An Evaluation of DTW Approaches for Whole-of-Body Gesture Recognition

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This paper systematically explores the capabilities of different forms of Dynamic Time Warping (DTW) algorithms and their parameter configurations in recognising whole-of-body gestures. The standard DTW (SDTW) (Sakoe and Chiba 1978), globally feature weighted DTW (Reyes et al. 2011) and locally feature weighted DTW (Arici et al. 2013) algorithms are particularly considered, while an enhanced version of the globally feature weighted DTW (EDTW) algorithm is presented. A wide range of configurable parameters: distance measures (Euclidean and Mahalanobis), combination of features (Cartesian velocity, angular velocity and acceleration), combinations of skeletal elements, reference signal count and k-nearest neighbour count are tested in order to understand the impact on final recognition accuracies. The study is conducted by collecting gesturing data from 10 participants for 9 different whole-of-body gesture commands. The results suggest that the proposed enhanced version of the globally feature weighted DTW algorithm performs significantly better than the other DTW algorithms. Given sufficient training data this study suggests that the Mahalanobis distance has the capability to better differentiate certain gestures compared to the Euclidean distance. Out of the features, Cartesian velocity combined with angular velocity provides the highest gesture discriminant capability while acceleration provides the lowest. When highly informative and stable skeletal elements are selected, the overall performance gain obtained by adding extra skeletal data is marginal. Also the recognition accuracies are sensitive to the reference signal count and the KNN percentage. Additionally, the presented results summarise the unique capabilities of certain configurations over others, highlighting the importance of selecting the appropriate DTW algorithm and its configurations to achieve optimal gesture recognition performances.

Whole-of-Body Gestures, Dynamic Time Warping, Spatio-Temporal Pattern Recognition

1. INTRODUCTION

Throughout the years, the keyboard and mouse have been the two main input modalities for human and machine interaction. However, a considerable amount of work has been conducted to seek for less intrusive input modalities (Bolt 1980; Krueger et al. 1985), either to replace the traditional input devices or to enhance the naturalness in human computer interaction. Gesture-based interaction is one such area of research that provides significant contributions towards the development of HCI. These goals include, efficiency (command and arguments could specify in the same movement), natural in communication, easy to learn, terse and powerful, direct and collaborative interaction, many interactive applications and novel tools (Wolf and Morrel-Samuels 1987; Baudel and Beaudouin-Lafon 1993; Schlenzig et al. 1994). However, to achieve such goals many inherent challenges need to be overcome. Finding a less intrusive gesture library (De Silva et al. 2013; Wobbrock et al. 2009; Ruiz et al. 2011; Obaid et al. 2012), handling spatial-temporal variability (Raytchev et al. 2000), differentiating between intentional and unintentional gestures (gesture spotting) (Lee and Kim 1999), and assigning correct gesture labels (gesture classification) (Alon et al. 2009) are considered as the major challenges in the field.

Many pattern recognition algorithms have been successfully used in gesture classification. Most of these algorithms are borrowed from speech recognition research due to the commonalities shared between the two disciplines. Hidden Markov Model (HMM) (Rabiner 1989), Dynamic Time Warping (DTW) (Sakoe and Chiba 1978) and Conditional Random Fields (CRF) (Wang et al. 2006) are a few of the widely used techniques that have been successfully employed in recognising
human gestures. To the best of our knowledge, most of the current studies only focus on recognising either one handed or two handed gestures. We believe that enabling whole-of-body gestures in Human Computer Interaction (HCI) makes the operating environment more natural and intuitive compared to the constrained single or two handed interaction. Hence, this study systematically explores the capabilities of the currently dominant pattern recognition algorithm for gesture recognition: DTW and its variations, in recognising whole-of-body gestures.

