

DYNAMIC TIME WARPING ANALYSIS IN POST-STROKE REHABILITATION

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Abstract

This paper presents the application of the Dynamic Time Warping (DTW) algorithm in the analysis of human functional movements in activities of daily living (ADLs). Dynamic Time Warping was originally developed for automatic speech recognition, though the method has been adopted by several fields of biomechanics. As a part of the post-stroke rehabilitation project COSMOSYS, the aim is to quantify the ADL performances of hemiparetic subjects, hence to be able to track their progress during physiotherapy.

Keywords: dynamic time warping, stroke rehabilitation

Introduction

Dynamic Time Warping in automatic speech recognition is used to measure the similarity of two audio sequences, which may vary in time and speed. The sequences are warped non-linearly in the time dimension to determine the „score” of their similarity independent of certain non-linear variations in pace. The sequences are warped non-linearly in the time dimension to determine the “score” of their similarity independent of certain non-linear variations in pace for various applications of DTW.^{1–6} The rehabilitation of hemiparesis after stroke demanded a comparison method that is able to express the correlation of two data sets. The aim is to evaluate the measured human functional movements also called Activities of Daily Living (ADLs), i.e. to qualify those with a single scalar. The difference of the measured and the reference ADL data sets can be used to evaluate the patients’ performance.

The present approach bridges the gap between the objective sensory information available on normal and pathological human movements on one side and the subjective qualitative evaluation of these motions by the skilled professional in the form of performance scales on the other side. While the latter have already been standardized among clinical professionals, the error of human motion cognition by objective evaluation is still remarkable: evaluation of human movements may differ due to the imperfection of human cognitive capabilities, or simply from training, practice, institution, location and nationality of the clinical professional. The error can be radically reduced by the proposed co-iterative analytical-statistical method. Feeding of the DTW metrics into the robot controller makes the robot driven physiotherapy biomedically determined. In present approach the DTW metrics have been produced from measurements by 3D motion analyser whereas the robot can measure the same parameters from their integrated sensors: the motor encoders.

ADL Measurements

The ADLs to be measured on both healthy and post-stroke patients were selected by therapists of the Hungarian National Institute for Medical Rehabilitation, and the Singaporean Tan Tock Seng Hospital.

These ADLs are the following:

- picking up a phone from the table and placing it back;
- picking up a mug by its handle, moving it to the mouth and placing it back onto the table;
- opening and closing a window by its handle;
- picking up a towel, moving it to the face and placing it back;
- doing and undoing a zipper on a vest.

Measurement Device

The motion capture device, shown in *Figure 1*, consists of the Smartsuit and the Smartglove, developed in Nanyang Technological University, Singapore. Smartsuit is an IMU (Inertial Measurement Unit) based motion analyser for measuring upper arm and lower arm orientations. Smartglove acquires finger flexion-

extension and palm orientation, by using optical encoders and an IMU. Finger flexion-extension data were excluded in the data mining analysis.

The pose of the hand is described by the feature vector $\mathbf{f}$, that is

$$\mathbf{f} = (\alpha_s, \beta_s, \gamma_s, \beta_e, \alpha_w, \beta_w, \gamma_w)^T \quad (1)$$

which contains the anatomic angles of the shoulder, elbow and the wrist. The definitions of these anatomic angles were inherited from the “Jack” human simulation software by Siemens PLM. The three IMUs in the Smartsuit and Smartglove provide the spatial orientations (roll, pitch, yaw) directly for the upper arm, lower arm and palm, while anatomic angles can be calculated afterwards. *Figure 2* illustrates the coordinate system and the reference points (S, E and W) on the arm. For a given length of the upper arm (L_{UA}), lower arm (L_{LA}) and palm (L_p), the coordinates of the reference points can be calculated as follows:

$$\mathbf{r}_{SE} = \mathbf{T}_y^{-\beta_s} \mathbf{T}_x^{\alpha_s} \mathbf{T}_z^{-\gamma_s} \mathbf{r}_{SE}^0, \quad (2)$$

$$\mathbf{r}_{SW} = \mathbf{T}_y^{-\beta_s} \mathbf{T}_x^{\alpha_s} \mathbf{T}_z^{-\gamma_s} (\mathbf{T}_y^{-\beta_e} \mathbf{r}_{EW}^0 + \mathbf{r}_{SE}^0), \quad (3)$$

