Dynamic Movement Monitoring
Algorithms for Real Time Exercise Movement Feedback

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Keywords: Movement Monitoring, Home Rehabilitation, Exergames.

Abstract: Following to an implantation of an artificial knee joint, patients have to perform rehabilitation exercises at home. The motivation to exercise can be low and if the exercises are not executed, an extended rehabilitation time or a follow-up operation is possibly required. Moreover, incorrect exercise executions over a long period can lead to injuries. Therefore, we present two Programming by Demonstration (PbD) algorithms, a Nearest-Neighbour (NN) model and the Alpha Algorithm (AlpAl), for measuring the quality of exercise executions, which can be used in order to give feedback in exergames. The models can locate an ideal posture depending on a patient's posture in a dynamic movement. Furthermore, they work in real time and independent of the execution speed, in order to suggest the correct exercise movement. To validate the functionality of the algorithms, four correct and incorrect test movements of four persons were analyzed from the monitoring algorithms. Each localized ideal movement from the algorithms as well as each ground truth movement were compared with an imitated test movement by a Dynamic Time Warping (DTW) algorithm. Since we expect a linear dependency between the DTW-distances, we calculated the linear correlation, which was significant high. Hence, we think that the proposed algorithms are appropriate to monitor physiotherapeutic exercises while playing an exergame.

1 INTRODUCTION

As a result of terminal arthritis in the knee, an artificial knee joint implantation is performed (Ayoade and Baillie, 2014; Mistry et al., 2016). In Germany alone, about 130 of 100.000 inhabitants get this implant and the number of follow-up operations after the implantation has increased in recent years (Raten, 2013). After the knee-operation, the full range of motion is attempted to be restored by rehabilitation measures, partly consisting of physiotherapeutic exercises (Mistry et al., 2016). These exercises are taught in a clinical area, which should be continued at home independently (Pachoulakis and Tsilidi, 2016) as well as regularly for a fast completion of the rehabilitation.

However, these are often not performed properly and there are several reasons for this: the patient does not know the purpose of the exercise, lack of motivation or little time in everyday life (Chandra et al., 2012). According to a visit to the ambulant rehabilitation centre Münster, it was confirmed through discussions with physiotherapists, that the patients often do not continue their exercises at home sufficiently, because some of them have no motivation to do their exercises. Additionally, patients do not receive professional feedback on movements at home (Ananthanarayan et al., 2013). Moreover, the clinical exercise time is short compared to the home exercise time (Da Gama et al., 2015; Laerhoven and Lo, 2004). Finally, while a patient is exercising, incorrect exercise executions over a long period can lead to injuries (Su, 2013). This is not only the case with the physiotherapeutic exercises movements (Kowsar et al., 2016).

Therefore, several approaches incorporating a Rehabilitation System (ReSys) to increase exercise motivation at home and to give feedback on movements exist. To implement such a system, motion capturing technologies, which acquire data for analysis of movements, can be used (Crocher et al., 2013; Su et al., 2014; Chandra et al., 2012; Da Gama et al., 2016). Such a ReSys should not replace a physiotherapist, but should serve as a supportive measure when the patient is exercising at home (Benettazzo et al., 2015). Among other things, the information about the entire rehabilitation status and feedback on trajectories as well as on postures of exercises should influence the motivation positively, too (Maclean et al., 2000; Velloso et al., 2013b; Gal et al., 2015). If this information is communicated to the user in an exergame, the exercise motivation can be increased. Thus, a faster

Tiator, M., Büntig, F. and Geiger, C.
Dynamic Movement Monitoring.
DOI: 10.5220/0006735001840191
In *Proceedings of the 4th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2018)*, pages 184-191
ISBN: 978-989-758-299-8

Figure 1: The user moves a huge tree trunk when doing the marching exercise from figure 3. While the user is exercising, coins have to be collected and flying pigs have to be avoided. The aim of the game is to get the most points. More collected coins and less time for the route will increase the score, whereas collisions with the pigs will decrease the score. The movement feedback as well as the movement monitoring is not yet integrated. Furthermore, the game is developed by the TA cooperation partner University Duisburg Essen.

rehabilitation can be achieved.

