Humanoid Assessing Rehabilitative Exercises

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Summary
Introduction: This article is part of the Focus Theme of Methods of Information in Medicine on “New Methodologies for Patients Rehabilitation”.

Background: The article presents the approach in which the rehabilitative exercise prepared by healthcare professional is encoded as formal knowledge and used by humanoid robot to assist patients without involving other care actors.

Objectives: The main objective is the use of humanoids in rehabilitative care. An example is pulmonary rehabilitation in COPD patients. Another goal is the automated judgment functionality to determine how the rehabilitation exercise matches the pre-programmed correct sequence.

Methods: We use the Aldebaran Robotics’ NAO humanoid to set up artificial cognitive application. Pre-programmed NAO induces elderly patient to undertake humanoid-driven rehabilitation exercise, but needs to evaluate the human actions against the correct template. Patient is observed using NAO’s eyes. We use the Microsoft Kinect SDK to extract motion path from the humanoid’s recorded video. We compare human- and humanoid-operated process sequences by using the Dynamic Time Warping (DTW) and test the prototype.

Results: This artificial cognitive software showcases the use of DTW algorithm to enable humanoids to judge in near real-time about the correctness of rehabilitative exercises performed by patients following the robot’s indications.

Conclusion: One could enable better sustainable rehabilitative care services in remote residential settings by combining intelligent applications piloting humanoids with the DTW pattern matching algorithm applied at run time to compare humanoid- and human-operated process sequences. In turn, it will lower the need of human care.

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1. Introduction

Longer life expectancy increases the number of seniors worldwide. It turned ageing population into one of the most important challenges of public health in recent years. The demand of remote care services for elderly population is steadily growing because of the demographic developments reducing the availability of caregivers. For this reason the care stakeholders are actively looking at the new enablers of remote Assistive Living services capable to filter care requests and/or satisfy some of them with minor involvement of human care actors (Figure 1).

The majority of older adults have at least one chronic condition. An essential component to keeping older adults healthy is preventing chronic diseases and reducing associated complications. Rehabilitation exercises are important to prevent exacerbation of several diseases. For example, pulmonary rehabilitation for chronic obstructive pulmonary disease (COPD) includes a program of exercises that helps people build their physical fitness. Many rehabilitation centers also teach people appropriate exercises, techniques, and strategies for living better with COPD. In the known art, the rehabilitative exercises are prepared by physiotherapists and offered in specialized care centers to patients individually or those in small groups. Whenever it is impossible to the patient to reach any care center because of the physical impairments, the healthcare professionals offer the necessary care in their residential settings. Because of the steadily reducing support ratio due to demographic developments, the sustainability of rehabilitative care at home could be achieved by using non human healthcare actors, for example by anthropomorphic robots. To offer valuable and sustainable care services using the telemedicine approach in general, the key aspects are a) the monitoring of Activities of Daily Living (ADL), b) the activity recognition and classification, and c) rule-based Decision Support System capable to trigger the relevant situations/events.

The use of humanoid robot as tutor to offer the rehabilitation at home relies on a number of cognitive capabilities, such as the capability a) to reach the position nearby patient at right moment/time, b) to persuade the patient to start doing exercises, c) to show the correct motions to follow, d) to observe how the patient is doing the exercise, and e) to make a judgment about the compliance of the exercise being made by patient to the one prepared by physiotherapist(s). Upon them, the robot can de-
While the senior is performing an action, the humanoid is recording and processing said capability to observe the happenings (actions performed by human), to compare them with the intended and formalized behavior, and to take a decision about the match and/or mismatch. The ultimate goal is to set up the pervasive remote care rehabilitative service in which the robot will filter automatically the situations non-needingspecific human interventions in order to concentrate the available limited workforce of healthcare professionals to the only planned interventions and the situations classified by the robot as “abnormal”.

