to get the corresponding angle vector $\vec{\theta}_i = (\theta_{ix}, \theta_{iy}, \theta_{iz})$ (Fig. 2b) computed as:

$$\vec{\theta}_i = \left(\arccos\frac{\vec{v}_i \cdot \hat{x}_0}{\|\vec{v}_i\|}, \arccos\frac{\vec{v}_i \cdot \hat{y}_0}{\|\vec{v}_i\|}, \arccos\frac{\vec{v}_i \cdot \hat{z}_0}{\|\vec{v}_i\|}\right) \quad (2)$$

Note that $0 \leq \theta_{ix}, \theta_{iy}, \theta_{iz} \leq \pi$.

Finally, we repeat the above procedure at each video frame n, thus obtaining a timeseries of 3D angles, one for each body part i, which we denote as $\vec{\theta}_i[n]$. We also compute the angular velocities $\vec{\omega}_i[n]$ and accelerations $\vec{\alpha}_i[n]$, using first order derivatives. Since differentiation amplifies high-frequency noise, after computing each derivative we apply a low-pass Gaussian filter to smoothen out the noise.

2.1 Evaluating user performance

Having defined a systematic representation of the patient's movement, we are at the position to evaluate the execution of an exercise. To this end, for each exercise we maintain an exemplary execution, recorded from an expert trainer. The patient evaluation is performed by comparing their execution to the exemplar. Since we represent movement as the timeseries triplet $\left(\vec{\theta}_i[n], \vec{\omega}_i[n], \vec{\alpha}_i[n]\right)$, the above problem reduces to timeseries similarity comparison. Consider the one-dimensional timeseries $x[n]$ and $y[n]$ with lengths N_x and N_y respectively, for which we are interested in computing a similarity metric m. For this purpose we have developed a set of metrics, which are described as follows.

Mean Value. We take the mean values of $x[n]$ and $y[n]$ over time, denoted as m_x and m_y; the metric is given by:

$$m = \frac{2m_x m_y}{m_x^2 + m_y^2} \tag{3}$$

Notice that $-1 \leq m \leq 1$, with $m = 1 \Leftrightarrow m_x = m_y$ and $m = -1 \Leftrightarrow m_x = -m_y$. A similar metric was presented in [11] for image quality assessment.

Variance. This is similar to the mean value metric but instead the variances of $x[n]$ and $y[n]$ over time are used in place of their means in (3).

K First Moments. This metric can be seen as a generalization of the mean value metric. Here, the first K moments of $x[n]$ and $y[n]$ are obtained over time and the metric is computed as $m = \prod_{k=1}^{K} 2\rho_x^k \rho_y^k / \{(\rho_x^k)^2 + (\rho_y^k)^2\}$. Here ρ_x^k and ρ_y^k are the k-th moments of $x[n]$ and $y[n]$ over time respectively. We also have $-1 \leq m \leq 1$. Notice that for $K = 1$ we recover the mean value metric.

Histogram Distance. We first compute the K-bin histograms of the values of $x[n]$ and $y[n]$, denoted as $h_x[k]$ and $h_y[k]$ respectively. Then, the metric is computed as the chi-square distance [7] between the histograms, as in (4). Note that the two histograms are equal if $m = 0$.

$$m = \frac{1}{2} \sum_{k=1}^{K} \frac{(h_x[k] - h_y[k])^2}{h_x[k] + h_y[k]} \tag{4}$$

RMS Error. This metric is the normalized Root Mean Square (RMS) error between $x[n]$ and $y[n]$, computed as:

$$m = \frac{\sqrt{\frac{1}{N_{xy}} \sum_{n=1}^{N_{xy}} (x[n] - y[n])^2}}{\sqrt{\frac{1}{N_x} \sum_{n=1}^{N_x} (x[n])^2}} \tag{5}$$

Here, $N_{xy} = \max(N_x, N_y)$ and the shortest timeseries is padded with zeros. This metric is characterized by its lack of shift-invariance, i.e. an exercise that was performed correctly but not at the right time will receive a low score.

Normalized Correlation Coefficient. It is computed as:

$$m = \frac{\sum_{n=1}^{N_{xy}} (x[n] - m_x)(y[n] - m_y)}{\sum_{n=1}^{N_x} (x[n] - m_x)^2 \sum_{n=1}^{N_y} (y[n] - m_y)^2} \tag{6}$$

Here, $N_{xy} = \max(N_x, N_y)$ and the shortest timeseries is padded with zeros. Note that due to the Cauchy-Schwarz inequality $-1 \leq m \leq 1$. This metric is also not shift-invariant.

DTW Distance. This metric is defined as the Dynamic Time Warping (DTW) distance [5] between $x[n]$ and $y[n]$. It may assign a high score to an exercise that was performed at a non-linearly different rate but otherwise correctly.

Having defined all the above comparison metrics, we are ready to compare the execution of an exercise between the patient and the exemplar. Suppose that for a particular exercise we obtain the set of angle timeseries $\{\theta_i[n]\}_{i=1}^{N}$, where $N = 13$ is the number of body parts. In total, we have $3N = 39$ couples of one-dimensional timeseries, for which we get $3N$ similarity scores, denoted as $\vec{s}_i = (s_{ix}, s_{iy}, s_{iz})$. Then, for each body part i, we compute a score s_i as in (7).

$$s_i = \frac{w_{ix}s_{ix} + w_{iy}s_{iy} + w_{iz}s_{iz}}{w_{ix} + w_{iy} + w_{iz}} \tag{7}$$

Finally we average all s_i's to obtain an overall score s for the whole skeleton as in (8).

$$s = \frac{\sum_{i=1}^{N} w_i s_i}{\sum_{i=1}^{N} w_i} \tag{8}$$

By performing the same on $\{\omega_i[n]\}_{i=1}^{N}$ and $\{\alpha_i[n]\}_{i=1}^{N}$, we get scores describing velocity and acceleration.

