Video-based Feedback for Assisting Physical Activity

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Abstract: In this paper, we explore the concept of providing feedback to a user moving in front of a depth camera so that he is able to replicate a specific template action. This can be used as a home based rehabilitation system for stroke survivors, where the objective is for patients to practice and improve their daily life activities. Patients are guided in how to correctly perform an action by following feedback proposals. These proposals are presented in a human interpretable way. In order to align an action that was performed with the template action, we explore two different approaches, namely, Subsequence Dynamic Time Warping and Temporal Commonality Discovery. The first method aims to find the temporal alignment and the second one discovers the interval of the subsequence that shares similar content, after which standard Dynamic Time Warping can be used for the temporal alignment. Then, feedback proposals can be provided in order to correct the user with respect to the template action. Experimental results show that both methods have similar accuracy rate and the computational time is a decisive factor, where Subsequence Dynamic Time Warping achieves faster results.

1 INTRODUCTION

It is essential for elderly people to keep a good level of physical activity in order to prevent diseases, to maintain their independence and to improve the quality of their life (Sun et al., 2013). Physical activity is also important for stroke survivors in order to recover some level of autonomy in daily life activities (Kwakkel et al., 2007). Post-stroke patients are initially submitted to physical therapy in rehabilitation centres under the supervision of a health professional, which mainly consists of recovering and maintaining daily life activities (Veerbeek et al., 2014). Usually, the supervised therapy session is done within a short period of time mainly due to economical reasons. In order to support and maintain the rehabilitation of stroke survivors, continuous home based therapy systems are being investigated (Langhorne et al., 2005; Zhou and Hu, 2008; Sucar et al., 2010; Hondori et al., 2013; Mousavi Hondori and Khademi, 2014; Chaaraoui et al., 2012; Ofli et al., 2016). Having these systems at home and easily accessible, the patients keep a good level of motivation to do more exercise. An affordable technology to support these home based systems are RGB-D sensors, more specifically, the Microsoft Kinect[1] sensor. Generally, these systems combine exercises with video games (Kato, 2010; Burke et al., 2009) or emulate a physical therapy session (Ofli et al., 2016; Sucar et al., 2010).

Existing works usually focus on detection, recognition and posterior analysis of performed actions (Kato, 2010; Burke et al., 2009; Sucar et al., 2010; Ofli et al., 2016). Recent works have explored approaches for measuring how well an action is performed (Pirsiavash et al., 2014; Tao et al., 2016; Wang et al., 2013; Ofli et al., 2016), which can be used as a home based rehabilitation application. Ofli *et al.* (Ofli et al., 2016) presented an interactive coaching system using the Kinect sensor. Their system provides feedback during the performance of exercises. For that, they have defined some physical constraints on the movement such as keeping the hands close to each other or keeping the feet on the floor, etc. Pirsiavash *et al.* (Pirsiavash et al., 2014) proposed a framework which analyses how well people perform an action in videos. Their work is based on a learning-based framework for assessing the quality of human actions using spatio-temporal pose features. In addition, they provide feedback on how the performer can improve his action.

Recently, Antunes *et al.* (Antunes et al., 2016b) introduced a system able to provide feedback in the form of visual information and human-interpretable messages in order to support a user in improving a movement being performed. The motivation is to sup-

[1] https://developer.microsoft.com/en-us/windows/kinect

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port the physical activity of post-stroke patients at home, where they are guided in how to correctly perform an action.

In this work, we explore the concept of a template action, which is a video that represents a specific action or movement, in order to provide feedback to a user performing an action, ideally in an online manner. For example, a template action can be a video created by a physiotherapist with a specific movement for the patient to reproduce. We propose to extend the framework of (Antunes et al., 2016b) in order to provide real-time feedback with respect to the template action instead of a single pose or presegmented video clips as (Antunes et al., 2016b). To that end, an important alignment problem needs to be solved between the performed action and the template action. The main challenge is that classical alignment methods, such as Dynamic Time Warping (DTW), require the first and the last frame of the two sequences to be in correspondence. This information is not available in our problem, since the action of interest is not presegmented, and the feedback provided ideally in an online manner. Two approaches from the literature are suitable for solving this problem, namely, Subsequence-DTW (SS-DTW) (Müller, 2007) and Temporal Commonality Discovery (TCD) (Chu et al., 2012). In this paper, we propose to adapt both SS-DTW and TCD for the feedback system in (Antunes et al., 2016b) and evaluate the performance of both alignment methods and the corresponding feedback.