Many research studies in care domain speak about the use of more or less intrusive wearable and environmental sensors for automated monitoring of people living independently. A review of the literature made by Achumba et al. in [4] highlights the focus on monitoring techniques, the use and placement of wearable sensors, the methods of data collection and elaboration techniques. An example of the selective activity monitoring is reported by Gupta et al. in [5]. Here we consider the human activity of “doing exercise” only. The transformation of the video into numeric sequences is made by the Kinect APIs. The uniformly time-sampled data items are converted into the motion segments – of variable durations – by using a kind of Variable-size Sliding Windows (VSW). In this ad-hoc implementation, each elementary motion step is annotated by using the Minkowski distances, while the accumulated motion is labeled by using the diagonal (Pythagorean) distances. The resulting pattern contains the points characterizing the speed variability being manifested along the motion path.

2. Objectives

The main objective is the use of humanoids in rehabilitative care (rehabilitation robotics). It requires the capability to localize patient, to move in the proximity of, to persuade, to present the activity, and to judge about the quality of the human-made exercises at run time. We investigate on computationally efficient methods than can support the near real time use.

The one-fit-all exercise does not exist. The valuable rehabilitative care by mobile robots is a complex mission articulated in a number of interlinked tasks. The personalized rehabilitation program should be offered depending on the current patient status. The picture (Figure 3) shows how the humanoid approaches a patient to perform the rehabilitative exercise. This figure represents the envisioned scenario and the project’s configuration.

To become an effective rehabilitation therapy mean, the robot has to use the repeatable and quantifiable metrics going to be used during the assessment of the performance of a patient. Here, we try to define the function \( f(N(t), \ldots) \) measuring motion in near real time. As on today, we are unaware of any other COPD care setup using robots for similar purposes.

The goals of this research task were: to implement pulmonary rehabilitation using humanoid robot; to induce elderly patient to undertake humanoid-driven rehabilitative exercise; and to evaluate the human actions against the correct template using easiest automated comparison technique. While the senior is performing an action, the humanoid is recording and processing the human’s movements. The artificial cognitive function uses pattern matching to

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**Figure 1**

Care model based on the use of robots

- **State of the art**
  - Patient
  - Physiotherapist
  - Care

- **Care model using robots**
  - Patient
  - Care robot
  - Care
  - Remote care human actor
  - Anomaly only

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elaborate input data (stream of motion pictures) in order to determine if the rehabilitation exercise matches the pre-programmed correct sequence.

3. Methods

Researches use cheap industrial motion sensors, Microsoft Kinect, and Nintendo Wii Remote to assist physicians and patients in implementing rehabilitation exercises. Static installations require patients to move themselves in pre-defined positions. This drawback could be removed by more expensive humanoid capable to localize patients and move in front of them [6]. Additionally, higher persuasive potential of humanoids is discussed in [23].

We adopted Aldebaran NAO joints to implement the correct body motion sequences and present them to patient(s). The humanoid positioned in front of the patient has the capacity to observe human actions. We used robot built-in sensors to acquire the video stream wirelessly. We processed the raw video stream by using APIs from Microsoft Kinect SDK to obtain positions of human joints. This SDK supports real-time tracking of 3D coordinates of 20 body joints. We have observed that only 7 out of 20 joints are relevant to implement the automated assessment of COPD respiratory rehabilitation exercises. Namely, we have to track left hand, right hand, left wrist, right wrist, left elbow, right elbow, and the head. All the elements are ordered in time dimension. Because of the availability of the encoding schemes for NAO robot showing the correct exercise, the individual sequences are available. The validity of our approach is supported by more recent paper Celebi et al about the use of weighted DTW [15].

We use the Aldebaran Robotics’ NAO humanoid to offer the physical exercises. We persuade people by moving humanoid in the proximity of user and by using the bodily and vocal cues [23]. We use the Microsoft Kinect SDK to extract motion path from the humanoid’s recorded video. We combine it with the Dynamic Time Warping (DTW) for sequence matching. We use other physical therapeutic metrics defined by medical experts (COPD specialists) in order to deliver feedback to the patient whether she/he performed the exercise correctly or not.