Therefore, the Therapy-Assist (TA) project aims to develop a home ReSys, which allows rehabilitation patients with an artificial knee joint, to exercise and receive feedback on movements while playing an exergame. A sensor platform, consisting of a Kinect and Inertial Measurement Units (IMUs), is developed, to acquire data for analysis of movements in order to give appropriate feedback. In the end, patients should exercise regularly when using the ReSys. A game from the TA project is depicted in figure 1, which gamifies the marching exercise in figure 3 b).

In this context we propose algorithms, which check the orientation of joints in real time, such that direct feedback can be given. In order to do so, postures are compared with ideal corresponding postures in a dynamic movement. In addition, the real time analysis allows a trainee to learn and execute movements independent of movement execution speed. Ultimately, it is possible to identify incorrect joint orientations in a dynamic movement. Two Programming by Demonstration (PbD) approaches are presented, namely a Nearest-Neighbour (NN) model and a self-developed algorithm, called Alpha Algorithm (AlpAl).

The document is structured as follows: Existing methods for the analysis of movements are described in section 2. In section 3 the NN model and the AlpAl are presented and examined by a correlation analysis. The method as well as the results are discussed and concluded in section 4. Finally, an outlook on future possibilities and investigations is given in section 5.

Figure 2: The upper two figures (a) show a correct execution of the marching exercise, whereas the lower two figures (b) show an incorrect execution, since the leg is twisted.

2 RELATED WORK

Appropriate feedback can increase the exercise motivation when it depends on a movement monitoring, which adapts to patients of different rehabilitation states (Benettazzo et al., 2015). Adaption can be implemented by parameterized models. Camporesi et al. parameterized dynamic movements by using plane-constraints (Camporesi et al., 2014). After a principal component analysis of a PbD recording, the maximum amplitude or the hold time of an exercise can be set. Due to the distance calculation from a joint position to the plane, twists of joints, where the joint position is still the same, cannot be detected. But this is a general problem, when using position based data for monitoring a joint orientation. If the monitoring uses position data of joints, a normalization of joint lengths can avoid a false feedback, in consequence of people with limbs of different length (Ruttkay and van Welbergen, 2008).

Besides that, parameters for describing movements, which are known by the user group, can make a monitoring system more user friendly. For example, Zhao et al. used the anatomical angles of a joint in a body plane (Zhao et al., 2014a). The choice of the anatomical angle as the monitoring parameter can be advantageous in the physiotherapy context, since physiotherapists measure in some cases the range of motion with a goniometer (Martin-Moreno et al., 2008).

The inclusion of temporal features (e.g. fixed exercise execution speed) in the movement monitoring (Ruttkay and van Welbergen, 2008; Anderson et al., 2013) could be disadvantageous when playing an exergame, because the user should focus more on the game than on the exercise execution at a fixed speed. In order to avoid temporal features in the monitoring, a Dynamic Time Warping (DTW) algorithm for comparison of movements can be used (Su, 2013). But this has the disadvantage, that a movement has to be executed and extracted in order to do the DTW analysis. Hence, there is at least a feedback latency of one exercise execution. This is also the case, if a sliding window is used (Velloso et al., 2013a).

In contrast to that, direct feedback can be given, when using a classifier for monitoring an exercise execution (Velloso et al., 2013a). Mistakes in an exercise could be summarized as classes. Obviously this technique can provide real time feedback, the training data has to be acquired and the classifiers have to be trained. This process can be very time consuming, which can make the creation of new exercises hard.

Movements can also be monitored by the definition of fixed rules. For example, Pachoulakis et al. have implemented a monitoring of a knee bend, among which one parameter of the exercise is the distance of the hip joint to the ground (Pachoulakis et al., 2015). Since the PbD approach was not used here, the monitoring of new movements means defining and implementing new rules. Apart from that, via a static rule it is difficult to monitor the postures of a dynamic movement, for instance, a limit value operation of a property (e.g. checking the hip height) enables adopting incorrect postures.