This paper is organized as follows: Section 2 introduces the problem formulation of the feedback system proposed in (Antunes et al., 2016b). Section 3 provides a brief introduction of temporal alignment and proposes to adapt SS-DTW and TCD for the feedback system. Experimental results, comparing the performance of SS-DTW and TCD, are shown and discussed in Section 4, and Section 5 concludes the paper.

2 PROBLEM FORMULATION

A human action video is represented using the spatial position of the body joints, e.g. (Vemulapalli et al., 2014; Antunes et al., 2016a). Let us define $\mathsf{S} = [\mathbf{j}_1, \cdots, \mathbf{j}_N]$ as a skeleton with N joints, where each joint is defined by its 3D coordinates $\mathbf{j} = [j_x, j_y, j_z]^\top$. An action $\mathsf{M} = \{\mathsf{S}_1, \cdots, \mathsf{S}_F\}$ is a skeleton sequence, where F is the total number of frames. The objective is to provide feedback proposals in order to improve the conformity between the action M that was performed and the template action $\hat{\mathsf{M}}$. Figure 1 shows an example of the data used in this work. The first row shows a template action and the sequence in the second row represents the action that was performed.

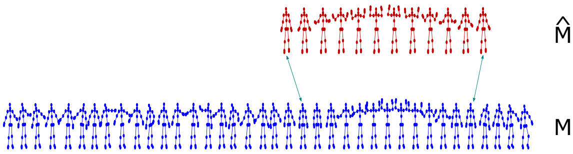
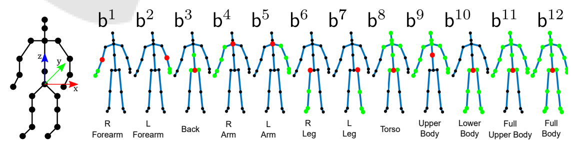


Figure 1: An illustration of the alignment between the template action (top row, red) and the performed action (bottom row, blue).

In order to compare two different actions, the skeleton sequences must be spatially and temporally aligned (Vemulapalli et al., 2014). The spatial registration is achieved by transforming each skeleton S such that the world coordinate system is placed at the hip center. In addition, the skeleton is rotated in a manner that the projection of the vector from the left hip to the right hip is parallel to the x-axis (refer to Figure 2(a)). In order to handle variations in the body part sizes of different subjects, the skeletons in M are normalized such that each body part length matches the corresponding part length of the template action skeletons in $\hat{\mathsf{M}}$. Remark that this is done without changing the joint angles. The temporal alignment of skeleton sequences is the main goal of this paper. This will be discussed in Section 3.

As proposed in (Antunes et al., 2016b), we represent a skeleton S by a set of body parts $\mathcal{B} = \{\mathsf{b}^1, \cdots, \mathsf{b}^P\}$, where P is the number of body parts and each body part b^k is defined by n^k joints $\mathsf{b}^k = [\mathbf{b}_1^k, \cdots, \mathbf{b}_{n^k}^k]$. Each body part has its own local reference system defined by the joint $\mathbf{b}_r^k$ (refer to Figure 2(b)).



(a) (b)

Figure 2: 2(a) Centered and aligned skeleton; 2(b) Representation of 12 body parts. The set of joints for each body part is highlighted in green and its local origin is the red colored joint (R=Right, L=Left).

Given two corresponding skeletons S_i of M and $\hat{\mathsf{S}}_{\hat{i}}$ of $\hat{\mathsf{M}}$, the goal of the physical activity assistance system proposed in (Antunes et al., 2016b) is to compute the motion that each body part of S_i needs to undergo to better match $\hat{\mathsf{S}}_{\hat{i}}$. This is achieved by computing for each body part b^k the rigid motion that increases the similarity between its corresponding body parts $\hat{\mathsf{b}}^k$. This is performed iteratively, where at each iteration, the body part motion which ensures the highest improvement is selected. Finally, the previous corrective motion is presented to the patient in the form of visual feedback and human interpretable messages (refer to Figure 5).