To summarise our approach: In order to explore the recognition accuracies of whole-of-body gestures using DTW algorithms and its variations, we have selected the gestures proposed by De Silva et al. (2013) for controlling an avatar in a 3D virtual environment (most of the publicly available libraries contain hand gesture data). The proposed gestures were elicited based on the results of a user-centric design experiment and an independent user evaluation conducted to test their acceptance. Having selected the gesture library for the experiments, real time gesture data are captured using a vision based technology and Inertial Measurement Units (IMUs). Thereafter, gesture signals are analysed and segmented to extract the meaningful/intended gestures. Subsequently, the filtered gesture data are represented as a function of Cartesian velocity, angular velocity and acceleration of different skeletal elements (head, arms, legs, etc.). To understand the impact of selecting different skeletal elements in recognising gestures, we have chosen three distinct body configurations. Further the recognition accuracies were calculated for the Standard DTW (SDTW) (Sakoe and Chiba 1978), Globally Feature Weighted DTW (GDTW) (Reyes et al. 2011), Enhanced GDTW (EDTW - proposed here) and Locally Feature Weighted DTW (LDTW) (Arici et al. 2013) algorithms by considering different number of reference signals and K-nearest neighbours in order to evaluate DTW algorithms in recognising whole-of-body gestures. EDTW is an algorithm we have proposed by modifying the weight calculation scheme of GDTW of Reyes et al. so as to achieve better performance. Further, to study the effect of different similarity measurements used in DTW for recognising gestures, Euclidean distance and Mahalanobis distance (Mahalanobis 1936) matrices were considered under the experimental setup.

The rest of the paper is organised as follows: First, work related to gesture recognition is presented. Thereafter, the experimental setup used to capture the real time gesture data is explained. Then a brief introduction to the configurable parameters is given in terms of features, skeletal elements, pattern recognition algorithms, reference signals and nearest neighbour count. Finally, the results and the findings are summarised in order to present the performance of DTW algorithms and their capabilities in recognising whole-of-body gestures.

2. RELATED WORK

Numerous pattern recognition algorithms such as Hidden Markov model (HMM) (Rabiner 1989), Dynamic Time Warping (DTW) (Sakoe and Chiba 1978) and Conditional Random Fields (CRF) (Wang et al. 2006) have been studied to explore the capabilities of recognising human gestures (Lee and Kim 1999; Reyes et al. 2011; Arici et al. 2013). HMM is one such generative model that has been widely used in learning gesture sequences. Despite its applicability, it is often criticised for many reasons. The amount of training data required to learn the model parameters, the difficulties in deciding the model architecture and conditional independence assumption made for the observations are the main criticisms that are prominent in the literature (Wobbrock et al. 2007; Arici et al. 2013; Carmona and Climent 2012; Wang et al. 2006). On the other hand, due to the use of exponential distribution in modelling time series data, CRF avoids the independence assumption made in HMM (Wang et al. 2006). However, as it is a discriminative model the output will not include sufficient information to determine the likelihood of the overall outcome (Wang et al. 2006).

DTW - a time-normalization algorithm based on dynamic programming by Sakoe and Chiba (1978) for spoken word recognition, has been widely used in gesture recognition due to the similarities shared between the two domains Corradini (2001); Reyes et al. (2011); Arici et al. (2013). In Reyes et al. (2011) a novel feature weighting mechanism is proposed as a similarity measurement in DTW based on inter-intra class variability to recognise gestures in real time. Five different gestures: jumping, bending, clapping, greeting and noting with the hand were considered and the relevant data were collected using Microsoft Kinect. However, apart from jumping and bending, all the gestures were either single or two handed gestures. In contrast, the gesture library considered in this study (Figure 1) is larger and more challenging in terms of gesture dynamics and skeletal elements involved. In their study, feature weights were calculated per skeletal element by considering their discriminatory capabilities. In order to calculate these feature weights, a symmetric cost matrix was created for each skeletal element and the average DTW distances were measured for all possible pairs of gesture classes using the reference
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3. EXPERIMENTAL SETUP

3.1. Apparatus

We have used the Micosoft Kinect (Shotton et al. 2013) and APDM wireless inertial measurement units (IMU) (El-Gohary et al. 2011) to obtain the kinematic data of gestures. The Microsoft Kinect outputs the 3D positional information of skeletal elements. The IMUs output the acceleration and orientation data calculated using in-built accelerometer, gyroscope and magnetometer sensors. Figure 2 represents the skeletal elements tracked by the Kinect, the locations the IMU sensors are mounted, and the experimental environment.