Another way to monitor dynamic movements without temporal dependency and give feedback in real time is the usage of a Finite State Machine (FSM), where parts of the movement define the states (Zhao et al., 2014b). The implementation of the FSM from Zhao et al. is unidirectional, such that only forward movements can be monitored. Such a monitoring could be inappropriate, when unpredictable forward as well as backward movements are executed in the exergame.

Instead of analyzing a movement to suggest a correct movement, it is also possible to combine movements with interactions and the achievement of goals, such that a patient executes a movement in a certain way. For this purpose, Anderson et al. have designed a game, that measures an activity score, which is measured by parameters of a Wii controller, the completion of tasks in the game and balance values from a Wii balance board (Anderson et al., 2010). If one player moves more than another, he receives a higher score. Thereby, the motivation to move more could be increased when playing a game.

Motivation and suggestion of certain movement can also be created by gesture recognition. Pachoulakis and Tsilidi developed a game, in which it is necessary to lead a ball by hand gestures over wooden planks (Pachoulakis and Tsilidi, 2016). The player risks a fall down of the ball, if the ball control gestures are not recognized. In other ways, patients have to move in an application of Yu et al. in order to catch stars, which are falling from the sky (Yu et al., 2011). Beyond that, audio-visual signs are used to support the movements. In an application of Assad et al., one have to follow a star trajectory, what comes close to the execution of a certain movement (Assad et al., 2011). This is also the case in a modified Fruit-Ninja variant developed by Khademi et al., in which the player has to carry out a cutting movement with the index finger (Khademi et al., 2014). These interactive methods of suggesting movements in a playful way allow that incorrect postures can be adopted and no monitoring algorithm is recognizing this.

3 MONITORING

Five different rehabilitation exercises were selected for the development of the ReSys in the TA project. In one exercise, a practitioner lies down on the back in a seated position and presses the feet against the wall (figure 3 a)). Since the joints do not move in this exercise, it is possible to compare the current pose of the practitioner with a reference pose. Furthermore, dynamic movements are also performed in some exercises. In figure 3 b) an exercise is shown in which a practitioner raises his legs by 90° in a marching movement on the spot alternately. During this exercise, some patients twist their legs (figure 2 b)), whereby a physiotherapist would apply a correction, if he would detect this twist. Therefore, a monitoring algorithm should analyze the motions in real time, such that the ReSys can provide real time feedback on incorrectly executed movements.

Additionally, the monitoring should depend on the PbD approach, in order to easily create new movements. Furthermore, dependence on temporal features should be avoided, such that the movements can be potentially learned in rest by a trainee. Moreover, the user should be able to focus on the exergame while he is exercising and the monitoring is analyzing his movements in order to give feedback. Apart from that, forward as well as backward movements[1] should be monitored equally. Finally, the monitoring mechanism should localize the ideal orientation of a joint. For example, if someone twists the leg in the marching exercise (figure 2 b)), it should be possible to determine the ideal corresponding orientation of the leg (figure 2 a)).

[1] A forward movement refers to the phase of leg lifting from the machinery exercise in figure 2.

Figure 3: a) shows a knee rehabilitation exercise, in which a practitioner presses with his feet against the wall while lying in a sitting position. b) shows another exercise, in which a practitioner marches on the spot and lifts the legs about 90° in the sagittal plane.

3.1 Nearest-Neighbour

The unweighted NN model searches for the nearest reference orientation[2] $q_r \in H$ by iteration of a PbD list (see algorithm 1). A reference pose p_r in a motion M can belong to the found orientation q_r in order to determine the orientations of all joints of the body. Since the NN model determines the nearest neighbour via distances, a suitable distance measurement for orientations has to be used.

```
Quaternion SearchNN(q_n)
1   dist = max
2   Quaternion q_nn
3   foreach Quaternion q_r ∈ ReferenceOrientations do
4       tmp_dist = ComputeDistance(q_n, q_r)
5       if tmp_dist < dist then
6           dist = tmp_dist
7           q_nn = q_r
    end
8   return q_nn
```

Algorithm 1: Pseudo-Code of the NN implementation. q_{nn} indicates the found nearest neighbour orientation. *dist* is the nearest neighbour distance and *tmp_dist* is a temporary distance for a neighbour.

