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Slope Finder – A Distance Measure for DTW based Isolated Word Speech Recognition

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Abstract- Speech can be recognized by machine using many algorithms like Dynamic Time Warping, Hidden Markov Model, Artificial Neural Networks etc.,. In this paper, an overview of Dynamic Time Warping and the various distance metrics used to measure the spectral distance are discussed. A new distance metric is proposed which reduces the computational complexity .

Keywords- Pattern Recognition; Dynamic Time Warping; Distance Measures; Slope distance

I. INTRODUCTION

Speech is a natural mode of communication for people. Speech has many advantages like easy to understand and contains emotion. Speech has many areas of research like speech recognition, speech synthesis, speech analysis etc., [1]. Speech Recognition is a task of converting speech signal into orthographical representation. Recognition of speech can be done with algorithms like Dynamic Time Warping (DTW), Hidden Markov Model (HMM), and Artificial Neural Networks (ANN) [2].

There are three approaches to speech recognition namely the acoustic phonetic approach, the pattern recognition approach and artificial intelligence approach [1]. The acoustic phonetic approach is based on the theory of acoustic phonetics that postulates that there exist finite, distinctive phonetic units in spoken language, and that the phonetic units are broadly characterized by a set of properties that are manifest in the speech signal or its spectrum over time.

Pattern recognition approach to speech recognition is basically one in which the speech patterns are used directly without explicit feature determination and segmentation. Pattern recognition is concerned with the classification of objects into categories, especially by machine [1]. A strong emphasis is placed on the statistical theory of discrimination, but clustering also receives some attention. Hence it can be summed in a single word: 'classification', both supervised (using class information to design a classifier – i.e. discrimination) and unsupervised (allocating to groups without class information – i.e. clustering). Its ultimate goal is to optimally extract patterns based on certain conditions and is to separate one class from the others.

Artificial Intelligence approach to speech recognition is a hybrid of the acoustic phonetic approach and the pattern recognition approach [1] in that it exploits ideas and concepts of both methods. The artificial Intelligence approach attempts to mechanize the recognition procedure according to the way a person applies its intelligence in visualizing, analyzing, and finally making a decisions on the measured acoustic features.

One of the simplest and earliest approaches to pattern recognition is the template approach. Matching is a generic operation in pattern recognition which is used to determine the similarity between two entities of the same type. In template matching the template or prototype of the pattern to be recognized is available. The pattern to be recognized is matched against the stored template taking into account all allowable pose and scale changes. Dynamic Time Warping is a pattern recognition technique.

II. DYNAMIC TIME WARPING

Dynamic Time Warping is a pattern matching algorithm with a non-linear time normalization effect. It is based on Bellman's principle of optimality[3] , which implies that, given an optimal path w from A to B and a point C lying somewhere on this path, the path segments AC and CB are optimal paths from A to C and from C to B respectively. The dynamic time warping algorithm creates an alignment between two sequences of feature vectors, (T_1, T2...TN) and (S_1, S_2...S_M). A distance d(i, j) can be evaluated between any two feature vectors T_i and S_j. This distance is referred to as the local distance. In DTW the global distance D(i,j) of any two feature vectors Ti and Sj is computed recursively by adding its local distance d(i,j) to the evaluated global distance for the best predecessor. The best predecessor is the one that gives the minimum global distance D(i,j)(see Eq.1)at row i and column j with m≤ i and k≤ j

$$D(i,j) = \min[D(m,k)] + d(i,j) \qquad (1)$$

Dynamic Time Warping (DTW) is used to establish a time scale alignment between two patterns. It results in a time warping vector w, describing the time alignment of segments of the two signals assigns a certain segment of the source signal to each of a set of regularly spaced synthesis instants in the target signal.

