

Comparative Study of One Dimensional and Two Dimensional Dynamic Time Warping

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ABSTRACT

Today's trend in Speech recognition applications include automatic answering machines, dictation systems, command control applications, speaker identification system etc. In this paper, early Patten matching technique DTW is studied used to find the similarity of speech data using MFCC and LPCC features. A small vocabulary containing command words used to test the already existing method in two ways. One-dimensional raw speech data of command words are considered as input the algorithm. In the second method, two-dimensional features of the same set of data were considered. Finally, these two methods were compared in terms of efficiency.

Keywords : Mel Frequency Cepstral Coefficient, Linear Predictive cepstral Co-efficient, Dynamic time warping

I. INTRODUCTION

Research in speech recognition applications are known for many years. Speech recognition algorithms can be comprehensively classified into speaker dependent and speaker independent. Speaker dependent system concentrates on building up a system to recognize unique voiceprint of the individuals whereas Speaker independent system concentrates only on identifying the word uttered by the speaker [1].

Based on the style of the speech data, it can be further classified into isolated, connected, continuous and spontaneous speech recognition system and based on the size of the vocabulary, speech applications classified as small vocabulary, medium and large vocabulary speech recognition systems. Since Dynamic time warping technique compares the variable length signals, it was used in speech recognition applications. Mel Frequency Cepstral Coefficients (MFCC's) are widely used features in automatic speech recognition and speaker recognition systems. In 1980's Davis and Mermelstein introduced the MFCC and have been state of the art ever since speech applications [7]. Prior to the introduction of MFCC, Linear Prediction coefficients (LPC's) introduced by Atal and Hanauer in 1971 and Linear Prediction cepstral coefficient (LPCC's) introduced by Atal and Sambur 1974 were used for

analysing speech signals. In the research work, DTW is developed using MFCC and LPCC to compare the similarity between saved templates and command word uttered.

II. LITERATURE SURVEY

Palden Lama et al. designed a speaker independent voice to text converter application using the technique DTW and they have implemented in MATLAB. They worked on both isolated and connected words. They used the speech data recorded with 32-bit mono channel encoding in 44 kHz sampling frequency using Audacity software [1].

Chunsheng Fang elaborated two non-linear sequence alignment techniques popularly known as pattern matching algorithms DTW and Hidden Markov Model. He stated that the algorithms share the concept of dynamic programming and addressed the issues in the techniques [2].

Stan Salvador et.al introduced Fast DTW, an approximation of DTW that has a linear time and space complexity. They used a multilevel approach with three key operations coarsening, projection and refinement. They analysed the accuracy of Fast DTW, compared with two other existing approximate DTW algorithms:

Sakoe-Chuba Bands and Data Abstraction, and stated that the results showed a large improvement in accuracy over the existing methods. Finally, they discussed the limitation of the Fast DTW algorithm, which does not guarantee the optimal solution. In speech processing applications, combined or hybrid approaches with DTW were also studied [3].

E- Hocine Bourouba et al presented hybrid approach for isolated spoken word recognition using Hidden Markov Model models (HMM) and Dynamic time warping (DTW) in which they combined the advantages of these two powerful pattern recognition techniques [4]. In this work, they used traditional Continuous Hidden Markov Models (GHMM) and the new approach DTW/GHMM for evaluation and proved the hybrid system increases the average recognition rate by 2-10% more than the HMM-based recognition method.

III. DYNAMIC TIME WARPING

Dynamic Time Warping is to quantify similarity between two time series, which may vary in time or speed [5]. The warping is used to find corresponding regions and determined the similarity between the two time series. The function of DTW is to compare two dynamic patterns and measure its similarity by calculating a minimum distance between the users [6]. The features of word are extracted and template for the reference pattern is created. Then, DTW algorithm is implemented to calculate the similarity distance between features of word uttered and reference templates. The word, which corresponds to least value among calculated scores with each template, is considered as the matched pattern. The extent of matching between two time series is measured in terms of distance factor.

DTW can analyse the data that can be turned into a linear representation and applied to the audio. DTW finds the optimal match between two times series on the off time that one time series might be "warped" non-linearly by extending or contracting it along its time series.

A. Problem Formulation

Let R be the reference sequence pattern consisting of N slices denoted by R_j where $1 \leq j \leq N$, M -length test sequence pattern T which consists of M slices (where i denote the sample of the data T , i.e. $1 \leq i \leq M$), then the objective is to find out the shortest distance score

between the reference pattern R and the test pattern T of length M . Here, the shortest distance implies the minimum matching cost between R and T under the following assumptions:

Assumption 1 : The first and last elements/slices of R must match to those of T ; that is,

- (1) $R_1 \sim T_1$ with a distance (or matching cost) $d(1, 1)$;
- (2) $R_n \sim T_m$ with a distance (or matching cost) $d(N, M)$;

where $d(i, j)$ can be defined as the absolute distance

$$d(i, j) = ||R_i - T_j|| \quad (1)$$

Assumption 2 : Three actions: Expansion, Match and Contraction are considered in calculating the distance score using Equation 1. The current state is defined as (i, j) , and it is transformed into another state by following transition rules, which consists of the following three actions:

- (1) Expansion: from (i, j) to $(i+1, j)$
- (2) Match (diagonally up): from (i, j) to $(i+1, j+1)$
- (3) Contraction (straight up): from (i, j) to $(i, j+1)$

Those three transitions are illustrated in Figure 1, where T is interpreted as a Test sentence compared with the some reference templates R .