This could be the rotation difference q_{nr} in eq. 1, i.e. a rotation from a current orientation q_n to a reference orientation q_r.

$$q_n * q_{nr} = q_r \Leftrightarrow q_{nr} = q_n^{-1} * q_r \tag{1}$$

This rotational difference can be converted into an euler vector and the amount of the euler vector can serve as a distance measurement (algorithm 1 at line 4 in function ComputeDistance (q_n, q_r)). Exclusive use of orientations results in a temporal independent localization. Furthermore, the PbD data has to be recorded once in order to create the list of reference orientations.

3.2 Alpha Algorithm

This algorithm uses the body planes, which got the same transformation as the stem joint. Beyond that, a PbD recording with the forward movement of the exercise should be present. When a movement is executed, the vector of the joint deflection is projected on a chosen body plane[3] (eq. 2), resulting in a vector $\vec{u_{j,p}} \in R^2$. The normal $\vec{n_p}$ of the body plane results from the cross product of two coordinate axes of the stem joint, which span the plane. Additionally, the 3D projected vector[4] $\vec{v_{j,p}}$ is rotated around the inverse root joint orientation q_{root}^{-1} in eq. 3, so that the joint deflection is axes aligned with the world coordinate system. Consequently, $\vec{u_{j,p}}$ obtains non-zero vector coordinates of $q'_{v,j,p}$ (eq. 3) in the axes that span the planes.

$$\vec{v_{j,p}} = \vec{v_j}' - \frac{\vec{v_j}' * \vec{n_p}}{|n_p|^2} * \vec{n_p} \tag{2}$$

$$\begin{aligned} q'_{v,j,p} &= q_{root}^{-1} * q_{v,j,p} * (q_{root}^{-1})^{-1} \\ &= q_{root}^{-1} * q_{v,j,p} * q_{root} \end{aligned} \tag{3}$$

The vector of the projected minimum joint deflection should correspond to a fixed reference vector $\vec{u_{ref,j,p}}$. This can be realized by a 2D rotation of $\vec{u_{min,j,p}}$ (eq. 4 to 7) with an angle of $\alpha_{min,p} = \angle \vec{u_{min,j,p}} \vec{u_{ref,j,p}}$.

$$R_{\alpha_{min,p}} * \vec{u_{min,j,p}} = \tag{4}$$

$$\begin{pmatrix} cos(\alpha_{min,p}) & -sin(\alpha_{min,p}) \\ sin(\alpha_{min,p}) & cos(\alpha_{min,p}) \end{pmatrix} * \vec{u_{min,j,p}} = \tag{5}$$

$$\vec{u_{ref,j,p}} = \tag{6}$$

$$\vec{u_{min,j,p}}' \tag{7}$$

In order to get the maximum deflection, a vector $\vec{u_{max,j,p}}$ is rotated by $R_{\alpha_{min,p}}$, whereby the operation results in $\vec{u_{max,j,p}}'$. After that, the angle $\alpha_{max,p}$ can be calculated[5]. At runtime, an angle of α_p (apply 2D

[2] In this contribution, all variables with a q indicate a quaternion.

[3] $\vec{u}$ indicates a vector in the 2D body plane. The index j stands for joint and p stands for a certain body plane.

[4] $\vec{v}$ stands for a vector of a joint deflection. .