2.1. Advantages of DTW [4]:

- Works well for small number of templates(< 20).
- Language independent
- Speaker specific
- Easy to train (end user controls it)
- DTW is a cost minimization matching technique in which a test signal is stretched or compressed according to a reference template.
- DTW is widely used in the small-scale embedded-speech recognition systems such as those embedded in cell phones. The reason for this is owing to the simplicity of the hardware implementation of the DTW engine, which makes it suitable for many mobile devices.
- Additionally, the training procedure in DTW is very simple and fast, as compared with the Hidden Markov Model (HMM) and Artificial Neural Networks (ANN) rivals.
- The accuracy of the DTW-based speech recognition systems greatly relies on the quality of the prepared reference templates.
- The computational complexity can be reduced by imposing constraints that prevent the selection of sequences that cannot be optimal

2.2. Disadvantages of DTW [4]

- Limited number of templates
- Speaker specific
- Need actual training examples
- It can produce pathological results. The crucial observation is that the algorithm may try to explain variability in the Y-axis by warping the X-axis. This can lead to unintuitive alignments where a single point on one time series maps onto a large subsection of another time series.
- They suffer from the drawback that they may prevent the "correct" warping from being found. In simulated cases, the correct warping can be known by warping a time series and attempting to recover the original.
- An additional problem with DTW is that the algorithm may fail to find obvious, natural alignments in two sequences simply because a feature (i.e. peak, valley, inflection point, plateau etc.) in one sequence is slightly higher or lower than its corresponding feature in the other sequence.
- The weakness of DTW is in the features it considers.
- The other main drawbacks of DTW were the explosion of the search space for continuous recognition tasks and poor speaker independent performance.
- One of the main problems in dynamic time-warping (DTW) based speech recognition systems are the preparation of reliable reference templates for the set of words to be recognized.

2.3. Applications of DTW

- speaker verification in forensic applications
- Voice/speech recognition
- Signature recognition systems
- Voice dialer[5]
- Simple command and control
- Speaker ID
- Motion capture problems[5]
- Practical applications of online handwritten character recognition.

2.4. DTW Algorithm

The DTW algorithm does the pattern matching of the input pattern and reference pattern using the following steps. The Figure 1 is a pictorial representation of the DTW algorithm.

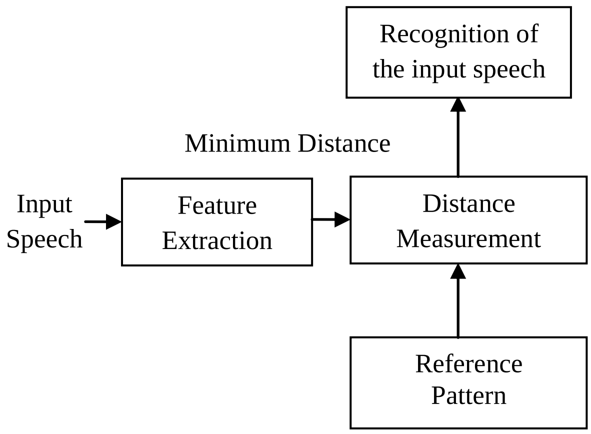

Figure 1: Dynamic Time Warping

1. Get the voice input from user
2. Perform Voice Activity Detection (VAD) algorithm to find the initial and end points of speech signal which consist of background silence, voiced and unvoiced sounds. [6]
3. Perform the Feature Extraction with Mel Frequency cepstral coefficient (MFCC).
4. For each word in the dictionary (say p) and the input word (say q) perform step 5.
5. Find the local distance matrix (d)(see Eq.2) between the Feature Vectors using Euclidean distance[7]

$$d[p] = \sum (p_i - q_j)^2 \qquad (2)$$

6. Calculate distance between the vector p and q using DTW Algorithm.
7. The signal with minimum distance is found and the word recognized which is shown in Figure 2.