3.2. Participants and Data acquisition

Real time gesture data was captured from 10 voluntary participants (5 males and 5 females) whose ages were between 20 and 40. 3 repetitions of the nine individual gestures were performed by each participant, which resulted in 30 recordings per gesture class (a total of 270 recording for the 9 different gesture classes). Each repetition was followed by a 3 second pause to make the segmentation task easier. After capturing the data, gravitational force was removed from the accelerometer data by rotating them to align with North, Up and West reference frame using the Quaternion information available on IMU sensors.

4. CONFIGURABLE PARAMETERS

4.1. Kinematic Features

Campbell et al. (1996) investigated invariant features for hand-arm gesture recognition. The raw position \((x,y,z)\), the Cartesian velocity \((dx,dy,dz)\), the polar velocity with angular velocity term \((dr, d\theta, dz)\) and the instantaneous speed \((ds)\) with local curvature \((\rho)\) were explored. The best overall performance was achieved utilising the polar velocity with angular velocity term, followed by the Cartesian velocity.
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Similarly, we have calculated the Cartesian velocity \((dx, dy, dz)\) relative to a world-centered coordinate system fixed to the Kinect and the angular velocities \((d\phi, d\theta)\) based on the change in azimuth \((\theta)\) and polar \((\phi)\) angles relative to a body-centred (hip centre) coordinate system as given in Figure 3. Additionally, three dimensional accelerometer data calculated by the IMU sensors was used in conjunction with the velocity features for the performance analysis.

4.2. Skeletal Elements

In order to understand the benefit of extra information obtained from different skeletal features, three different configurations were examined. Under the core configuration of 5 joints, the Kinect and accelerometer data from the head, wrists (left and right), and ankles (left and right) were considered. Thereafter, a more compact and centrally located Kinect data (accelerometer data were not collected due to the resource constraints) from 4 joints, consist of elbows (left and right) and knees (left and right) was tested. Finally, a 9 joints configuration which consists of Kinect data from both 5 and 4 joints configuration was used in the evaluation. The hands and feet were purposely omitted due to the instability in Kinect output.

4.3. Distance Measurements

In a wide range of studies (Reyes et al. 2011; Arici et al. 2013; Corradini 2001)) the Euclidean distance has been used to measure the similarity of an unknown gesture signal to a reference signal. As it measures the straight line distance between two points, it fails to capture the correlations observed in data. In contrast, the Mahalanobis distance is an alternative similarity measurement which considers the statistical relationships present in the data when calculating the distances. Therefore, to test the impact of selecting different distance measurements, recognition accuracies of gestures under the Euclidean distance and Mahalanobis distance are analysed. Equation 1 and equation 2 form the Euclidean \((D_E)\) and Mahalanobis \((D_M)\) distances between two points given reference data \((R)\) and test data \((T)\). The covariance \((C)\) required for the Mahalanobis distance was estimated per class using the data in reference signals (Prekopcsk and Lemire 2012).

\[
D_E(T_i, R_j) = \sqrt{(\vec{T}_i - \vec{R}_j)^T (\vec{T}_i - \vec{R}_j)} \quad (1)
\]

\[
D_M(T_i, R_j) = \sqrt{(\vec{T}_i - \vec{R}_j)^T C^{-1} (\vec{T}_i - \vec{R}_j)} \quad (2)
\]
4.4. Dynamic Time Warping

Table 1 summarises the DTW cost calculation algorithm adopted for whole-of-body gestures. Once the costs are calculated for each reference gesture (r) in all the classes (c), the class of the unknown gesture (t) could be decided by considering the frequency of class labels in the neighbourhood (KNN percentage). Table 2, Table 3 and Table 4 summarise the weight calculation schemes for GDTW, LDTW and EDTW algorithms which are included in the cost calculation formula given in line 5 of Table 1. Here, the measured distances (\(D_{c_i,r,k}(i,j)\)) are weighted (refer line 5 of Table 1) by the calculated global weights (\(globalWeight_{sk}\)) or local weights (\(localWeight_{c_i,k}\)) selected based on the algorithm, reference signal’s class (\(c_i\)) and considered joint (\(k\)).