[5] The α-angles are calculated via $\angle \vec{u_{j,p}} \vec{u_{ref,j,p}}$.

rotation and α-angle calculation to $\vec{u_{j,p}}$) has to be determined and it must be proofed, if α_p is within the range of 0° to $\alpha_{max,p}$. Since the angle calculation $\angle\vec{xy}$ only represents values from 0° to 180°, the function $a(\alpha_p)$ (eq. 8) is used to model movements, which include a deflection more than 180° in a body plane[6].

$$\alpha'_p = a(\alpha_p) = \begin{cases} 360° - \alpha_p & \text{, if } \vec{u_{j,p}}'_x < 0 \\ \alpha_p & \text{, else} \end{cases} \quad (8)$$

However, this presupposes a sense of rotation in the 2D plane, whereby a clockwise rotation is chosen as in figure 4.

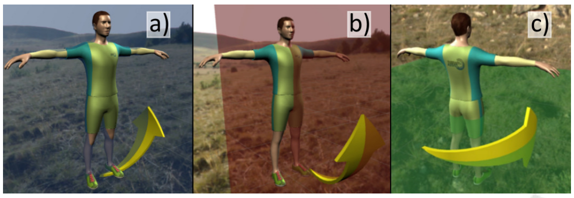

Figure 4: The right turn in the body planes is symbolized by a yellow arrow. In contrast, a turn in the other direction is a left-hand turn. Moreover, a) shows the frontal plane, b) the sagittal plane and c) the transverse plane.

The next step is to interpolate joint orientations of the previously made PbD recording from sampling point to sampling point via the spherical linear interpolation function. Each resulting interpolated joint movement is processed according to the equations eq. 2 to 8, so that an angle of α'_p is calculated. An interpolated orientation is stored as a reference orientation, if a certain sampling rate of $\alpha_{s,p} \pm \alpha_{f,p}$ is fulfilled ($\alpha_{f,p}$ is a tolerance for the non-compliance of the sampling rate $\alpha_{s,p}$). At the end of this interpolation process, an array of reference orientations is available for the runtime, whereby poses can be also assigned to the orientations as well. At runtime, a α'_p must be clamped to the range of motion by eq. 9 to 11, since these orientations were only stored in the interpolation process.

$$\begin{aligned} \alpha''_p &= \\ c(\alpha'_p) &= \begin{cases} f(\alpha'_p) & \text{, if } \alpha'_p > \alpha'_{max,p} \\ \alpha'_p & \text{, else} \end{cases} \quad (9) \\ \text{with} & \\ f(\alpha'_p) &= \begin{cases} \alpha'_{max,p} & \text{, if } \alpha'_p < \alpha'_{g,p} \\ 0° & \text{, else} \end{cases} \quad (10) \\ \alpha_{g,p} &= 180° + \frac{\alpha'_{max,p}}{2} \quad (11) \end{aligned}$$

Finally, an index is obtained from the angle α''_p, which is assigned to a reference orientation. This is done by dividing the angle α''_p by the sampling rate $\alpha_{s,p}$. This quotient is rounded down to the next integer by eq. 12.

$$i = \lfloor \frac{\alpha''_p}{\alpha_{s,p}} \rfloor \quad (12)$$

Finally, by inserting the index i in the array of orientations, which were created in the interpolation process, the reference orientation is localized. After the ideal pose localization, the joint orientations of the current reference posture can be compared by eq. 1.

3.3 Method

We want to validate the functionality of the proposed algorithms. Motions can be compared by pearson correlation (Velloso et al., 2017), but repetitions of exercises can have different durations. This means, that an interpolation of the movement data is necessary. In order to avoid an interpolation, the DTW algorithm is used to compare two sequences of movements with different durations in the euler domain. Furthermore, a correctly imitated test movement is expected to have a low DTW distance to a reference movement. Similarly, a localized movement should have a low DTW distance to a correctly imitated test movement. The DTW distances from test to a localized movement and test to a reference movement should have a high positive linear correlation coefficient. This correlation is then checked for significance by a directed t-test. The null hypothesis $H_0 : \rho \leq 0$ and the alternative hypothesis $H_1 : \rho > 0$ were examined.