KSERA project [1, 6] obtained ethical clearance for its experiments and fulfilled the Helsinki Declaration. The humanoid solution was tested in the context of an EU-funded project respecting the European Charter and Code for Researchers. Before sitting the tests, participants sign the consent form – in their language – approved by the project’s Advisory Board on Ethics.

First of all, the collection of notably correct sequences of rehabilitation needs to be prepared in cooperation with healthcare professionals to ensure the compliance with the corresponding care plans and physical therapeutic metrics. Once sequences are designed, the next step is to encode them into correct hierarchical state machines playable by mobile robots. For example it is implemented in KSERA [1] using the known art SMACH for ROS [27].

Before selecting the appropriate exercise and its difficulty level, the robot has to assess the today’s context. To personalize pulmonary exercises for COPD care, we used ready-made daily SpO$_2$ measurements. Lacking the today’s value, KSERA humanoid moves nearby the patient and reminds to take a measurement using oxypulsimeter [1, 6]. Based on the today’s SpO$_2$ measurement, a corresponding difficulty level – easiest, regular, and advanced – is chosen.

If the patient accepts the proposed activity, the rehabilitation starts. The next step is to ensure the appropriateness of the humanoid position to observe correctly the patient’s body and its movements. Thus, the humanoid starts playing the sequence $S_{robot}$ and observes the patient’s movements $S_{patient}$.

Let us trace the positions of the same skeleton’s node $N_i$ in time dimension. It gives the sequence of $N_i(t)$. Let us denote...
the spatial distances between two time points as \( d(N_i, t_k, t_l) = |x_i(t_k) - x_l(t_l)|^2 + |y_i(t_k) - y_l(t_l)|^2 \) for each node \( N_i \) having the coordinates \( x_i(t), y_i(t), \) and \( z_i(t) \). Let us denote the time interval \([t_k, t_l]\) as \( \Delta t_{kl} \). Until the spatial distance between the positions of the same node varying/neighbor in time dimension remains small, the whole time segment is classified as “no action” or Pause. The time intervals between two adjacent Pauses are classified as Doing-Activity. The annotated patient’s mobility becomes a sequence \( S_i = \) [Action\((t_1, t_1 + 1)\), Pause\((t_2, t_1 + 2)\), Action\((t_3, t_3 + 1)\), …].

Frequently one has to compare two time-series \( S_1(t) \) and \( S_2(t) \), of which \( n = \text{length}(S_1) \) and \( m = \text{length}(S_2) \). The brute force matching algorithms have exponential complexity. Dynamic programming methods cut the complexity up to \( O(n \cdot m) \).

Dynamic Time Warping (DTW) is a deterministic pattern matching algorithm indicated for non-linear sequence alignment. It has vast range of practical applications, such as string matching, DNA matching, speech recognition, and similar tasks. DTW seeks an optimal mapping between the test sequence and the known template. It allows a monotonic distortion – also known as warping – of test sequences. Proposed in 1978 for speech recognition [7], the DTW has been applied to different tasks.

In order to express a judgment about the quality of pulmonary rehabilitation exercise, the authors use the robot eyes to acquire the sequence of video frames at a standard rate. The video sequence is submitted to the video-analysis software in order to transform it in the motion vectors. This step is made using the commercially available libraries containing the Skeleton class of Kinect software. A similar approach is documented by Rakhomov et al. in [17]. The motion vector is processed in order to extract the time constrains corresponding to each activity element. To simplify the task, in this study we measure the moving arm/leg duration and the time intervals between the mobility periods (Figure 4).