3 TEMPORAL ALIGNMENT

In this section, we propose to adapt and apply SS-DTW and TCD to the physical activity assistance system of (Antunes et al., 2016b). An interval measurement is also proposed in order to quantitatively evaluate performance of the two methods. A brief introduction of how two sequences are aligned using DTW (Müller, 2007) is provided, and the boundary constraint assumed by DTW is discussed. This constraint can be removed using recent methods, of which two were selected and are presented bellow.

DTW (Müller, 2007) is a widely known technique to find the optimal alignment between two temporal sequences which may vary in speed. Let us assume two skeleton sequences $\mathsf{M} = \{\mathsf{S}_1, \cdots, \mathsf{S}_F\}$ and $\hat{\mathsf{M}} = \{\hat{\mathsf{S}}_1, \cdots, \hat{\mathsf{S}}_{\hat{F}}\}$, where F and $\hat{F}$ are the number of frames of each sequence, respectively. A warping path $\phi = [\phi_1, \cdots, \phi_L]$ with length L, defines an alignment between the two sequences. The warping path instance $\phi_i = (m_i, \hat{m}_i)$ assigns the skeleton S_{m_i} of M to the skeleton $\hat{\mathsf{S}}_{\hat{m}_i}$ of $\hat{\mathsf{M}}$. The total cost C of the warping path ϕ between sequences M and $\hat{\mathsf{M}}$ is defined as

$$C_\phi(\mathsf{M}, \hat{\mathsf{M}}) = \sum_{i=1}^{L} c(\mathsf{S}_{m_i}, \hat{\mathsf{S}}_{\hat{m}_i}), \quad (1)$$

where c is a local cost measure. Following (1), the DTW distance between the sequences M and $\hat{\mathsf{M}}$ is represented by $\mathrm{DTW}(\mathsf{M}, \hat{\mathsf{M}})$ and is defined as

$$\mathrm{DTW}(\mathsf{M}, \hat{\mathsf{M}}) = \min\{C_\phi(\mathsf{M}, \hat{\mathsf{M}})\}. \quad (2)$$

As discussed in (Müller, 2007), DTW assumes three constraints regarding the warping path: the boundary, the monotonicity and the step size constraints. We aim at analysing approaches that leverage the boundary constraints, and we refer the reader to (Müller, 2007) for a thorough description of the remaining constraints.

The boundary constraint in DTW assumes that the first and the last frames of both sequences are in correspondence. This is mathematically expressed as

$$\phi_1 = (1, 1) \text{ and } \phi_L = (F, \hat{F}). \quad (3)$$

Figure 3(a) illustrates the boundary constraint of DTW. As it requires the alignment of the first and the last frames, this method is not suitable for our problem, because the template action will be in many cases a sub-interval of the action that was performed.

There are some recent methods for suppressing the boundary constraint (Gupta et al., 2016; Kulkarni et al., 2015; Zhou and Torre, 2009; **?**). We selected two of them based on the following: SS-DTW (Müller, 2007) is a simple and natural extension of DTW, and TCD (Chu et al., 2012) was recently shown to work well for human motion analysis. These approaches are described next.

3.1 SS-DTW

SS-DTW (Müller, 2007) is a variant of the DTW that removes the boundary constraint. Referring to our problem, this method does not align both sequences globally, but instead the objective is to find a subsequence within the performed action that best fits the template action.

Given $\hat{\mathsf{M}}$ and M the objective is to find the subsequence $\{\mathsf{S}_s : \mathsf{S}_e\}$ of M with $1 \leq s \leq e \leq F$, that best matches $\hat{\mathsf{M}}$, where s is the starting and e is the ending point of the interval. This is achieved by minimizing the DTW distance in (2) as follows:

$$\{\mathsf{S}_{s^*} : \mathsf{S}_{e^*}\} = \underset{(s,e)}{\operatorname{argmin}} \left(\mathrm{DTW}(\hat{\mathsf{M}}, \{\mathsf{S}_s : \mathsf{S}_e\})\right), \quad (4)$$

where $\{\mathsf{S}_{s^*} : \mathsf{S}_{e^*}\}$ is the optimal alignment interval. Figure 3(b) illustrates the result of the SS-DTW algorithm between two sequences, where it is able to find a good alignment in a long sequence M.