Therefore, the problem of DTW is to minimize, $Dist(D)$, is the same as Forward Dynamic Programming of deterministic shortest path algorithm [9]. Therefore it can be converted from (ordinary) backward to forward, and can be modelled as a finite state system.

B. One dimension DTW

The problem formulation is completed. Then we find a distance between two time series. Then, distance is measured by equation 2.

$$D(i, j) = \min[D(i-1, j-1), D(i-1, j), D(i, j-1)] + d(i, j) \quad (2)$$

The template corresponding to least distance is the word detected. There are three conditions applied in DTW algorithm:

1. Monotony – the path never returns, that means that both indices i and j used for crossing through sequences never decrease.

- Continuity – the path advances increasingly, step by step; indices i and j add to by maximum 1 unit on a step.
- Boundary – the path begins from left-down corner and ends with right-up corner [21].

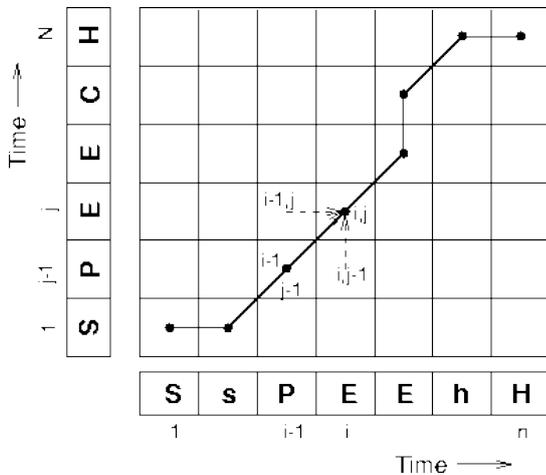


Figure1. A sample line graph for DTW

C. Two Dimensional DTW

Extending the Dynamic Time Warping method to two dimensions is not a simple task. The input data is no longer a 1-dimensional series but rather a 2-dimensional matrix. This matrix can represent images or any other 2-dimensional data. A two dimensional dynamic warping algorithm could be used for a variety of applications such as text and facial recognition and is described as a fundamental technique for pattern recognition. Various algorithms have been proposed to solve the problem. Solution are proposed in [16, 17] but both unfortunately exhibit exponential time complexity. It is shown in [18] that the 2-dimensional warping problem is NP-complete. Approximation methods have been described in [19]. A polynomial-time and supposedly accurate algorithm for 2D warping based on DTW is proposed in [20]. This algorithm, its improvement, extension, and testing are the subjects of the rest of this report. The result of 2D-DTW were showed in the table 3.

i. Preprocessing

The speech signal is decomposed into a sequence of overlapping frames. The frame size of 25 ms and 10ms frame shift is used for the analysis of speech signal. The input speech data are pre emphasized with coefficient of 0.97 using a first order digital filter. The samples are weighted by a Hamming window for avoiding spectral distortions. The resulting windowed

frames are used to extract both features MFCC and LPCC. The result of 1-DTW showed in the table 2.

ii. MFCC

Figure 2 shows block diagram of extraction of MFCC feature from a signal.

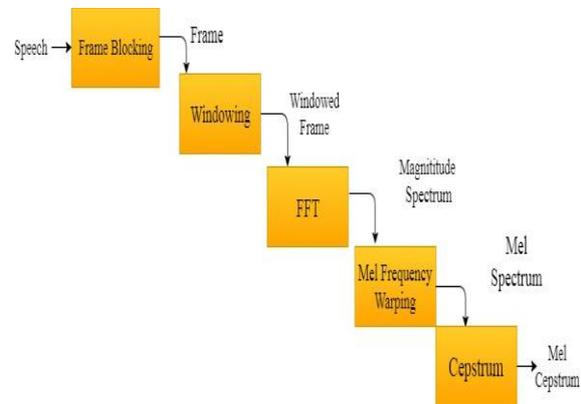


Figure 2. Block diagram for the feature extraction process of MFCC

Mel Filter Bank is use to determine the frequency content across each filter. The Mel filter bank is built from triangular filters. The filters are overlapped in such a way that the lower boundary of one filter is situated at the center frequency of the next filter. 1000 Hz was defined as 1000mels. An approximate formula to compute the Mels for a given frequency in Hz is using equation 3 [8].

$$F(\text{Mel}) = [2595 * \log_{10} \left[1 + \frac{f}{700} \right]] \quad (3)$$

We are just inspired by generally how much vitality happens at each spot. Here an arrangement of 26 triangular filters are taken. To compute channel bank energies we increase each channel keep money with the energy range, and after that include the coefficients. Once this is performed we are left with 26 numbers that give us an sign of how much energy was in each filter bank. Discrete Cosine Transform (DCT) takes after logarithm for these 26 energy values. DCT is ascertained utilizing condition appeared in equation 4.