Another similar sequence corresponding to the storyboard of the exercise encoded for the humanoid robot is available in the Knowledge Base (\( S_{\text{Robot}} \)). It could be used as the known pattern for the comparisons between \( S_{\text{Patient}} \) and \( S_{\text{Robot}} \). The original problem about judging about the quality of exercises is simplified and replaced by the question AreSimilar\((S_{\text{Robot}}, S_{\text{Patient}})\)? Two sequences have the same structure, so the comparison in terms of similarity and timing is possible. Based on the results of comparison, one can trigger the cases requiring human care interventions. The authors implement the filtering and the corresponding control action as IF AreSimilar\((S_{\text{Robot}}, S_{\text{Patient}}) = \text{True} \) THEN Tell("Ok") ELSE AdvertDoctor(). As pointed by Rakhomov in [17], some delay between all the \( t_i \) terms in \( S_{\text{Patient}} \) and the corresponding – if any – \( t_j \) terms in \( S_{\text{Robot}} \) exist because the robot starts first. The normal delay between two actions is \( dt = |t_1 - t_2| \). The patient can decide to follow the robot or to do something else. By following the pulmonary rehabilitative program shown by robot, each human action could have different duration compared with the robot’s one. For each term in \( S_{\text{Robot}} \), being compared with the corresponding term in \( S_{\text{Patient}} \), we calculate the time warping coefficients \( k_i = (t_{i+1} - t_i)/(t_{j+1} - t_j) \). These coefficients compare the speed of doing the same movement by the humanoid therapist and by the patient. Our ambition is the cognitive capability to let robots judging.

![Figure 4](image_url) Modeling the human activity: timing and its formal representation

![Figure 5](image_url) The rehabilitation program encoded in software and shown by humanoid physiotherapist
To operate with variable durations we have encoded the concept of the correct timing (▶Figure 4). Until the duration of the segments stays in the allowed range, e.g. 0.8 < k_j < 1.2 (e.g. +/- 20%), the timing is judged as acceptable/correct.

One intended pulmonary rehabilitation program made by doctors was encoded in software for NAO robot (▶Figure 5). As such, the exact durations of program components are known since the beginning (S_{Robot}). At the beginning of human-robot interaction, the humanoid starts performing the exercise. The correctness of S_{Patient} and its timing are checked at this stage.

At the next stage patient (adult healthy volunteer only in our usability settings) starts the exercise following the robot. The humanoid robot observes the sequence of human actions (▶Figure 6). To deliver useful feedback, the robot has to judge about the correctness of the exercise in near real-time. The algorithm analyses the speed of the motion and produces a pattern containing sub-sequences, those annotated by letters from a) to g).

Using the proposed approach, the video registered by the robot’s eyes is transformed by the commercial API in a numeric sequence measuring the exercise through the quantity of motion. Ad hoc algorithm breaks it in a chain of elementary chunks/tokens/vectors. The software compares S_{Robot} with S_{Patient} using these scalar values then (▶Figure 7). In this example the motion lasting 13 sec was represented by seven segments.

The pattern matching is operated using the Dynamic Time Warping method known also as DTW [12, 18]. In our algorithms, the DTW is used to identify a-posteriori the optimal alignment between two time series S_{Robot}(t) and S_{Patient}(t). Although the DTW is designed for full sequence matching (the exercise is a sequence composed by several segments/actions), it can be also used for sub-sequence matching (for example moving the left arm up). Our algorithm checks the full match first (▶Figure 7). It stops when no matches were found. Elsewhere, it looks for more sub-sequent occurrences by using a sliding time window. The starting timestamp of the first cycle is always used to characterize the exercise being executed. To collate adjacent windows as a single process, the timestamps are compared: If the comparison (t_k - t_l) gives more than 10 seconds, the authors decide to abort the sequence. Once the enumeration of classifications Event_1 = (moving, t_k); Event_2 = (moving, t_l); Event_3 =
(moving, $t_m$), ... becomes available, the initial $E(t)$ sequence could be unloaded from the memory. The main classification loop produces the sequence of $\{(xxx, t_1), (xxx, t_2), ..., \}$ going to be stored in the knowledge base. The role of DTW in this process is fundamental because the duration of patient’s mobility segments is never known a-priori.