For this purpose, four test movements were defined, which were executed by four test persons correctly and incorrectly from their perspective. The subjects were healthy adults in the age of 20 to 27. They were instructed about the movements and trained them a few times. After that, a recording of the exercises was made. Thus, for each movement exist $N = 8$ different versions. The movement of lifting the left leg was chosen from the marching exercise (Ex11, figure 2). The spreading of the right leg of a hip abduction (Ex12) was monitored. In order to monitor more complex movements, two capoeira kicks (Ex13, Ex14) of the right leg were monitored, which include the main deflection in more than one degree of freedom. Since the sensor platform from the TA project has not yet been developed, the movement data was acquired by an IMU suit. The sensors of the suit are differently attracted from subject to subject. Therefore, a certain deviation from the basic IMU-orientations of the person who has made the PbD recording was taken into account.

[6] $\vec{u_{j,p}}'_x$ stands for the x-component of $\vec{u_{j,p}}'$.

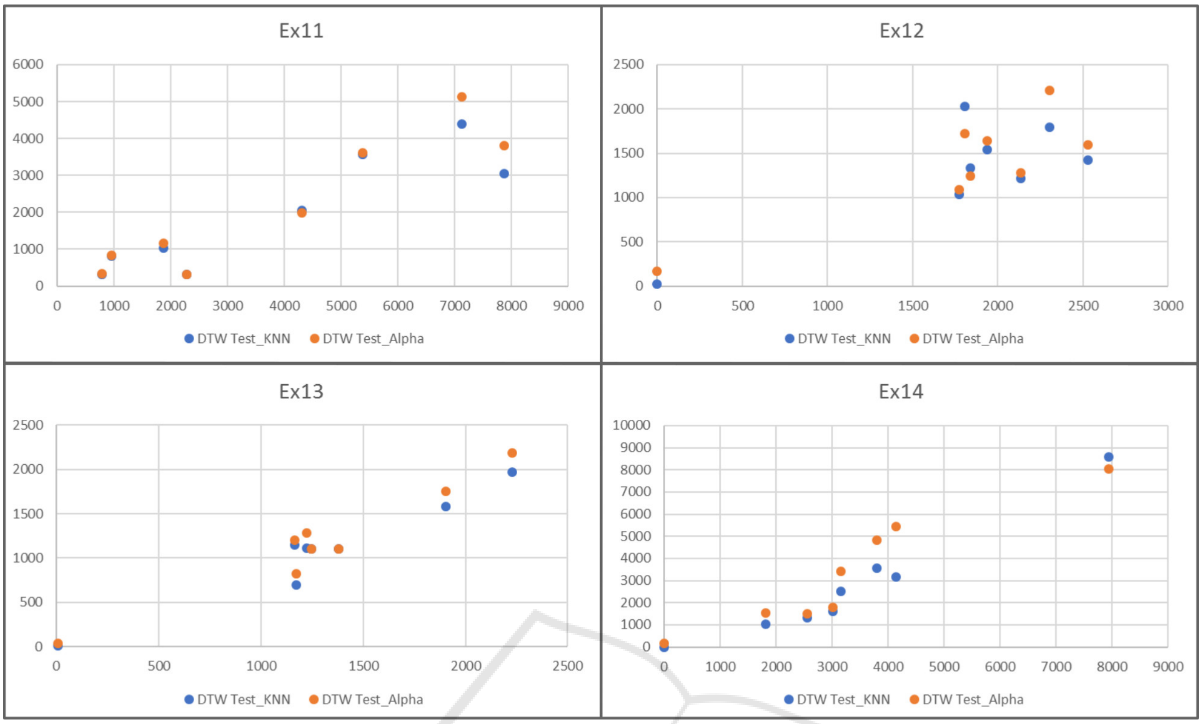

Figure 5: The DTW distances from the test to reference movements are plotted on the x-axis, whereas the distances from test to localized movements are plotted on the y-Axis. The blue dots represent the NN-model and the orange dots represent the AlpAl.

3.4 Results

The linear correlation coefficients of all movements are significant ($p < 0.05$). The explicit correlation coefficients are given in table 1. The correlation coefficients of the DTW distances from test to reference movement and test to NN localization data are given under ρ_{NN} (The same principle applies to the AlpAl).