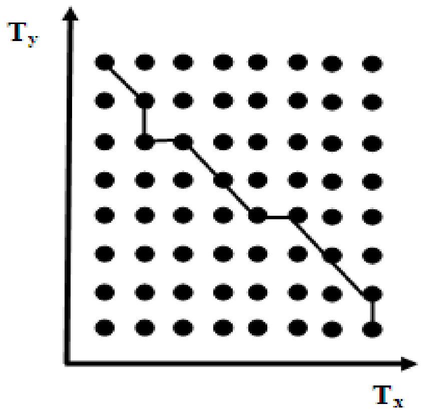

Figure 2: Sample of time normalization of two sequential patterns to a common time index

III. DISTANCE MEASURES OF DYNAMIC TIME WARPING

In the pattern classification process of DTW, the unknown test pattern is compared with each reference pattern and a measure of similarity is computed. A local distance is first found between the two patterns then the global time alignment [8] is done. The DTW algorithm uses a Euclidean distance to measure the local distance between two signals. There are many other distance measures available. The following section describes the distance measures available and the local distance is found using five existing distance measures with the same set of data. The proposed distance measure slope distance is also used to find the local distance for the same set of data. The result of the six distance measures is compared.

The distance measures are also called as similarity measures or dissimilarity measure. There are nineteen distance measures which are derived from eight basic distance measures. Distances are measured using distance functions, which follow triangle inequality. The triangle inequality [9] states that for any triangle, the sum of the lengths of any two sides must be greater than the length of the remaining side which is shown in Eq.3. Figure 3 shows a triangle where the lengths of the sides are given as X, Y and Z.

$$Z < X + Y \tag{3}$$

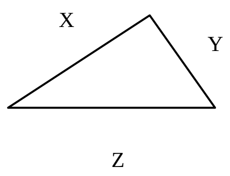

Figure 3: Triangle Inequality

In the distance measures discussed in the following sections, x and y represents the patterns vectors of test and the reference signal. The length of x and y vector is assumed to be 'n'. In real time implementation of the distance measures to a speech signal, the length of x and y vector need not be same. The formulas Eq.4 to Eq.26 can be used only after Time Normalization [1].

3.1. Euclidean Distance

Euclidean distance [10] is the most widely used distance measure of all available. In the Eq.4, the data in vector x and y are subtracted directly from each other.

$$d_E = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{4}$$

3.2. Normalized Euclidean distance

The normalized Euclidean distance [10] is calculated by dividing the Euclidean distance between vector x and y by the square root of length 'n' as given in Eq.5.

$$d_N = \frac{d_E}{\sqrt{n}} \tag{5}$$

3.3. Harmonically summed Euclidean Distance

It is a variation of the Euclidean distance, here the terms for the different dimensions are summed inversely as shown in Eq.6 and is more robust against outliers compared to the Euclidean distance [10].

$$d = \left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{x_i - y_i}\right)^2\right]^{-1} \tag{6}$$

3.4. Manhattan Distance

It is also known as City Block or Taxi Cab distance [11]. It is closely related to the Euclidean distance. The Euclidean distance corresponds to the length of the shortest path between two points, the city-block distance is the sum of distances along each dimension as shown in Eq.7. This is equal to the distance a traveler would have to walk between two points in a city. The Manhattan distance cannot move with the points diagonally, it has to move horizontally and vertically which is shown in Figure 4. The city-block distance is a metric, as it satisfies the triangle inequality. As for the Euclidean distance, the expression data are subtracted directly from each other, and therefore should be made sure that they are properly normalized.

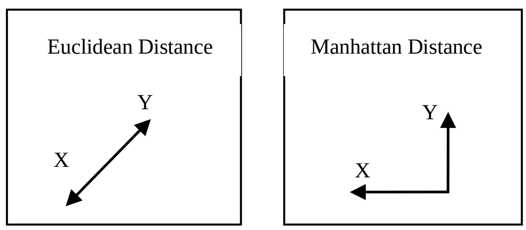

Figure 4: Difference between Euclidean and Manhattan Distance

$$d = \sum_{i=1}^{n} |x_i - y_i| \tag{7}$$

3.5. Normalized Manhattan Distance

The Normalized Manhattan Distance is a version of Manhattan distance where the Manhattan distance is divided by the length n as shown in Eq.8.