Now let us forget any numeric data: the patterns observed by the robot are the patterns of human behavior. It is important to note that robot is not expected to comment on the correctness of each segment to avoid the noisy dialogs. Despite the precision of this technology is lower than 100%, the above functionality could operate with real time data in a satisfactory manner because it is sufficient to react few times during/after the exercise. This example illustrates the implementation of DTW when two sequences are strings in discrete time-space. The distance $d(x, y) = |x - y|$ was used to determine the timestamp and the duration of the doing exercise processes. The results of the KSERA usability tests are reported in [6].

### 4. Results

Previously, KSERA assessed whether people like doing exercises with a robot by asking them to fill out a Godspeed questionnaire [25] before and after doing an exercise with a robot [26]. The results suggest that performing physical exercise with a robot improves the attitude of people toward it in terms of Likeability. There were no negative effects on the other dimensions of the Godspeed questionnaire. Further details are documented in [6].

Adult volunteers participated in this session. The experiment was performed in batch mode with completed sequences only. Correct training sequences being encoded in the robot were those lasting 11–20 seconds each. The overall duration of the scenario is longer because of several additional elements, e.g. the dialogues, the time to take $\text{SpO}_2$ measurements, the time to communicate feedback, the time to ask permission to start and to get answer, the time to walk in the appropriate position, the time to perform some additional computations and so on. Once the full $S_{\text{Patient}}(t)$ sequence is acquired by humanoid, it is supplied as input to the new algorithm to evaluate the feasibility only due to the DTW approach. The numbers – the duration of sessions, the age/sex – have limited validity because the sample composed by healthy volunteers only is not statistically representative. The authors have collected some sequences from few individuals following the robot in doing exercises.

To verify the applicability of the DTW-based approach to the wider targets manifesting different physical performances, several additional simulated datasets were produced by seeding these correct (Identity) and incorrect (Null) real data as realistic situations. The intermediate fuzzy pictures of other process sequences (doing training correctly/doing incorrectly/doing nothing) were obtained by applying stretching to both time- and space-dimensions and by combining components in linear manner. The larger data collection of simulated datasets shown in Table 1 was used to compare pairs of sequences by using the DTW method.

<table>
<thead>
<tr>
<th>Set</th>
<th>Patient activity</th>
<th>Correct duration</th>
<th>Duration by DTW</th>
<th>Similarity coeff.</th>
<th>Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.0t*Amplitude</td>
<td>10</td>
<td>10</td>
<td>1.00</td>
<td>Y</td>
</tr>
<tr>
<td>2</td>
<td>3.0t*Amplitude</td>
<td>10</td>
<td>10</td>
<td>1.00</td>
<td>Y</td>
</tr>
<tr>
<td>5</td>
<td>0.3t*Amplitude</td>
<td>10</td>
<td>10</td>
<td>1.00</td>
<td>Y</td>
</tr>
<tr>
<td>9</td>
<td>1.2t*time</td>
<td>10</td>
<td>12</td>
<td>0.83</td>
<td>Y</td>
</tr>
<tr>
<td>10</td>
<td>1.1t*time</td>
<td>10</td>
<td>11</td>
<td>0.91</td>
<td>Y</td>
</tr>
<tr>
<td>11</td>
<td>0.9t*time</td>
<td>10</td>
<td>9</td>
<td>1.11</td>
<td>Y</td>
</tr>
<tr>
<td>12</td>
<td>0.8t*time</td>
<td>10</td>
<td>8</td>
<td>1.25</td>
<td>Y</td>
</tr>
<tr>
<td>13</td>
<td>0.7t*time</td>
<td>10</td>
<td>7</td>
<td>1.43</td>
<td>N</td>
</tr>
<tr>
<td>16</td>
<td>0.4t*time + 6</td>
<td>10</td>
<td>4</td>
<td>2.50</td>
<td>N</td>
</tr>
<tr>
<td>18</td>
<td>0.6t + 5 and 6°</td>
<td>10</td>
<td>10</td>
<td>1.00</td>
<td>N</td>
</tr>
<tr>
<td>19</td>
<td>Null</td>
<td>10</td>
<td>20</td>
<td>0.50</td>
<td>N</td>
</tr>
<tr>
<td>20</td>
<td>Identity</td>
<td>10</td>
<td>10</td>
<td>1.00</td>
<td>Y</td>
</tr>
<tr>
<td>21</td>
<td>0.5 t + 7 and 0.5°</td>
<td>10</td>
<td>5</td>
<td>2.00</td>
<td>N</td>
</tr>
<tr>
<td>22</td>
<td>1.7 t + 3 and 0.1°</td>
<td>10</td>
<td>17</td>
<td>0.59</td>
<td>N</td>
</tr>
<tr>
<td>23</td>
<td>0.7 t + 3 and 0.1°</td>
<td>10</td>
<td>7</td>
<td>1.43</td>
<td>N</td>
</tr>
<tr>
<td>26</td>
<td>0.7 t + 3 and 0.5°</td>
<td>10</td>
<td>7</td>
<td>1.43</td>
<td>N</td>
</tr>
<tr>
<td>28</td>
<td>0.8 t + 8 and 0.1°</td>
<td>10</td>
<td>8</td>
<td>1.25</td>
<td>Y</td>
</tr>
</tbody>
</table>