| 1. for each reference gesture \(r\) in class \(c_i\)  
| 2. for each point \(i\) in reference gesture \(r\)  
| 3. for each point \(j\) in unknown gesture \(t\)  
| 4. for each joint \(k\)  
| \(D_{c_i,r,k}(i,j) = D_x(i,j) + \min\{D_{c_i,r,k}(i-1,j), D_{c_i,r,k}(i,j-1), D_{c_i,r,k}(i-1,j-1)\}\)  
| 6. end  
| 7. end  
| 8. end  
| \(cost(c_i,r) = \sum_{k=1}^{no.of.joints} D_{c_i,r,k}(n,m)\)  
| 10.end  
| \(//n,m\) - length of the reference and test signals  
| \(//D_x\) - distance function given in Equation 1 or Equation 2  
| \(//D_{c_i,r,k}(i,j)\) - distance between the \(j^{th}\) point in test signal and \(i^{th}\) point in reference signal \(r\), belongs to class \(c_i\) and joint \(k\). |

Table 1: SDTW Sakoe and Chiba (1978) adapted for whole-of-body gestures.

In the proposed algorithm (EDTW - Table 4), weights of the joints were determined per gesture class based on the average DTW cost calculated between a class and the other classes (including itself) using the reference signals. The minimum joint weight (\(\beta\)) is a sensitivity parameter between 0.0 and 1.0. The empirically determined \(\beta\) value for the current dataset was set at 0.2.

4.5. References and K-Nearest Neighbour

In order to explore the optimal reference signal count and the nearest neighbour threshold to be used in the model, a series of experiments were conducted. In each experiment, using the 30 recordings obtained for each class, the reference signals used as templates was systematically changed from 1 to 29 and the remaining signals were used as the test signals. Also within each reference signal configuration, KNN percentage has been varied from 10% to 100% (by a step size of 10%) which resulted in \(29 \times 10 = 290\) experiments per joint configuration, feature type and DTW algorithm. As an example 14 references with 50% KNN percentage resulted in the use of 14 reference signals in each class as templates, 16 gesture signals as unknown or test signals and 7 as the KNN count. Further, the data for each reference configuration (1 to 29) were selected from a subset of all Leave-N-Out possibilities in order to manage the required computational power. As a result, 30 random samples were drawn for each reference configuration as it covers all the possibilities in Leave-1-Out configuration.
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Figure 4: Minimum, maximum and average recognition rates over the KNN percentage in both Euclidean and Mahalanobis space for SDTW and Euclidean space for GDTW, LDTW and EDTW algorithms. Mahalanobis space is not considered for GDTW, LDTW and EDTW algorithms as it performed poorly for 3 different activities in SDTW.

Figure 5: Box plots representing the median (red bar), 25% quartile, and 75% quartile, mean (diamond icon), whiskers and outliers (points away from the whiskers) based on the average recognition rates of individual activities in Euclidean and Mahalanobis space using SDTW, GDTW, LDTW and EDTW algorithms under the optimal KNN configuration. The X-axis represents the activities, FWD (Forward Walk), BWD (Backward Walk), CLOCK (Turn Clockwise), COUNTER (Turn Counterclockwise), RUN, PRONE, PICKUP, COMPASS and FREE, while the Y-axis represents the average recognition accuracies.
for each joint k
  for each class c_i
    for each class c_j
      \( D_k(c_i, c_j) = \text{mean}(SDTW(c_i, c_j)) \)
    end
  end
end

// N - number of classes
// \( D_k \) - the average SDTW cost between the reference
// signals in class \( c_i \) and \( c_j \)
// \( \beta \) - a value between 0 and 1 to provide a minimum
// contribution

**Table 4:** EDTW proposed for whole-of-body gestures.

5. RESULTS

Average recognition accuracies were calculated in order to evaluate the performance of DTW algorithm variations under different parameter configurations and the results are presented. Firstly, the performances of the algorithms are presented against the varied KNN percentages. This enables us to subsequently conduct the analysis employing the optimal KNN percentage for each algorithm. As seen in Figure 4, at the 10% of KNN, SDTW (82.0%), GDTW (82.2%) and LDTW (70.7%) in Euclidean space gave the optimal results while at 30% of KNN, EDTW in Euclidean space (87.4%) gave its optimal results. For SDTW in Mahalanobis space (71.6%), increases in KNN percentage resulted in better performances up to the 90% mark.

