BACHELOR THESIS PROPOSAL

Comparing and Optimizing Geometric Distance Measures for Human-Motion Tracking

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2 Topic/Motivation

The advent of virtual reality (VR) motion capture technology has led to an increased interest in automated feedback systems for human motion. In this context, Felix Hülsmann et al. developed a pipeline that provides real-time feedback for sports coaching in VR [Hül+18]. The work of these researchers builds upon existing coaching systems, which either provide a rudimentary assessment of the performed motion or generate feedback, by combining the two to generate verbal as well as augmented visual feedback. This system's versatility makes it an especially interesting case, as it can be readily adapted to accommodate a wide range of human motions.
While the pipeline managed to achieve higher accuracy than KNN-DTW and a modern neural-network-based approach, we aim to optimize its accuracy and efficiency. A crucial part of this pipeline is the utilization of Dynamic Time Warping (DTW) in order to align input vectors (i.e., skeleton data from a motion capture system) with the requisite temporal frame as defined by the support vector machine (SVM), which is employed for the purpose of classification. It should be noted that input vectors must be of a fixed size in order for the SVM to function optimally.
This thesis will examine the comparison and optimization of several DTW variants and other algorithms for the alignment of time series, including the Frechet distance based on the aforementioned pipeline. Additionally, several distance functions will be explored and evaluated with regard to their accuracy in classifying the movement data. To assess the efficacy of these variations, we will compare our implementations with those presented in Hülsmann's paper, as well as the reference implementations utilized by Hülsmann to assess the performance of his pipeline. Furthermore, we will analyze the algorithms with regard to time and space complexity.

3 Current state of research

This thesis directly builds on the pipeline developed by Hülsmann et al. [Hül+18, **page** 49]:

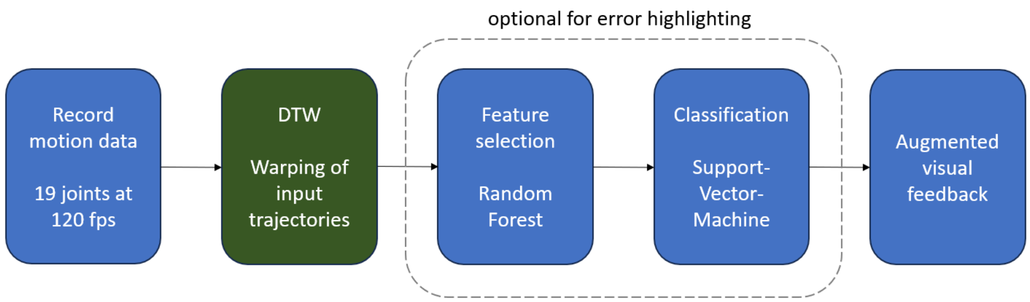

Figure 1: Hülsmann et al's feedback pipeline

As shown in fig. 1 the pipeline starts by recording motion data at 120 Hz for 19 joints where for each frame the rotation and position of each joint is recorded. In the second step, Dynamic Time Warping is employed to align each frame of the data to be analyzed to a reference trajectory of fixed time frame. Next, Random Forests are used to filter out irrelevant features, such as wrist rotations in the context of a back exercise. Finally, a Support Vector Machine is employed to classify the motion data and provide the basis for the visual augmented feedback, which essentially highlights the faulty areas on the trainee's body.

In his conclusion, Hülsmann remarked that for augmented feedback, classification is not always necessary [Hül+18, **page** 57]. Guiding the attention of a trainee to the body part, relating to the error only requires the first part of the pipeline, the temporal warping. For this purpose there are a lot of algorithms that will be explored in this thesis.

3.1 Dynamic Time Warping

Dynamic Time Warping (DTW) is an algorithm used in the analysis of time series to measure the similarity between two time series $X = x_1, x_2, \ldots, x_n$ and $Y = y_1, y_2, \ldots, y_n$ that may vary in time or speed [Sen08]. It uses dynamic programming to calculate the distance between two matching points

(x_i, y_j), aiming to minimize the overall alignment cost, calculated by a predetermined distance function $d(x_i, y_j)$.

Algorithmus 1 DTW(v_1, v_2) [Fon12]

Eingabe: Time series $v_1 = (a_1, \ldots, a_n)$ and $v_2 = (b_1, \ldots, b_n)$
Ausgabe: $n \times m$ matrix S storing the similarity measure (überarbeiten)

$S[0,0] \leftarrow 0$
for i $\leftarrow$ 1 to m **do**
  $S[0,i] \leftarrow \infty$
end for
for i $\leftarrow$ 1 to n **do**
  $S[i,0] \leftarrow \infty$
end for
for i $\leftarrow$ 1 to n **do**
  for i $\leftarrow$ 1 to n **do**
    $cost = d(v_1[i], v_2[i])$
    S[i][j] $= cost + \text{MIN}(S[i-1,j], S[i,j-1], S[i-1,j-1])$
  end for
end for
return $S[n,m]$

The algorithm has a space- and time-complexity of $\mathcal{O}(N \cdot M)$. The resulting alignment of the amplitudes x_i and y_i and their corresponding timestamps t_i and t_j can be calculated by iterating the path from $S[M][N]$ to $S[0][0]$. In each iteration, the offsets $(-1,0)$, $(0,-1)$ or $(-1,-1)$ are evaluated, and the path with the lowest cost is selected. Since the mapping of the indices of both sequences is monotonically increasing, the time complexity of the alignment is $\mathcal{O}(M+N)$.

K-Nearest-Neighbors-DTW K-Nearest-Neighbors (KNN) is an algorithm which finds the k nearest data points for a query input based on a predetermined distance measure. KNN-DTW employs DTW distance to calculate the similarity between two time series. Once the DTW distance has been calculated between the query time series and all other time series in the dataset, the algorithm identifies the k-nearest neighbors based on the smallest DTW distances [MOC18].

Sliding-Window DTW As opposed to classic DTW, Sliding-Window DTW does not compare the entire sequences at once, but breaks the time interval into small segments or windows and applies DTW separately on these windows. This approach can significantly accelerate the computation of DTW on large time series because the many small time intervals are less costly than one large interval due to the quadratic time complexity [Tan+22].

3.2 Other algorithms

- Frechét-distance [EM94]
- ANN-Frechét distance [DP21]
- Multiscale DTW [Dil+20]
- Edit distance, LCSS [**doi:10.1080/13658816.2016.1199806**]
- several distance-functions [**doi:10.1080/15481603.2021.1908927**]
- Cross-correlation, FFT [**doi:10.1080/13658816.2016.1199806**]
- Other input data:
    1. Coordinates
    2. Euler-angle
    3. velocity-vectors

4 Methodology and Approach

In this thesis we are going to examine two principal approaches. At first, we are going to work with the entire pipeline, isolating the alignment. In this case we will explore different DTW variants, mentioned in section 3. The algorithms will be implemented in C++ and incorporated into the pipeline so that their efficacy can be evaluated by comparing the accuracy scores of the algorithms to those provided in Hülsmann's paper. The second approach entails only examining the first part of the pipeline, the temporal warping, for cases where the trainee only needs to be made aware of the joints of the erroneous movement. In this case DTW, Frechét-distance and Edit-distance can be used to calculate the deviation of the sample trajectory and

the reference trajectory and visual feedback can be provided without the need of classifiers.
In both approaches we are going to explore several distance functions for x,y,z-coordinates, velocity-vectors and Euler-angles, retrieved from the .bvh files. In a final step, time and space consumption are going to be compared using Google Benchmark.

5 Timeline

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