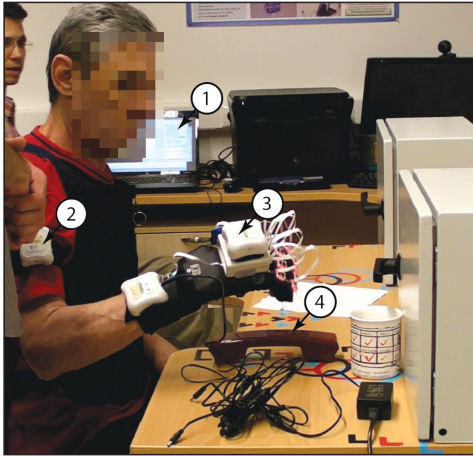


Figure 1. ADL measurement

1: data acquisition software; 2: Smartsuit;
3: Smartglove; 4: ADL items

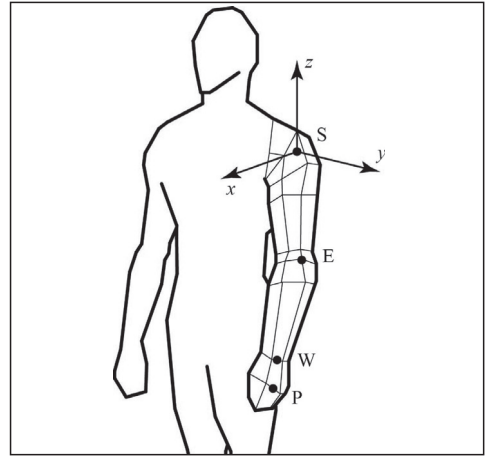


Figure 2. Base coordinate system and reference points on the human arm

$$\mathbf{r}_{SP} = \mathbf{T}_y^{-\beta_s} \mathbf{T}_x^{\alpha_s} \mathbf{T}_z^{-\gamma_s} \left(\mathbf{T}_y^{-\beta_c} \left(\mathbf{T}_z^{-\beta_w} \mathbf{T}_x^{\alpha_w} \mathbf{T}_y^{-\gamma_w} \mathbf{r}_{WP}^0 + \right. \right. \\ \left. \left. + \mathbf{r}_{EW}^0 \right) + \mathbf{r}_{SE}^0 \right) \quad (4)$$

where $\mathbf{r}_{SE}^0 = (0, 0, -L_{UA})^T$, $\mathbf{r}_{EW}^0 = (0, 0, -L_{LA})^T$, $\mathbf{r}_{WP}^0 = (0, 0, -L_p)^T$, with superscript 0 referring to the initial state, and $\mathbf{T}_x^\alpha$, $\mathbf{T}_y^\beta$, $\mathbf{T}_z^\gamma$ are the rotation matrices with superscripts referring to the angle of rotation about the corresponding axes noted in the subscripts.

Dynamic Time Warping

A wide-spread method for computing the similarity between two time series is the Dynamic Time Warping algorithm, which is based on the alignment of significant patterns by locally deforming the time axis (hence the name warping) in order to minimize the cumulative difference between the aligned points. In order to obtain the optimal alignment, local compressions and shifts are achieved, thus, the method is suitable for matching time series containing patterns that are qualitatively similar but have different lengths and paces.¹