Figure 5 summarises the average recognition rates per individual activity for different distance measurements and DTW algorithms under their respective optimal KNN percentage found. Given the higher recognition accuracies and lower spread, Mahalanobis distance showed a better capability in differentiating most of the gestures (Mean: 95.5% S.D: 3.4% - overall recognition accuracy except Pickup, Compass and Free activities) compared to the Euclidean distance (Mean: 83.7% S.D: 15.3% - overall recognition accuracy without Pickup, Compass and Free activities). The signiﬁcance of this result is conﬁrmed by a two sample t-test (p < 0.05). However the Mahalanobis based approach completely failed to recognise the Pickup and Compass activities. Therefore, we have eliminated the consideration of Mahalanobis distance measurement when evaluating the rest of the algorithms (i.e. GDTW, LDTW and EDTW).
Figure 6 depicts the results of the experiments carried out to explore the impact on recognition accuracies due to varying reference signal count. In SDTW, GDTW and LDTW under the Euclidean space, two local maxima were observed at 10 and 20 reference counts. A performance gain of 13.6% in SDTW, 13.8% in GDTW and 17.7% in LDTW was achieved by having 10 templates (as opposed to a 1 template configuration). By increasing the reference signals from 10 to 20, a performance gain of 3.5%, 3.7% and 6.7% was observed for SDTW, GDTW and LDTW respectively. In SDTW using the Mahalanobis metric a 14.0% improvement in recognition accuracy was observed for 10 templates. However, by increasing the reference signals from 10 to 29 only a further 3.8% improvement achieved. Similarly, in EDTW most of the performance improvement was achieved by having 6 reference signals (19.3% gain), compared to the 4.6% improvement gained by increasing the reference signal count from 6 to 29.

Further, a continuous performance improvement could be observed under all algorithms by increasing the number of reference signal counts used in the recognition. This improvement is more prominent in SDTW, GDTW and LDTW in Euclidean space compared to the EDTW in Euclidean space and SDTW in Mahalanobis space.

As shown in Figure 7, the classification accuracy achieved using the 4 joints configuration, 5 joints configuration and 9 joints configurations were mean: 82.3% (s.d: 6.9%), mean: 83.9% (s.d: 8.6%) and mean: 85.2% (s.d: 8.3%) respectively. Hence, more joints leads to a higher classification accuracy, but the improvements resulting from utilising additional joints were marginal.

On average (Figure 8), the experiments carried out using the combination of Cartesian velocity and angular velocity (Mean: 84.1% S.D: 7.5%) provided the overall optimal results followed by angular velocity (Mean: 83.8% S.D: 9.1%), Cartesian velocity (Mean: 83.7% S.D: 7.8%), combination of Cartesian velocity, angular velocity and acceleration (Mean: 61.3% S.D: 8.8%), and acceleration (Mean: 50.9% S.D: 19.0%) itself. Two sample t-tests showed no significant changes in performances for using the combination of Cartesian velocity, angular velocity, Cartesian velocity itself, angular velocity itself as well as Cartesian velocity, angular velocity with acceleration term and acceleration itself. However, the rest of the pairwise differences were significant (e.g. Cartesian velocity and acceleration).

Based on the overall performance presented in Figure 9, the best overall recognition accuracy achieved under the proposed algorithm (EDTW in Euclidean space) (Mean: 87.4% S.D: 9.9%)
compared to SDTW (Mean: 82.0% S.D: 13.5%), GDTW (Mean: 82.2% S.D: 12.7%), LDTW (Mean: 70.7% S.D: 20.1%) in Euclidean space and SDTW (Mean: 71.4% S.D: 4.5%) in Mahalanobis space. One-way analysis of variance showed the significance of the result (p <0.05) and confirmed by two sample t-tests.