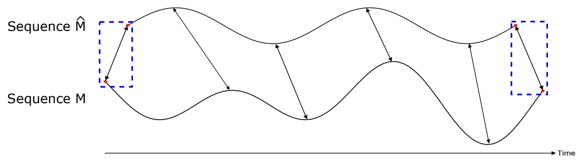
3.2 Unsupervised TCD

The TCD algorithm (Chu et al., 2012) discovers the subsequence that shares similar content between two or more video sequences in an unsupervised manner.

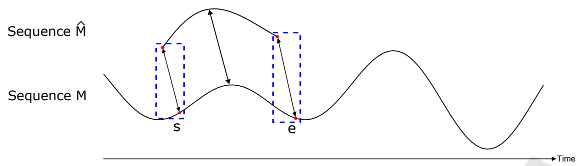
Given two skeleton sequences M and $\hat{\mathsf{M}}$, where M contains at least one similar action as the template action $\hat{\mathsf{M}}$. The objective is to find the subsequence $\{\mathsf{S}_s : \mathsf{S}_e\}$ of M that better matches the subsequence $\{\hat{\mathsf{S}}_{\hat{s}} : \hat{\mathsf{S}}_{\hat{e}}\}$ of $\hat{\mathsf{M}}$. Referring to our problem, the objective is to find the best subsequence $\{\mathsf{S}_s : \mathsf{S}_e\}$ that better fits the template action $\hat{\mathsf{M}}$. This can be achieved by minimizing the distance d between two feature vectors $\psi_{\hat{\mathsf{M}}}$ and $\psi_{\{\mathsf{S}_s:\mathsf{S}_e\}}$ defined as

$$\min_{s,e} d(\psi_{\hat{\mathsf{M}}}, \psi_{\{\mathsf{S}_s:\mathsf{S}_e\}}), \quad (5)$$

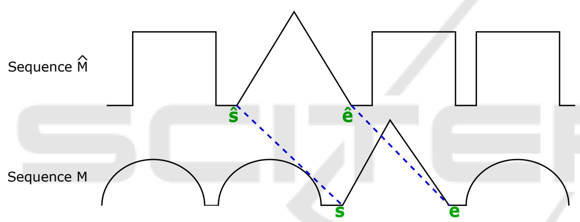
such that $e - s \geq l$, where l is the minimal length to avoid the case of an empty set. Assuming A as a sequence of skeletons, where each skeleton is expressed by the 3D coordinates of the human body joints. The feature vector ψ_A is represented as the histogram of temporal words (Chu et al., 2012). In order to find the optimal solution to (5), TCD uses a Branch and Bound (B&B) algorithm. Figure 3(c) shows an example of TCD, where the result is the interval of each sequence that shares similar pattern. After the detection of the matching intervals, the standard DTW can be applied to align the obtained subsequence $\{\mathsf{S}_s : \mathsf{S}_e\}$ of M with the template action $\hat{\mathsf{M}}$.



(a) Alignment between two temporal sequences using DTW.



(b) Alignment between $\hat{\mathsf{M}}$ and the sequence M using SS-DTW.



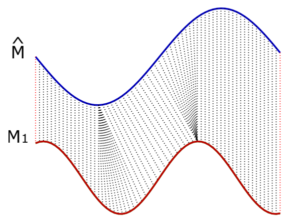
(c) Discovered common content between two sequences using TCD.

Figure 3: Described methods of temporal alignment and similar content detection. Sub-figures 3(a) and 3(b) show that the SS-DTW is capable to remove the boundary constraint of DTW. The blue rectangles highlight the removal of this constraint. Sub-figure 3(c) illustrates the intervals obtained from TCD algorithm, where both sequences share similar triangles.