$$d = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (8)$$

3.6. Canberra Distance

The Canberra distance [12] is a numerical measure of the distance between pairs of points in a vector space, introduced in 1966 and refined in 1967 by G. N. Lance and W. T. Williams. It is a weighted version of Manhattan distance. The Canberra distance has been used as a metric for comparing ranked lists and for intrusion detection in computer security. Eq.9 shows the Canberra Distance.

$$d = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - y_i|}{(x_i + y_i)} \quad (9)$$

3.7. Bray –Curtis Distance

The Bray–Curtis dissimilarity, named after J. Roger Bray and John T. Curtis, is a statistic used to quantify the compositional dissimilarity between two different vectors, based on counts at each vector as shown in Eq.10. The Bray–Curtis dissimilarity is bound between 0 and 1 [13], where 0 means the two vectors have the same composition and 1 means the two vectors do not have composition. The Bray–Curtis dissimilarity is often erroneously called a distance. The Bray–Curtis dissimilarity is not a distance since it does not satisfy triangle inequality, and should always be called a dissimilarity to avoid confusion.

$$d = \frac{\sum|x_i - y_i|}{\sum(x_i + y_i)} \quad (10)$$

3.8. Maximum Coordinate Difference Distance

It is also known as chessboard distance. It is a metric defined on a vector space where the distance between two vectors is the greatest of their differences along any coordinate dimension [11] as shown in Eq.11.

$$d_{max} = \max|x_i - y_i| \quad (11)$$

3.9. Minimum Coordinate Difference Distance

As shown in Eq.12, the minimum coordinate difference distance is similar to Maximum coordinate difference distance [11]. It is defined on a vector space where distance between two vectors is smallest of their difference along any coordinate dimension.

$$d_{min} = \min|x_i - y_i| \quad (12)$$

3.10. Dot Product

The dot product distance [11] as shown in Eq.13 and Eq.14 is the distance between two vectors found by the product elements in the vectors x and y.

$$d_o = -xoy \quad (13)$$

$$\text{where } xoy = \sum_{i=1}^{n} x_i * y_i \quad (14)$$

3.11. Pearson’s Correlation Coefficient Distance

In statistics, the Pearson product-moment correlation coefficient (sometimes referred to as the PPMCC or PCC, or Pearson's r [14] is a measure of the linear correlation (dependence) between two variables X and Y as shown in Eq.15 and Eq.16, giving a value between +1 and −1 inclusive. It is widely used in the sciences as a measure of the strength of linear dependence between two variables. It was developed by Karl Pearson from a related idea introduced by Francis Galton in the 1880s

$$r = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma_x}\right)\left(\frac{y_i - \bar{y}}{\sigma_y}\right) \quad (15)$$

$$d_P = 1 - r \quad (16)$$

In which $\bar{x}, \bar{y}$ are the sample means of x and y respectively and σ_x, σ_y are the sample standard deviations of x and y. It is a measure for how well a straight line can be fitted to a scatter plot of x and y. If all the points in the scatter plot lie on a straight line, the Pearson correlation coefficient is either +1 or -1, depending on whether the slope of line is positive or negative. If it is equal to zero, there is no correlation between x and y. As the Pearson correlation coefficient fall between [-1, 1], the Pearson distance lies between [0, 2].

3.12. Absolute Pearson’s Correlation Distance

By taking the absolute value of the Pearson correlation, a number between [0, 1] is obtained as shown in Eq.17 [10]. If the absolute value is 1, all the points in the scatter plot lie on a straight line with either a positive or a negative slope. If the absolute value is equal to 0, there is no correlation between x and y.

$$d_{AP} = 1 - \left|\frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma_x}\right)\left(\frac{y_i - \bar{y}}{\sigma_y}\right)\right| \quad (17)$$

The absolute value of the Pearson correlation coefficient falls in the range [0, 1], so the corresponding distance falls between [0, 1] as well. In the context of gene expression experiments, the absolute correlation is equal to 1 if the gene expression data of two genes/microarrays have a shape that is either exactly the same or exactly opposite. Therefore, absolute correlation coefficient should be used with care.