Definitions

The inputs of the DTW algorithm are two data sequences, not necessarily containing the same number of samples. Let these sequences be noted by $\mathbf{F}^I = (\mathbf{f}_1^I, \dots, \mathbf{f}_n^I, \dots, \mathbf{f}_n^I)$ and $\mathbf{F}^{II} = (\mathbf{f}_1^{II}, \dots, \mathbf{f}_j^{II}, \dots, \mathbf{f}_m^{II})$, where $\mathbf{f}_i^I, \mathbf{f}_j^{II} \in \mathbb{R}^q$ for $i \in [1, n]$, $j \in [1, m]$ and q is the dimension of the feature space. The outputs are the warping curve (Φ^I, Φ^{II}) and the DTW distance δ , where $\Phi^I = (\phi_1^I, \dots, \phi_k^I, \dots, \phi_K^I)$ and $\Phi^{II} = (\phi_1^{II}, \dots, \phi_k^{II}, \dots, \phi_K^{II})$. These vectors contain the sample indices of $\mathbf{F}^I$ and $\mathbf{F}^{II}$ that should be selected to obtain the optimal fit $(\Phi^I, \Phi^{II} \in \mathbb{Z}^K)$. In order to calculate the warping curve, the constrained minimization problem

$$(\Phi^I, \Phi^{II}) = \arg \min_{\Psi^I, \Psi^{II}} \sum_{k=1}^K D(\mathbf{f}_{\phi_k^I}^I, \mathbf{f}_{\phi_k^{II}}^{II}) \quad (5)$$

should be solved where D is the scalar-valued penalizing function that represents the distance between two feature vectors as detailed in (1). Several different sets of constraints can be found in the literature¹ for the warping curve (Φ^I, Φ^{II}) . In this study, the following set is applied:

– asymmetric start-point constraint: $\phi_1^I = 1$ and/or $\phi_1^{II} = 1$,

– end-point constraint: $\phi_K^I = n$ and $\phi_K^{II} = m$,

– monotonicity: $\phi_{k+1}^I \geq \phi_k^I$ and $\phi_{k+1}^{II} \geq \phi_k^{II}$.

Following the determination of Φ^I, Φ^{II} , the DTW distance δ is calculated as follows:

$$\delta = \sum_{k=1}^K D(\mathbf{f}_{\phi_k^I}^I, \mathbf{f}_{\phi_k^{II}}^{II}). \quad (6)$$

Comparison of Arm Postures, Penalizing Function

The similarity of two samples (i.e. feature spaces) can be quantified by evaluating the penalizing function $D(\mathbf{f}_i^I, \mathbf{f}_j^{II})$. As shown in (1), the feature vector of a sample contains the anatomic angles of the shoulder, elbow and wrist:

$$\mathbf{f}_i^I = (\alpha_{s_i}^I, \beta_{s_i}^I, \gamma_{s_i}^I, \beta_{e_i}^I, \alpha_{w_i}^I, \beta_{w_i}^I, \gamma_{w_i}^I)^T \quad (7)$$

$$\mathbf{f}_j^{II} = (\alpha_{s_j}^{II}, \beta_{s_j}^{II}, \gamma_{s_j}^{II}, \beta_{e_j}^{II}, \alpha_{w_j}^{II}, \beta_{w_j}^{II}, \gamma_{w_j}^{II})^T \quad (8)$$

The penalizing function is defined by

$$D(\mathbf{f}_i^I, \mathbf{f}_j^{II}) = |\mathbf{f}_i^I - \mathbf{f}_j^{II}| + P_v \frac{1}{\tau} (|\mathbf{f}_{i+1}^I - \mathbf{f}_i^I| - \\ - |\mathbf{f}_{j+1}^{II} - \mathbf{f}_j^{II}|) \\ + P_h \left(1 - \frac{\mathbf{f}_i^I \cdot \mathbf{f}_j^{II}}{|\mathbf{f}_i^I| |\mathbf{f}_j^{II}|} \right) \quad (9)$$

where τ is the sampling time, while P_v and P_h are weight parameters of the penalizing function for velocity and angle differences, respectively. The last term for the angle difference

represents $1 - \cos \epsilon$, where ϵ is the angle between the two feature vectors, which calculated by their scalar product.

In most of the automatic speech recognition applications the penalizing function consists only of the angle term, since the amplitude, i.e. the volume of the speech is not considered to increase or decrease the difference between two input sequences. Contrarily, in our case the feature vectors are containing the anatomic angles and/or anatomic positions of the human arm, therefore the Euclidean distances cannot be neglected, moreover, jerky motion (opposite to smoothly performed ADLs) has to be penalized by means of the term for velocities.