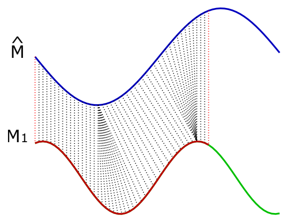
3.3 Proposed Interval Measure

In order to evaluate the performance of the interval detection using the temporal alignment methods described previously, we first use standard DTW to align the template action $\hat{\mathsf{M}}$ with the same action performed by a different subject M_1, where F_1 is the number of frames of M_1. Let us assume the alignment between $\hat{\mathsf{M}}$ and M_1 using $\phi = [\phi_1, \cdots, \phi_L]$. After the alignment, the action M_1 is divided in 3 different subsequences with different lengths:

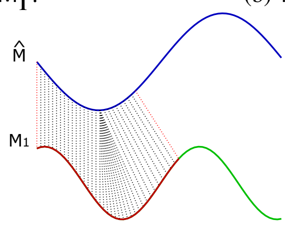
1. Complete sequence, $\mathsf{M}_\mathbf{1}^\mathbf{L} = \mathsf{M}_1$ - the whole warping path $\phi = [\phi_1, \cdots, \phi_L]$, Figure 4(a);
2. $\frac{3}{4}L$ of the sequence, $\mathsf{M}_\mathbf{1}^{\mathbf{L}'}$, where $L' = \frac{3}{4}L$ - warping path $\phi = [\phi_1, \cdots, \phi_{L'}]$, Figure 4(b);
3. $\frac{1}{2}L$ of the sequence, $\mathsf{M}_\mathbf{1}^{\mathbf{L}''}$, where $L'' = \frac{1}{2}L$ - warping path $\phi = [\phi_1, \cdots, \phi_{L''}]$, Figure 4(c);



(a) $\mathsf{M}_\mathbf{1}^\mathbf{L}$.



(b) $\mathsf{M}_\mathbf{1}^{\mathbf{L}'}$.



(c) $\mathsf{M}_\mathbf{1}^{\mathbf{L}''}$.

Figure 4: Temporal alignment between the sequences $\hat{\mathsf{M}}$ and M_1 using DTW. The blue sequence represents the sequence $\hat{\mathsf{M}}$ and the green sequence is the sequence M_1. The red color corresponds to the subsequences with 3 different lengths.

Then, for evaluating the performance of the alignment methods, we generate new sequences M using the resulting 3 subsequences from M_1. Considering this, the objective is to evaluate the accuracy in the detection of the start, s, and end point, e, of the interval obtained from SS-DTW and TCD. To compute the accuracy, we use s and e from the subsequence of M_1 (introduced in M) to calculate the difference with the results from both methods. If the difference between the corresponding points is higher than a pre-defined threshold ε, then it is considered as an outlier. Otherwise, the accuracy is defined as

$$Acc = 1 - \frac{|diff(s_{\mathsf{M}_1}, s)|}{F_1}, \tag{6}$$

where $diff(s_{\mathsf{M}_1}, s)$ is the the difference between ground-truth start points s_{M_1} from M_1 and s from the alignment methods (same for the end points).

4 EXPERIMENTS

We validate SS-DTW and TCD quantitatively using a public dataset UTKinect (Xia et al., 2012) and also qualitatively using data captured by the Kinect v2 sensor.

4.1 Quantitative Evaluation

The UTKinect dataset consists of 10 actions performed by 10 subjects. We select an action from the dataset to be the template action $\hat{M}$ (*e.g.* wave hands). An action to be aligned M is generated by concatenating random actions from the dataset before and after the action of interest, which is divided in 3 subsequences with different lengths as described before.

According to Table 1 and Table 2, both methods have better results when detecting the start point of the performed action, and also, the more information existing in the performed action (the greater the length of the introduced subsequence), the better the results. The accuracy and the outlier rate for both methods are very similar. Considering that TCD requires more computational effort and posterior alignment using standard DTW, SS-DTW is recommended in the case where the computational time is an important factor. Comparing the runtime of each method, the SS-DTW achieves faster results than TCD, where the time for SS-DTW is on average 0.021s and for TCD is 0.073s.

Table 1: Accuracy and outlier rate of the start point using SS-DTW and TCD for the 3 different lengths of the alignment. In this evaluation, we used $\varepsilon = 6$ frames. All reported accuracies are computed using (6) and provided in %.

	M_I^{L}		$M_I^{L'}$		$M_I^{L''}$	
	Accuracy	Outliers	Accuracy	Outliers	Accuracy	Outliers
SS-DTW	91.58	31.43	85.35	24.29	79.27	20.00
TCD	90.13	30.00	80.64	33.57	75.58	55.00

Table 2: Accuracy and outlier rate of the end point using SS-DTW and TCD for the same experiments as in Table 1.