The above schema has the advantage of being adaptable to various exercises. In fact, the only element which needs to be defined for each exercise separately is the set of weights $W = \{w_i, (w_{ix}, w_{iy}, w_{iz})\}_{i=1}^{N}$. By appropriately defining W it is possible to give more focus on particular body parts which may be more relevant to a particular exercise. In *arms lifting* and *arms stretching*, the weights that refer to the arms are set high and those referring to shoulders, legs and torso are set low. In *torso twisting* only shoulder and torso weights are set high, while in *torso bending* the weights that refer to the arm that is lifted are also given a high value.

3. EXPERIMENTAL RESULTS

An experiment for data collection was set up in a daycare center of the Greek Association of Alzheimer's Disease. Initially, for each exercise, an exemplary execution was recorded from an expert trainer. At the next stage, 15 elderly MCI patients executed all exercises, being guided and recorded by our tool. Using our proposed approach, each execution video registered by the Kinect depth sensor was processed and compared to the trainer's repetition.

In order to evaluate the effectiveness of the comparison metrics described in section 2, all the recorded exercise repetitions were manually annotated as "GOOD" or "BAD" by an expert, depending on their similarity to the repetitions of the trainer. Next, we performed analysis of variance (ANOVA) on the results of each metric, so as to compare each metric's effectiveness in discriminating among "GOOD" and "BAD" repetitions. Table 1 summarizes the metrics that led to significant discrimination for each exercise. Based on the data, one can observe that a different set of comparison metrics was found to be effective in evaluating each exercise.

In *arms lifting*, most of the metrics produced good discrimination results. Due to the rigid state of the torso during this exercise and the steady rate at which the limbs typically move, the *Histogram Distance*, *Mean Value*, *Variance* and *K First Moments* metrics were effective in evaluating the angle and velocity in each repetition. On the other hand, the *RMS Error* and *Normalized Correlation Coefficient* metrics failed to successfully compare the angle timeseries, mainly due to their lack of shift-invariance. Similarly, in *arms stretching*, the *Histogram Distance*, *Mean Value*, *Variance* and *K First Moments* metrics were effective in comparing the repetitions. However, due to the smaller range of movement, the rest of the metrics failed to produce satisfactory results. In *torso bending*, the continuous movement of the torso rendered ineffective most of the metrics, especially for the angle timeseries. The *Normalized Correlation Coefficient* and

DTW Distance metrics were the most effective in describing this specific exercise. Finally, in *torso twisting* most of the metrics failed to produce satisfactory results in comparing the angle timeseries, mainly because of the small range of movement, low speed and general lack of variation between the repetitions. However, the *Histogram Distance*, *Mean Value* and *Variance* were successful in evaluating patient performance via angular acceleration-based comparison.

ARMS LIFTING		*F-Value*	*p*
Angle	Histogram	14,758	0,001
	DTW	6,673	0,015
	Mean Value	5,947	0,021
	Variance	6,347	0,018
	K First Moments	22,479	<0,001
Velocity	Histogram	7,96	0,009
	Variance	4,207	0,050
	Correlation	4,822	0,037
	K First Moments	6,652	0,015
Acceleration	Mean Value	4,213	0,050
	RMS	9,888	0,004
	K First Moments	5,203	0,030
ARMS STRETCHING			
Angle	Histogram	6,420	0,021
	Variance	8,148	0,011
	K First Moments	10,333	0,005
Velocity	Mean Value	5,293	0,034
	Variance	12,422	0,002
	K First Moments	6,035	0,024
Acceleration	Mean Value	9,592	0,006
	Variance	5,626	0,029
TORSO BENDING			
Angle	Correlation	6,827	0,016
Velocity	Correlation	5,589	0,028
Acceleration	DTW	7,189	0,014
	Mean Value	7,425	0,013
TORSO TWISTING			
Acceleration	Histogram	12,609	0,002
	Mean Value	4,908	0,037
	Variance	7,012	0,015
Velocity	RMS	5,129	0,034

Table 1: ANOVA results of metrics for each exercise

4. CONCLUSIONS

This paper presented a new tool to monitor and support physical exercise interventions for the elderly, focusing on MCI and AD patients. Our tool guides the execution of physical exercises with a virtual trainer and simultaneously tracks user movement via markerless skeletal joint estimation. Using a set of metrics we developed based on viewpoint-invariant angular skeletal information, our tool is capable of evaluating the similarity between the user's attempts and the optimal movement of a real trainer, providing objective feedback over the user's capacity to perform the target exercises. Preliminary experimental evaluation showed that our developed metrics have significant potential to differentiate between good and bad attempts of patients performing the supported exercises. Based on these results, further elaboration of our tool is planned, so as to (a) evaluate its capacity in enabling doctors assess patient performance in physical exercises over time and (b) extend the set of supported exercises. Our tool can support future studies further examining the connection between physical exercise and cognitive state, as well as open the possibility of physical exercise performance to serve as an indicator for cognitive assessment.

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