6. DISCUSSION

A natural and intuitive whole-of-body gesture library was chosen to explore the recognition performance that could be obtained by DTW algorithm and its variations. Real time gesture performance data was captured from 10 participants using the Microsoft Kinect and APDM inertia measurement units. Thereafter, meaningful gestures were extracted by visually analysing the spatial-temporal data. Four different DTW algorithms were analysed, including the novel algorithm proposed in this study. The performance of each algorithm was measured by varying many configurable parameters in order to determine the optimal algorithm and its configuration required to successfully recognise whole-of-body gestures. In particular, similarity measurements, feature combinations, reference signal count, KNN count, and different skeletal elements were considered in the analysis.

According to the results, for certain gestures the Mahalanobis distance is an alternative similarity measurement that could outperform the recognition rates obtained using the Euclidean distance. However, its performance depends on gesture type (did not properly identify Pickup, Compass and Free gestures) which is an undesirable property. Amongst the algorithms, Arici et al. (2013) suggested that the LDTW performed better than the SDTW and GDTW in the analysis of hand gesture recognition in their study. However, in this study we have shown that the algorithm fails significantly (refer Figure 9). We argue that the main flaw lies in the fundamental assumption made in the weight calculation scheme. In particular, LDTW assigns higher weights for the skeletal elements that have significant movements as compared the elements with fewer movements. Therefore, LDTW ignores the importance of the discriminant capabilities provided by the non-moving skeletal elements compared to the moving skeletal elements. However, the performance of the proposed DTW (EDTW) algorithm was superior due to the use of a more appropriate weight calculation scheme and local weight assignment. The performance analysis of different algorithms under the individual activities suggests that none of the algorithms are 100% accurate in recognising all 9 gestures. However, certain algorithms have the capability to recognise a subset of the gestures with a comparatively higher accuracy over the other algorithms. This observation could lead towards an ensemble approach where the algorithms are combined in order to leverage their individual capabilities to achieve a better outcome.

Based on the experiments carried out to explore the optimal reference signal count, the proposed algorithm (EDTW) required the minimum amount of reference data (6 reference signals) in order to achieve acceptable recognition results. However, for the rest of the algorithms, the required amount of reference data is not infeasible as the recognition rate curves are flattening around 10 signals (approximately). For most of the algorithms, consideration of 10% of the neighbourhood (KNN) is sufficient to achieve optimal results. Conversely, EDTW in Euclidean space and SDTW in Mahalanobis space required 30% and 90% of the neighbourhood consideration to obtain the optimal results. Even though 9 joints configuration outperformed the 4 and 5 joints configuration respectively, the performance gain obtained by adding extra joint details are marginal. These results suggest that when stable and informative skeletal elements are selected either 4, 5 or 9 joints configuration has the capability to recognise gestures successfully. With regard to feature exploration, features with the acceleration component performed poorly compared to the rest of the features. This could be due to the fact that there is less useful information encapsulated in acceleration data. As we have not applied any filters to sensory data (Kinect and IMUs), an amount of unfiltered noise could be another reason for the poor performance of approaches that utilised the acceleration data. However, the results suggest that Cartesian velocity combined with angular velocity are the preferred representation of gestures in order to maximise the recognition accuracy. The proposed algorithm outperforms the rest of the algorithms under the given non-trivial gesture library. Also SDTW and GDTW in Euclidean space behaved similarly and LDTW performed poorly. Despite being unable to recognise gestures intended for 3 different activities, SDTW in Mahalanobis space outperformed most of the algorithms except the EDTW in Euclidean space.

7. CONCLUSIONS

In this study, we have proposed a novel feature weighted DTW algorithm which outperformed the standard DTW algorithm and its variations in recognising whole-of-body gestures. By using the overall optimal configuration (combined Cartesian and angular velocity feature, 9 skeletal elements, Euclidean space) an average recognition rate of 95.9% (S.D 5.6%) was achieved under EDTW, 89.6% (S.D 3.4%) in SDTW, 89.3% (S.D 3.4%) in
GDTW, 74.2% (S.D 8.9%) in LDTW. Based on these results, a minimum of 6.3% improvement is achieved by the proposed algorithm (EDTW) compared to the DTW based gesture recognition algorithms previously found in the literature. This suggest that, it is possible to build a reliable automatic recogniser to recognise whole-of-body gesture commands which will open up new challenges such as managing fatigue and finding an optimum gesture mix that need to be solve by the HCI scholars.

REFERENCES