	M_I^{L}		$M_I^{L'}$		$M_I^{L''}$	
	Accuracy	Outliers	Accuracy	Outliers	Accuracy	Outliers
SS-DTW	80.77	42.14	81.91	25.71	67.97	25.00
TCD	82.21	45.71	82.58	30.71	84.47	45.00

Given an optimal alignment between the template action $\hat{M}$ and the performed action M, feedback proposals are provided for each instance and they are presented in the form of visual arrows and also as human interpretable messages. The feedback proposals are achieved by reproducing the method presented in (Antunes et al., 2016b). Figure 5 shows an example of the alignment and the feedback proposals. The first row (blue) is the template action $\hat{M}$ (wave hands), the second row (green) is the generated action M and the aligned subsequence $\{S_s : S_e\}$ of M is represented by the red rectangle. In addition, for each instance, feedback proposals are provided to the highlighted body parts (red) that need to be improved in order to match the template action at the corresponding instance.

4.2 Qualitative Evaluation

The data was captured using the Kinect v2 sensor (example of the captured data is shown in Figure 7(a)). The main idea of this dataset is to simulate a specific

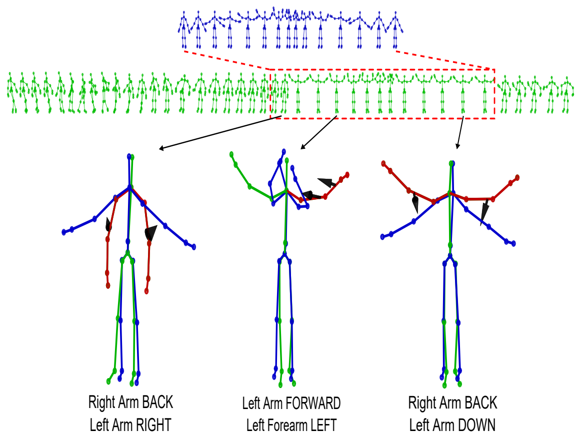


Figure 5: The first row represents the template action $\hat{M}$ (blue), the second row (green) is the generated action M and the subsequence $\{S_s : S_e\}$ inside the red rectangle is the result from SS-DTW. Then, feedback proposals are presented for the body parts that need to be improved to best match the template action for that instance. These body parts are colored in red to help the user to understand which body part he should move following the arrows and the text messages.

scenario considering post-stroke patients with the objective of helping the patients in such a way that they keep to regularly practice the proposed movements. In order to simulate the difficulty in the movements of a post-stroke patient, we use a *"bosu"* balance ball to introduce the problem of the body balance and also used a *kettle-bell* to simulate possible arm paralysis. Figure 6 illustrates the equipment used to simulate the post-stroke patient. The scenario consists of the following: first, a template action is shown; then, the patient tries to reproduce the same action after a starting sign and within a fixed time (refer to Figure 7(a)).

Given two sequences, a template action $\hat{M}$ and a simulated post-stroke patient action M, we applied both methods (SS-DTW and TCD) and then computed feedback proposals in order to support the patient to improve and correct the action. Note that, the template action can be a video created by a physiotherapist with a specific movement, then the patient can understand, practice and improve the movement by following the feedback proposals. This can be seen as a motivation for the patient to maintain the continuity of the rehabilitation at home. Figure 7 shows the results of the temporal alignment methods (SS-DTW and TCD) and the feedback proposals are provided to correct the user.

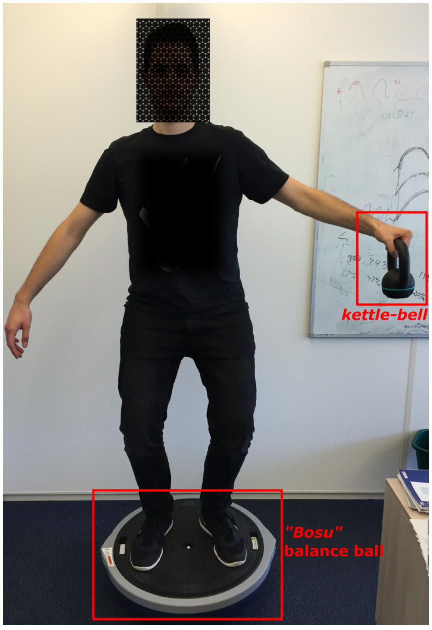


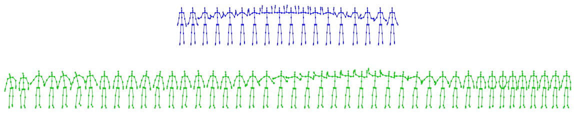
Figure 6: Simulation of a post-stroke patient. The balance problem is simulated by using a *"bosu"* balance ball and to simulate the problem related to the arm paralysis, a *kettle-bell* is used.