Table 1: Linear correlation coefficients of the DTW distances from the reference and localized movements to test movements.

Exercise	ρ_{NN}	ρ_{AlpAl}
11	≈ 0.908	≈ 0.931
12	≈ 0.814	≈ 0.858
13	≈ 0.970	≈ 0.972
14	≈ 0.972	≈ 0.944

According to the significant results, there is a non-random correlation between a localized motion sequence of the two models and the reference to the test motion sequences. Therefore, the localization models can indicate where a joint of a person should be located, if an incorrect posture is taken in a dynamic movement.

Additionally, the requirements from section 3 are fulfilled. A new movement can be adapted via a PbD recording. The monitoring of the joints in a dynamic movement is independent of a certain execution speed or temporal window. Furthermore, direct feedback can be given, since the methods do not require any extraction of an exercise repetition.

Figure 6: This figure shows a silhouette of the ideal posture of the body depending on the posture of a practitioner.

The localization can be exemplary visualized as feedback by a transparent silhouette (ghost) in relation to the own body movement (figure 6). The color of the ghost changes, depending on the deviation from the reference orientation. Red stands for an inappropriate imitation of the movement and green stands for an appropriate imitation.

4 DISCUSSION & CONCLUSION

The DTW algorithm for the comparison of two motions uses the euclidean distance. This has the disadvantage, that two obvious euler angles can be far away when euler jumps occur. For example, one coordinate of a degree of freedom can be 358° and the next could be 2°, resulting in the absolute euclidean distance of 356°, even though the shortest way is only 4°. Since there are no euler jumps in the data, this disadvantage can be neglected for the evaluation.

Figure 5 shows the DTW distances, whereby the reference data was also used as test data. Here, the NN model has a zero DTW distance, but the AlpAl has produced a small deviation due to the interpolation process of the reference movement. The interpolation process of the two capoeira kicks ends in half of the movement, since the maximum leg deflection is already reached in half of the movement. Unfortunately, the hip cannot be chosen as an observable joint, because it represents the stem joint of the body and has a globally dependent hip deflection. This prevents an influence of the localization from the alignment of a patient in the room. The NN algorithm has the advantage over the AlpAl, that it can be used without parameters, except for the choice of a joint to be monitored. In contrast to this, parameters have to be selected in the interpolation process of the AlpAl. On the other hand, the AlpAl comes with a constant runtime complexity of $O = 1$ and offers a motion independent calculation duration for the movement monitoring. The NN algorithm is associated with a linear runtime complexity in the length of the PbD recording. According to the constant runtime complexity, the AlpAl can be used to develop a graphically or rather logically elaborated exergame. Thus, developers can plan the system resources in the temporal execution independent of the PbD recording. These algorithms can be used with any motion capturing system, which measure local joint orientations in a hierarchical way, such that at least one parent joint exist.

The proposed algorithms enable monitoring of movements in an exergame, in which feedback to the movements can be given. This can increase exercise motivation, but further investigations are necessary in order to find out, how the movement feedback is related to the exercise motivation. However, the feedback based on the monitoring can ensure, that inappropriate movements are detected and possible injuries be avoided. Moreover, patients can re-learn exercises (e.g. with the ghost feedback), if they have forgotten them.

5 FUTURE WORK

Since it is still unclear, how fast a feedback should react and which movement analysis in an exergame is most suitable for certain movements to increase exercise motivation, we want to compare several movement analysis methods with the user group from the TA project. Being able to define the maximum amplitude of an exercise like Camporesi et al. (Camporesi et al., 2014) may be a sensible addition of the monitoring algorithms. This could be done in the AlpAl by modifying the $\alpha_{max,p}$ parameter. In addition, the search of the NN algorithm could be sped up by starting the search at the last found neighbour and setting a threshold to localize the nearest neighbour. Supplementary to this, we want to extend both models, such that more complex movements can be monitored (e.g. a dance performance).

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