Computing the optimal alignment

In the first step, the calculation of the optimal alignment begins with the comparison of each sample $\mathbf{f}_i^I$ to all other samples $\mathbf{f}_j^II$, and the results obtained by the evaluations of the penalizing function are stored in matrix $M_{ij} = D(\mathbf{f}_i^I, \mathbf{f}_j^II)$. Due to the term of the velocity differences, the last samples in each data sets cannot be used in the first and third term of the penalizing function (9), $i \in [1, n-1]$, $j \in [1, m-1]$. Matrix $\mathbf{M}$ is illustrated in Figure 3, in case of the comparison of two healthy subjects performing the same ADL (measured data shown in Figure 5, left column).

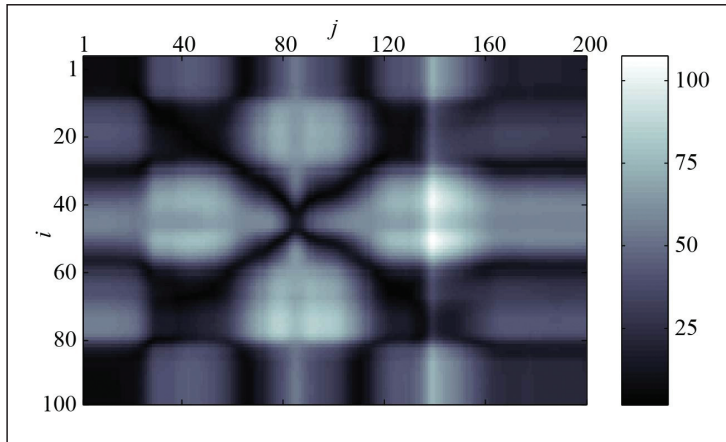


Figure 3.

Illustrating matrix $\mathbf{M}$, for the comparison of data shown in Figure 5, see colorbar on the left for the values of each matrix element

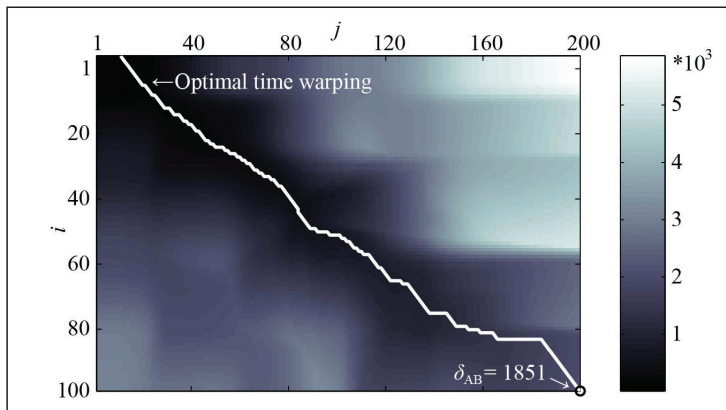


Figure 4.

Illustrating matrix $\mathbf{C}$ and the optimal time warping, in case of the comparison of data shown in Figure 5, see colorbar on the left for the values of each matrix element

Following the calculation of matrix $\mathbf{M}$, the cumulated matrix $\mathbf{C}$ should be determined. Each element C_{ij} of matrix $\mathbf{C}$ represents the least possible sum of those elements of $\mathbf{M}$, on which a step is taken when considering all the steps along the possible paths that connect elements M_{11} and M_{ij} fulfilling all the constraints listed in 3.1 including the monotonicity one (see Figure 4). The bottom right corner element of $\mathbf{C}$ defines the DTW distance δ .

Results

Comparison of ADL Performances

Figure 5 and 6 illustrate the results of two DTW analyses. In Figure 5 the comparison of two healthy subjects (person A solid line and person B dashed line) is shown; both subjects are performing the same ADL, opening and closing a window. As it can be seen from the

original measurement data (shown in the left column), there is a significant difference in the paces of the functional movements. Person A finishes in cca. 5 seconds, while person B needs cca. 10 seconds to complete the movement. The right column of the figure presents the aligned, that is the warped data in case of the optimal alignment (for penalizing parameters $P_v=25$ and $P_h=10$, the resulted DTW distance is $\delta_{AB}=1851$).