5 CONCLUSION

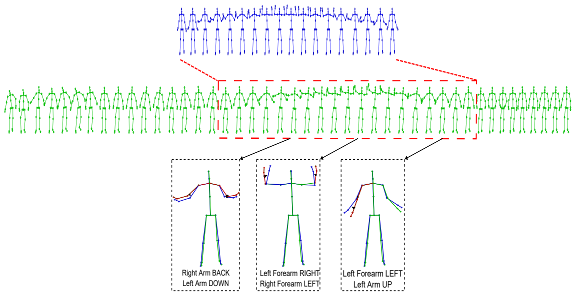
In this paper, we propose a system to guide a user in how to correctly perform a specific movement. This is achieved by applying appropriate temporal alignment methods, namely, SS-DTW and TCD, and then using the feedback system of (Antunes et al., 2016b). Both of these methods can leverage the "static" physical activity assistance system proposed in (Antunes et al., 2016b).

The accuracy and the outlier rate of SS-DTW and TCD, as can be seen in Table 1 and Table 2, are very similar. Since TCD involves complex computations, such as the representation of the skeleton information in a new descriptor space, and also requires the posterior alignment using standard DTW, we recommend the use of SS-DTW in the case where the computational time is an important factor.

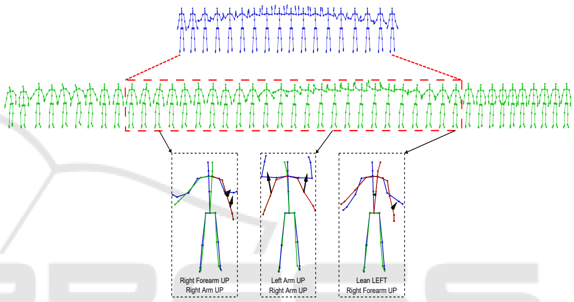
Nevertheless, both methods were not specifically designed for working in an online manner. This means that every time that a new frame is captured, the complete pipeline needs to be run again. An appropriate approach that iteratively rejects irrelevant data would certainly increase the efficiency of the temporal alignment.



(a) Proposed scenario.



(b) Alignment from SS-DTW.



(c) Discovered interval from TCD and then DTW alignment with the template action.

Figure 7: Temporal alignment using SS-DTW and TCD, and computed feedback proposals. The template action $\hat{\mathsf{M}}$ is the top sequence (blue) of each sub-figure, and the bottom sequence (green) is the performed action M. The interval retrieved from both methods ($\{\mathsf{S}_s : \mathsf{S}_e\}$) is represented by the red rectangle. Feedback proposals are shown for the same instance for both methods in order to correct the position with respect to the template action.

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REFERENCES

Antunes, M., Aouada, D., and Ottersten, B. (2016a). A revisit to human action recognition from depth sequences: Guided svm-sampling for joint selection.

In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1–8.

Antunes, M., Baptista, R., Demisse, G., Aouada, D., and Ottersten, B. (2016b). Visual and human-interpretable feedback for assisting physical activity. In *European Conference on Computer Vision (ECCV) Workshop on Assistive Computer Vision and Robotics Amsterdam,*.

Burke, J. W., McNeill, M., Charles, D., Morrow, P., Crosbie, J., and McDonough, S. (2009). Serious games for upper limb rehabilitation following stroke. In *Proceedings of the 2009 Conference in Games and Virtual Worlds for Serious Applications*, VS-GAMES '09, pages 103–110, Washington, DC, USA. IEEE Computer Society.

Chaaraoui, A. A., Climent-Pérez, P., and Flórez-Revuelta, F. (2012). A review on vision techniques applied to human behaviour analysis for ambient-assisted living. *Expert Systems with Applications*.