Both positive and negative deviations from the intended timing of the exercise. Assuming as “reasonable” the time deviations [$t_{\text{robot}} - 20\%$; $t_{\text{robot}} + 20\%$] manifested while following the robot, the DTW approach triggers above-mentioned situations by choosing the similarity coefficient set to 1.04 ca. Therefore the similarity condition ($S_{\text{Robot}} \approx S_{\text{Patient}}$) could be evaluated through the Boolean operator $D T W(S_{\text{Robot}} + S_{\text{Patient}}) \in [0.83, 1.25]$. The above operator works in near real-time.

### 5. Discussion

Robotic systems for rehabilitation at home can be generally used to record information about the motor performance during active movements. The attributes being posted under constant monitoring could be positions, trajectories, interaction forces and impedances. To downscale the rehabilitation therapy from the specialized centers to patient’s homes, the capacity to approach patients and persuade them to initiate rehabilitation exercise is a first premise. Once completed, the robot has to illustrate the correct sequences by moving its own body joints. The robot has to start...
simultaneously the observation of patient’s physical activities. The most important cognitive capability required in this situation is to assess the correctness of the patient’s made training program, e.g., the correspondence between the robot made and human made motion sequences.

One of the possible approaches to the use of robots in the rehabilitative care is shown by Qiu et al. in [16]. However, their use at home seems not yet widely discussed. KSERA project uses the humanoid robot to assist sufferers of Chronic Obstructive Pulmonary Disease (COPD) living independently at their homes. COPD is the occurrence of commonly co-existing diseases of the lungs in which the airways narrow over time causing shortness of breath (dyspnea). This limitation is poorly reversible and usually gets progressively worse over time. For these reasons the COPD care does include a pulmonary rehabilitation program which can be done nearly anywhere. The physical and breathing exercises build the muscle strength and endurance to reduce shortness of breath. Accordingly the care guidelines, the difficulty levels of pulmonary rehabilitation programs can vary depending on the SpO₂ levels. In KSERA, each pulmonary rehabilitation exercise is developed by healthcare professionals and encoded by engineers in software program executable by the robot. The correct sequences are stored in the Knowledge Base. The system keeps awareness about the duration of each element included in the sequence. The Ubiquitous Monitoring sub-system (UMS) of KSERA detects the conditions triggering the rehabilitative exercises. The measurement of the blood’s SpO₂ level using the wearable oxi-pulsimeter governs the choice of an appropriate exercise. The humanoid robot starts the rehabilitation program. It detects where the patient is, it moves nearby the patient, it stops in front of him/her. The robot invites the patient to follow the exercise and starts showing the pre-programmed sequence of actions. During the exercise, the robot remains in the position permitting to meter the human activities by direct observation.