The comparison of a healthy (person A, solid line, same as in Figure 5) and a stroke affected (person C, dashed line) subject's ADL performances is shown in Figure 6. Though person C completes the function movement within roughly the time as person B, the DTW difference between A and C is significantly greater ($\delta_{AC}=3923$) than between A and B, hence this difference is induced by the variance in the measured anatomic angles (note that $\delta_{BC}=2661$).

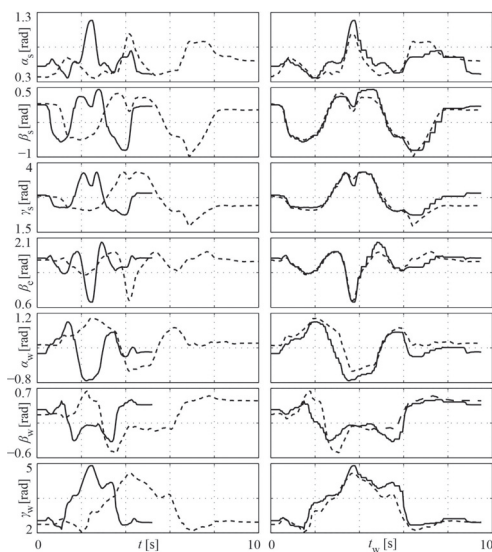


Figure 5. Comparison of two healthy ADL performances, person A solid line and person B dashed line, $\delta_{AB}=1851$

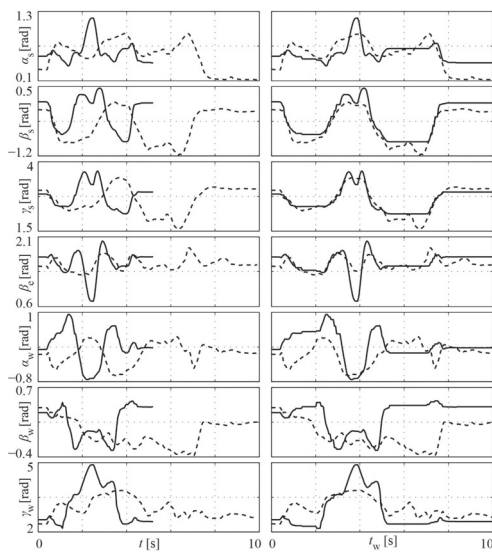


Figure 6. Comparison of a healthy and a stroke affected ADL performance, person A solid line and person C dashed line, $\delta_{AC}=3923$

Multidimensional Scaling Method

Following the determination of the DTW distances for all possible dataset-pairs, multidimensional scaling (MDS) is a commonly used method for visualizing the level of similarity of individual cases.⁷ In this study, classical MDS method⁸ is used. For a given distance matrix **D** that contains the pairwise differences of individual objects, MDS algorithm aims to place each object in an *N*-dimensional space such

that the between-object distances are preserved as well as possible. Therefore, the difference matrix does not need to be an Euclidean distance matrix.

Scatter Plots of ADL Measurements

Since the DTW algorithm can produce such pairwise distances, that does not even obey the triangle inequality, MDS method is needed to optimize object locations for a two-dimension-

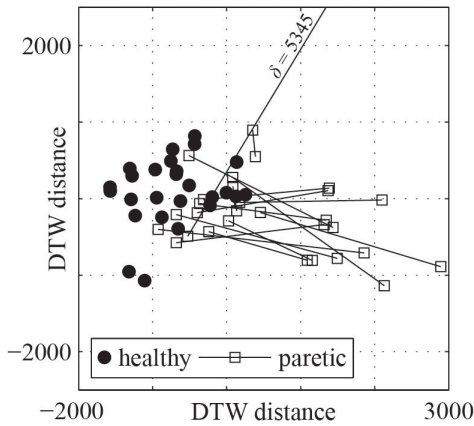


Figure 7. Scatter plot of ADL 1 performances (picking up a mug)