Chu, W.-S., Zhou, F., and De la Torre, F. (2012). Unsupervised temporal commonality discovery. In *ECCV*.

Gupta, A., He, J., Martinez, J., Little, J. J., and Woodham, R. J. (2016). Efficient video-based retrieval of human motion with flexible alignment. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*.

Hondori, H. M., Khademi, M., Dodakian, L., Cramer, S. C., and Lopes, C. V. (2013). A spatial augmented reality rehab system for post-stroke hand rehabilitation. In *MMVR*.

Kato, P. M. (2010). Video Games in Health Care: Closing the Gap. *Review of General Psychology*, 14:113–121.

Kulkarni, K., Evangelidis, G., Cech, J., and Horaud, R. (2015). Continuous action recognition based on sequence alignment. *International Journal of Computer Vision*, 112(1):90–114.

Kwakkel, G., Kollen, B. J., and Krebs, H. I. (2007). Effects of robot-assisted therapy on upper limb recovery after stroke: a systematic review. *Neurorehabilitation and neural repair*.

Langhorne, P., Taylor, G., Murray, G., Dennis, M., Anderson, C., Bautz-Holter, E., Dey, P., Indredavik, B., Mayo, N., Power, M., et al. (2005). Early supported discharge services for stroke patients: a meta-analysis of individual patients' data. *The Lancet*.

Mousavi Hondori, H. and Khademi, M. (2014). A review on technical and clinical impact of microsoft kinect on physical therapy and rehabilitation. *Journal of Medical Engineering*, 2014.

Müller, M. (2007). *Dynamic Time Warping*. Springer.

Ofli, F., Kurillo, G., Obdrzálek, S., Bajcsy, R., Jimison, H. B., and Pavel, M. (2016). Design and evaluation of an interactive exercise coaching system for older adults: Lessons learned. *IEEE J. Biomedical and Health Informatics*.

Pirsiavash, H., Vondrick, C., and Torralba, A. (2014). Assessing the quality of actions. In *Computer Vision–ECCV 2014*, pages 556–571. Springer.

Rakthanmanon, T., Campana, B., Mueen, A., Batista, G., Westover, B., Zhu, Q., Zakaria, J., and Keogh, E. (2012). Searching and mining trillions of time series subsequences under dynamic time warping. In *Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '12, pages 262–270, New York, NY, USA. ACM.

Sucar, L. E., Luis, R., Leder, R., Hernandez, J., and Sanchez, I. (2010). Gesture therapy: a vision-based system for upper extremity stroke rehabilitation. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*.

Sun, F., Norman, I. J., and While, A. E. (2013). Physical activity in older people: a systematic review. *BMC Public Health*.

Tao, L., Paiement, A., Damen, D., Mirmehdi, M., Hannuna, S., Camplani, M., Burghardt, T., and Craddock, I. (2016). A comparative study of pose representation and dynamics modelling for online motion quality assessment. *Computer Vision and Image Understanding*.

Veerbeek, J. M., van Wegen, E., van Peppen, R., van der Wees, P. J., Hendriks, E., Rietberg, M., and Kwakkel, G. (2014). What is the evidence for physical therapy poststroke? a systematic review and meta-analysis. *PloS one*.

Vemulapalli, R., Arrate, F., and Chellappa, R. (2014). Human action recognition by representing 3d skeletons as points in a lie group. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*.

Wang, R., Medioni, G., Winstein, C., and Blanco, C. (2013). Home monitoring musculo-skeletal disorders with a single 3d sensor. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 521–528.

Xia, L., Chen, C., and Aggarwal, J. (2012). View invariant human action recognition using histograms of 3d joints. In *Computer Vision and Pattern Recognition Workshops (CVPRW), 2012 IEEE Computer Society Conference on*, pages 20–27. IEEE.

Zhou, F. and Torre, F. (2009). Canonical time warping for alignment of human behavior. In Bengio, Y., Schuurmans, D., Lafferty, J. D., Williams, C. K. I., and Culotta, A., editors, *Advances in Neural Information Processing Systems 22*, pages 2286–2294. Curran Associates, Inc.

Zhou, H. and Hu, H. (2008). Human motion tracking for rehabilitationa survey. *Biomedical Signal Processing and Control*, 3(1):1–18.