The basic DTW variant used the idea of deterministic dynamic programming. Since many of real signals are stochastic processes, a stochastic DTW algorithm was proposed in 1988 by Nakagawa et al. [8]. Earlier DTW uses local distances and path costs. Stochastic DTW uses conditional probabilities and transition probabilities instead. Mathematically, given two time series X, and Y, of lengths |X| and |Y|, one tries to build a warp path W of length |W|: max(|X|, |Y|) ≤ |W| < |X| + |Y|, where \( w_k = (i, j) \) with i being an index from time series X, and j being an index from time series Y. The warp path starts at the beginning of each time series at \( w_1 = (1, 1) \) and finish at the end of both time series at \( w_{|W|} = ([|X|, |Y|]) \). The i and j monotonically increase in the warp path to avoid overlap of the warp path (lines). Given \( w_k = (i, j) \) and \( w_{k+1} = (i', j') \), \( i \leq i' \leq i+1, j \leq j' \leq j+1 \), the optimal warp path is the minimum-distance warp path. Typically, the Dist(W) is the Euclidean distance of warp path W made by summing up the distances between pairs of data point indexes – one from X and one from Y – in the k-th element of the warp path. In this formulation, the function Dist(W) to minimize can be modeled as a finite state system. The standard DTW has become a baseline algorithm in most of state-of-the-art applications. There were several attempts to improve its speed and scalability, and to apply it to other application classes. For example the weighted DTW method was discussed by Reyes in [9]. Recently, the use of fuzzy approach is described by Su [10, 11].

In our vision, the DTW approach is particularly interesting because of the availability of its scalable implementation described in [12]. In process comparison tasks, one aspect is the similarity search quality [21]. An example from surgery is [22]. However, the time taken for similarity search is the main bottleneck for almost all data mining algorithms operating with time series. Humanoid employed in rehabilitative care needs real time reasoning. Rakthanmanon and Keogh in the above paper demonstrate that in large datasets it is possible to exactly search under DTW much more quickly than the current state-of-the-art Euclidean distance search algorithms. The most relevant driver to opt for the DTW is the [13] stating that their DTW application for gesture recognition on multi-touch screens took 128.26 minutes to run the 14,400 tests for a given subject’s 160 gestures, while Rakthanmanon and Keogh reproduce the experiment in under 3 seconds. We observe that human motion sequence is a temporal sequence. It is possible to employ DTW to classify motions in the video stream acquired by robot observing rehabilitation exercises made by human. The validity of this approach was tested by Adistamba et al. in [14]. Since the judgment is required in real-time, the comparison tool needs to be quick and scalable enough. From the applied mathematics’ viewpoint the simulation is valid because of the continuity. From the medical viewpoint, other supporting elements come from [24].

6. Conclusions

This paper has described an engineering proof of concept to set up remote rehabilitative care of patients living independently at their homes. In the current demographic scenario, it exemplifies a possible approach to reduce the percentage of the human rehabilitative care. The experimental results support the feasibility only of the approach/method, but the numbers have limited validity because the sample is not statistically representative. Instead, the simulation covered almost all possible situations in which patients repeat the rehabilitation program fully correctly, partially correctly, not correctly, or not at all. The monitoring of the activities performed by patients following the robot could be made by using fully scaled robots or the cheaper ones, without additional and/or specialized sensors [19, 20].

The proposed DTW-based approach could enable better sustainable rehabilitative care services in remote residential settings because of lowering the need of human care. Sophisticated robot navigation algorithms and standardized market leading video processing techniques ensure the consistent positioning of the robot and taking the time measures. Compared with other signal processing techniques (the correlation is an example), the use of Dynamic Time Warping is very promising because let to detect quickly the incorrect
instances of doing exercises characterized by variable durations.

The ready-made availability of DTW pairs – numeric sequences annotated by timestamps – could become a better precise tool for automatic monitoring. Compared with time-consuming manual annotation of timestamps contained in huge video streams, by mining data in numeric sequences ready-made by the robot, one could look for disease progression markers in a simpler way. The proposed approach is computationally cheap. At the time being, the hardware installation is costly because of the humanoid robot. The future work is to refine the method and to experiment it at wider scale.

References