3.13. Uncentered Pearson’s Correlation Distance

This is the same as for regular Pearson correlation coefficient, except that sample means $\bar{x}, \bar{y}$ are set equal to 0 as shown in Eq.18, Eq.19 and Eq.20. The uncentered correlation may be appropriate if there is a zero reference state. For instance, in the case of gene expression data given in terms of log-ratios, a log-ratio equal to 0 corresponds to green and red signal being equal, which means that the experimental manipulation did not affect the gene expression [10]. As the uncentered correlation coefficient lies in the range [-1, 1], the corresponding distance falls between [0, 2].

$$d_U = 1 - \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i}{\sigma_x^{(0)}}\right)\left(\frac{y_i}{\sigma_y^{(0)}}\right) \quad (18)$$

$$\sigma_x^{(0)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \quad (19)$$

$$\sigma_y^{(0)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} y_i^2} \quad (20)$$

3.14. Absolute Uncentered Pearson's Correlation Distance

The Absolute Uncentered Pearson's Correlation [10] is similar to Uncentered Pearson's Correlation where the absolute value of the Uncentered Pearson's Correlation Coefficient is taken as shown in Eq.21.

$$d_{AU} = 1 - \left| \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i}{\sigma_x^{(0)}} \right) \left(\frac{y_i}{\sigma_y^{(0)}} \right) \right| \quad (21)$$

3.15. Pearson's Linear Dissimilarity Distance

This is the dissimilarity version [10] of the Pearson linear correlation between two vectors as shown in Eq.22. If d_p value is 0 indicates perfect similarity and 1 indicates maximum dissimilarity. □□

$$d_p = \frac{1 - \frac{(x - \bar{x}) o (y - \bar{y})}{\sigma_x \sigma_y}}{2} \quad (22)$$

3.16. Pearson's Absolute Value Dissimilarity Distance

It is version of Pearson Correlation Coefficient. The Eq.23 shows the Pearson's Absolute Value Dissimilarity where d_N is the Euclidean Distance calculated using Eq.4.

$$d = \sqrt{\frac{n}{n-1}\left(d_E^2 - \left[\frac{1}{n}\left(\sum_{i=1}^{n} x_i - \sum_{i=1}^{n} y_i \right) \right]^2 \right)} \quad (23)$$

3.17. Spearman's Rank Correlation Distance

The Spearman rank correlation is an example of a non-parametric similarity measure. It is useful because it is more robust against outliers than the Pearson correlation [10]. To calculate the Spearman rank correlation, each data value is replaced by their rank if the data in each vector is ordered by their value as shown in Eq.24. Then the Pearson correlation between the two rank vectors instead of the data vectors is calculated. Weights cannot be suitably applied to the data if the Spearman rank correlation is used, especially since the weights are not necessarily integers.

$$d_s = 1 - r_s \quad (24)$$

where r_s is the Spearman rank correlation.

3.18. Kendall's τ Distance

The Kendall tau rank distance is a metric that counts the number of pair wise disagreements between two ranking lists as shown in Eq.25. The larger the distance, the more dissimilar the two lists [15]. Kendall tau distance is also called bubble-sort distance since it is equivalent to the number of swaps that the bubble sort algorithm would make to place one list in the same order as the other list. The Kendall tau distance was created by Maurice Kendall.

$$d = \sum_{i=1}^{n} (x_i - y_i) \quad (25)$$

3.19. Cosine Distance

Cosine similarity is a measure of similarity between two vectors of an inner product space that measures the cosine of the angle between them as shown in Eq.26. The cosine of 0° is 1, and it is less than 1 for any other angle. It is thus a judgment of orientation and not magnitude: two vectors with the same orientation have a Cosine similarity of 1, two vectors at 90° have a similarity of 0, and two vectors diametrically opposed have a similarity of -1, independent of their magnitude [16]. Cosine similarity is particularly used in positive space, where the outcome is neatly bounded in [0, 1].