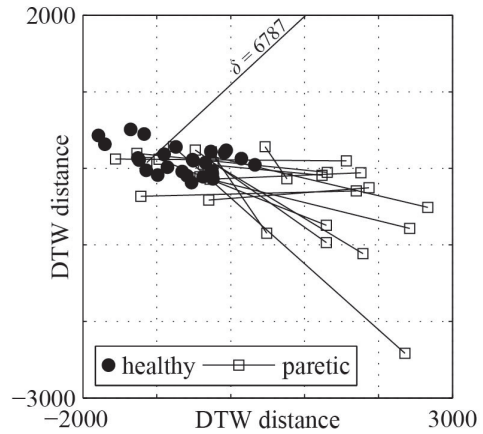


Figure 8. Scatter plot of ADL 2 performances (picking up a phone)

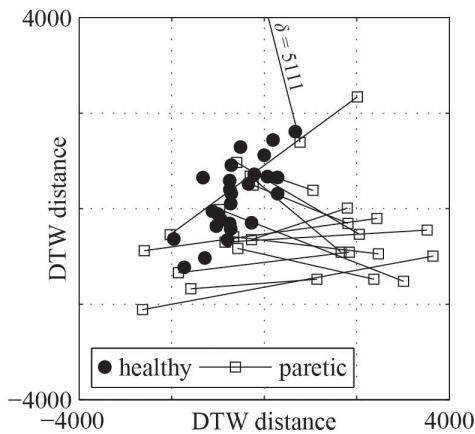


Figure 9. Scatter plot of ADL 3 performances (picking up a towel)

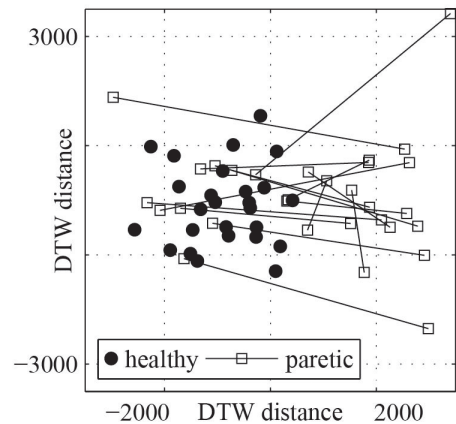


Figure 10. Scatter plot of ADL 4 performances (opening and closing a window)

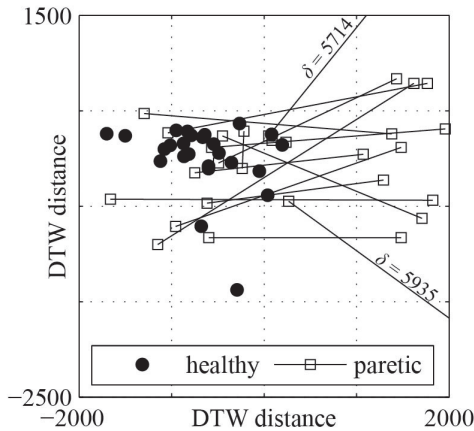


Figure 11. Scatter plot of ADL 5 performances (doing and undoing a zipper)

al scatter plot. These scatter plots are presented for all the 5 ADLs in Figures 7–11. In these figures solid discs represent healthy subjects, and squares represent the hemiparetic subjects, solid lines connect left and right hands of each stroke affected patient. By tuning P_v

and P_h parameters in the penalizing function (9), two clusters had been evolved in the scatter plots. One contains the performances regarding both arms of healthy subjects and the non-paretic arm of hemiparetic subjects, and the other cluster is built up by the paretic arms of the stroke affected subjects.

Conclusions

According to the presented results, the performance of a post-stroke patient can be quantified as its distance from the cluster consisting of the reference ADL performances, i.e. the rehabilitation progress can be tracked by an objective, sensory based scale, lacking the possible errors due to human motion cognition. Due to the authors' expectations, in the future standardized clinic scales, such as Fugl-Meyer, Asworth, Barthel, can be aided by DTW metrics. In order to achieve a good correlation with clinic scales, further evaluations are needed involving clinical professionals.

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