BACHELOR THESIS PROPOSAL

Comparing and Optimizing Geometric Distance Measures for Human-Motion Tracking

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Contents

1 Title

Comparing and Optimizing Geometric Distance Measures for Human-Motion Tracking

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 K-Nearest-Neighbors and a modern neural-network-based approach, we aim to investigate diverse geometric distance measures to identify their influence on both performance and accuracy. 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) [CR08], 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 Frechét distance based on motion capture data, recorded for 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 differences of these variations, each input trajectory, which is labelled with the occurring error pattern, will be matched to the reference trajectories recorded by experts. Subsequently, the performance of these algorithms in the detection of these error patterns will be evaluated. Furthermore, we will analyze the algorithms with regard to time and space complexity.

3 Current state of research

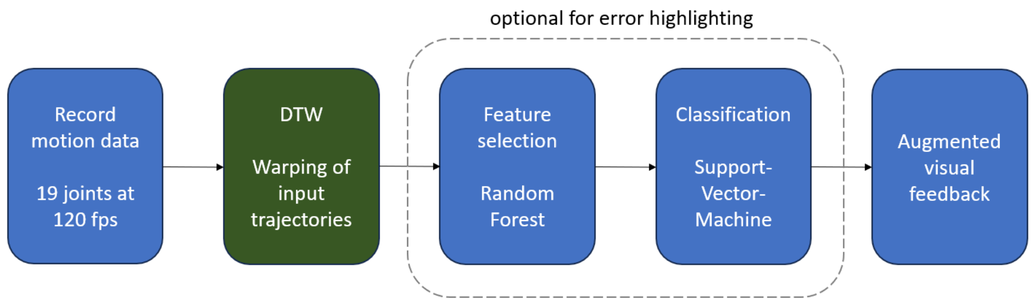


Figure 1: Hülsmann et al.'s feedback pipeline

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, p. 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 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 pre-determined distance function $d(x_i, y_j)$.

Algorithm 1 DTW(X, Y) [Fon12]

Require: Time series $X = (x_1, \ldots, x_n)$ and $Y = (y_1, \ldots, y_n)$
Ensure: $n \times m$ matrix S storing the similarity measure

```
S[0,0] ← 0
for i ← 1 to m do
  S[0,i] ← ∞
end for
for i ← 1 to n do
  S[i,0] ← ∞
end for
for i ← 1 to n do
  for i ← 1 to n do
    cost = d(x_i, y_i)
    S[i][j] = cost + 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 Geometric Distance Measures and Input Variation

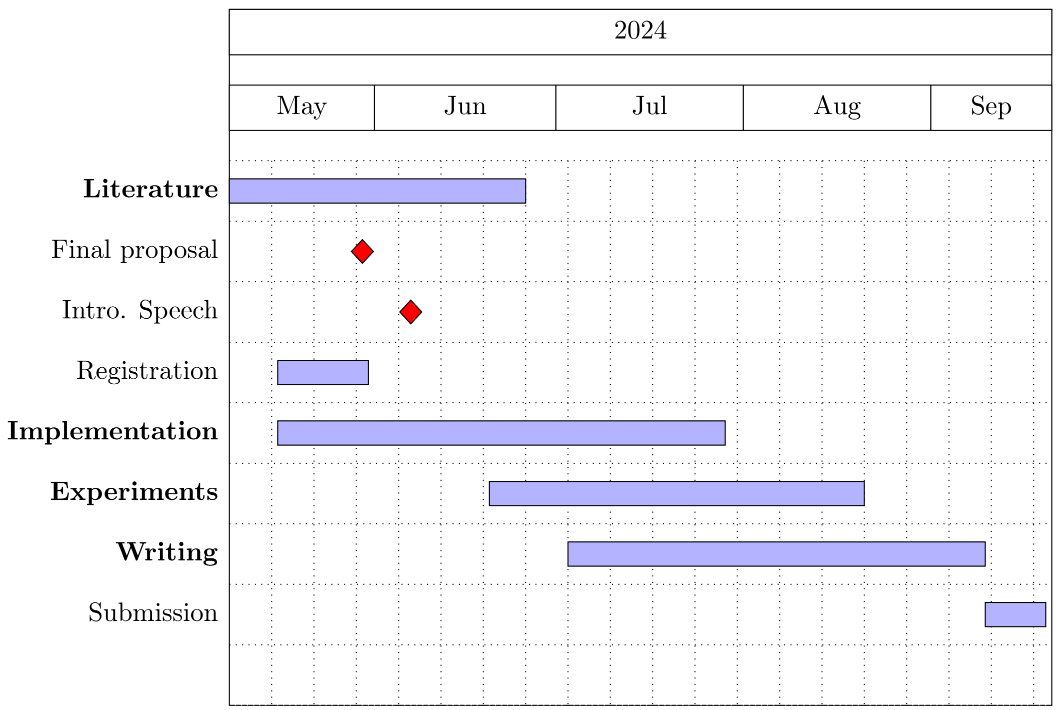
- Frechét-distance [EM94], discrete partial Frechét distance [HW07]
- Locally correct Fréchet matchings [Buc+19]
- Lexicographic Fréchet matchings [Rot14]
- Multiscale DTW [Dil+20]
- Edit distance, ED on real sequences, Time-Warp-ED, LCSS [Max17]
- several distance-functions [Yag21]
- Cross-correlation, FFT [Max17]
- Other input data:
  1. Coordinates
  2. Euler-angle
  3. Velocity-vectors ("temporal information could be included via adding velocity as well as information on the warping function extracted from DTW" [Hül+18, p. 57])

4 Methodology and Approach

In this thesis we are going to work with the motion data from the ICSPACE motion files used in Hülsmanns pipeline. Each row in the motion data represents a single frame of motion capture with relevant components such as timestamp, root translation, joint rotations, joint translations and meta data. The metadata includes information on the occurrence of select error patterns like "feet-distance-not-sufficient" with confidence parameters. We are going to align the input squats to the reference squats and examine the labels for each frame to see where and how the input deviates from the

reference. In this context, the extraction of joint translations, represented as absolute positions in the x, y, z-coordinates from the root joint, and angles, represented as quaternions (w, x, y, z) relative to the hierarchy, or both, from the motion files depends on the algorithm. The objective of this study is to investigate the extent to which the choice of algorithms, input type, and distance functions influence the quality of error pattern classification. To enhance the comparison, we will incorporate all reference squats and apply k-NN based on the alignment cost from each algorithm.
The algorithms will be implemented in C++ and time and space consumption are going to be compared using Google Benchmark [Goo24].

5 Timeline



Milestones

Nr.	Milestone	Deadline
1	Finalize proposal	29.05.2024
2	Introductory speech	06.06.2024
3	Registration	16.-30.05.2024
4	Final speech and submission	16.-30.09.2024

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