$$d = \frac{\sum_{i=1}^{n} x_i y_i}{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i} \quad (26)$$

IV. SLOPE FINDER DISTANCE – A NEW DISTANCE MEASURE

The Slope Finder Distance is calculated by finding the slope between two points. Let p and q be two vectors of the test and reference signals with size 'n'. If p_i and q_i are some point in the vectors p and q. The slope can be found by using Eq.27. In mathematics, the slope or gradient of line describes its steepness, incline, or grade. A slope can be positive, negative, or equal to zero. When the slope is equal to zero, we say that there is no slope.

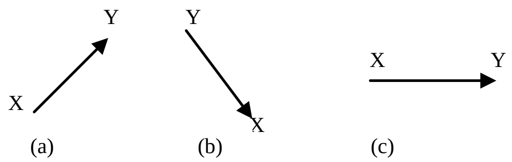

Figure 5: (a) Positive slope (b) Negative Slope (c) No slope

$$d_{SF} = \sum_{i=1}^{n} \frac{q_{i-1} - q_i}{p_{i-1} - p_i} \quad (27)$$

V. EXPERIMENTAL RESULT

5.1. Dataset

Data present in the database are 6 signal S1 to S6 having the sound of Alphabet A to F of a single user recorded using Audacity. The local distance measures such as Euclidean Distance (E), Normalized Euclidean Distance (NE), Manhattan Distance (M), Canberra Distance (C), Bray-Curtis Distance (B) and Slope Finder Distance (SF) are taken into consideration and used in DTW. The user inputs a signal of Alphabet B as test signal.

5.2. Comparison of Distance Measures

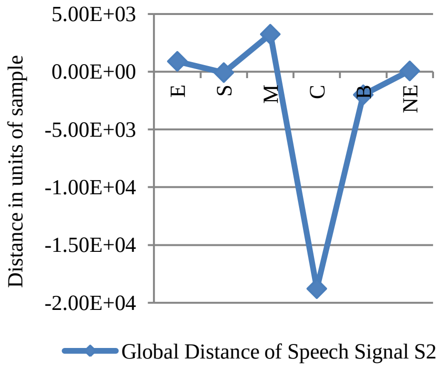

Figure 6: Global Distance Measured Manipulated by DTW for Test signal of alphabet B

The signals S1 to S6 are used in Dynamic Time Warping algorithm as reference signals. The 13 MFCC coefficients of the reference signal are manipulated and stored. When a test signal is received for recognition, the 13 MFCC coefficients of the test signal is computed and the test and reference patterns are given as input to Dynamic Time Warping (DTW) Algorithm. The Local Distance is manipulated using the distance measures Euclidean Distance (E), Normalized Euclidean Distance (NE), Manhattan Distance (M), Canberra Distance (C), Bray-Curtis Distance (B) and Slope Finder Distance (SF). A global distance manipulated for the test signal of alphabet B with the reference pattern signal of alphabet B is given in Figure 6.

It can noticed from Figure 6 that the DTW algorithm implemented using the local distance measures such as Euclidean Distance, Manhattan Distance, Normalized Euclidean Distance and Slope Finder Distance provide better recognition result when compared to Canberra and Bray-Curtis Distance. It is also observed that the DTW with Slope Finder is having the Minimum Global Distance.The signals S1 to S6 are identified correctly with Euclidean, Normalized Euclidean, Manhattan and Slope Finder distance measures.

VI. CONCLUSION

The DTW algorithm can use any of the distance measure discussed in the paper. The most suitable and easy to compute is the slope Finder which minimizes the global distance. The measures Canberra Distance (C) and Bray-Curtis Distance (B) are not suitable with DTW for the given dataset. The DTW Algorithms sued in this paper is speaker dependent. A Speech Recognizer using DTW Algorithms need more training data for each speaker as they are speaker dependent. Hidden Markov Model (HMM) is a speaker independent algorithm. The future work will be to develop a new methodology based on HMM.

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