$$C_n = \sum_{k=1}^k (\log S_k) \left[n(k) - \frac{1}{2} \right] \frac{\pi}{K} \quad (4)$$

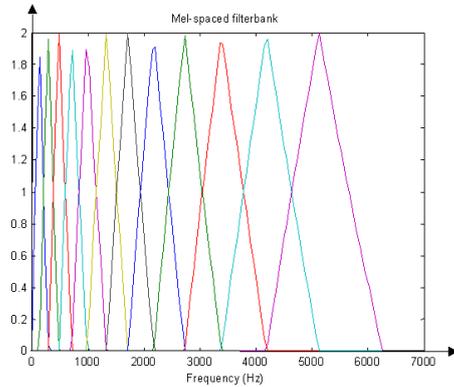


Figure 3. A Mel Frequency Scale

The overlapping windows in the frequency domain can be directly used. The energy within each triangular window is obtained and followed by the DCT to achieve better compaction within a small number of coefficients and results are known as MFCC. The data will be stored in the database and take to compare with the voice input at the testing phase with same steps of process.

First and derivative coefficients are calculated for each frame as given in equations 5 and 6.

$$\Delta f_k[n] = f_{k+M}[n] - f_{k-M}[n] \quad (5)$$

$$\Delta^2 f_k[n] = \Delta f_{k+M}[n] - \Delta f_{k-M}[n] \quad (6)$$

iii. LPCC

Let assessing the fundamental parameters of a speech signal, LPCC has turned out to be one of the predominant methods. The essential subject behind this strategy is that one speech sample at the current time can be predicted as a linear combination of past speech samples. Algorithm for LPCC is appeared in Figure 3.

The first phase of the algorithm is pre-processing. After pre-preprocessing, the speech signal is subdivided into frames. This process is the same as multiplying the entire speech sequence by a windowing function. The windowing process to be completed means move on to next phase. The next phase is Linear Predictive Analysis (LPA). LPA is grounded on the theory, that the shape of the vocal tract chooses the character of the sound being delivered. A computerized all-post channel is utilized to demonstrate the vocal tract and has a move work spoke to in z area as in equation 7.



Figure 4. Block diagram for the feature extraction process of LPCC

$$V(z) = \frac{G}{1 - \sum_{k=1}^p a_k z^{-k}} \quad (7)$$

where $V(z)$ is the vocal tract transfer work. G is the gain of the filter, $\{a_k\}$ is a the set of auto regression coefficients known Linear Prediction Coefficients (LPC), p is the request of the all-pole filter. One of the efficient techniques for assessing the LPC coefficients and the filter gain is Autocorrelation technique [10]. Last phase of this algorithm is cepstral analysis, which refers to the process of finding the cepstrum of speech sequence. Fundamentally, there are two types of cepstral approaches: FFT cepstrum and LPC cepstrum. In the previous case the real cepstrum is characterized as the backwards FFT transform of the logarithm of the speech size range characterized by following equation 8.

$$\hat{s}[n] = \frac{1}{2\pi} \int_{-\pi}^{+\pi} \ln[s(\omega)] e^{j\omega n} d\omega \quad (8)$$

Where and demonstrates the Fourier spectrum of a signal and cepstrum separately [11]. Be that as it may, one more method for evaluating these cepstral coefficients is from the LPC by means of a set of recursive technique and the coefficients in this way acquired are known as straight Linear prediction cepstral coefficients (LPCC).

iv. Stochastic DTW

Juang [12] presented stochastic dynamic time warping method for speaker independent recognition, which combines a standard dynamic time warping method with a Hidden Markov model [13]. Let S and A be the state sequence and observed sequence, $O(s_1, s_2, \dots, s_i; o_j)$ denote the probability that the Markov model has produced s_1, s_2, \dots, s_i ; and is in state o_j . The probability can be calculated using approximate equation also known as Viterbi algorithm, which employs dynamic programming. The viterbi algorithm gives an efficient way to find the most likely state sequence in the maximum a posteriori probability sense finite-state discrete-time Markov process.

IV. RESULTS AND DISCUSSION

A. Data

Commands words uttered in English are recorded with the help of a unidirectional microphone in a calm environment is considered as data set. Data are recorded using a recording tool audacity in a closed room. The sampling rate used for recording is 16 kHz. The description about the data used is also given in Table I.

Table I. Results of DTW With Eight Command Words

S.No	Uttered words	Sample words duration time(ms)	No. Of Samples
1	Start	0.0627	10031
2	Left	0.0929	14861
3	Right	0.0579	9845
4	Forward	0.0685	10959
5	Backward	0.0679	13375
6	Up	0.0522	8359
7	Down	0.0418	5699
8	Stop	0.0114	8916

Table II. Results of 1-DTW with Eight Command Words

	Start	Left	Right	Forward	Backward	Up	Down	Stop
Start	0	30.5988	22.0397	66.7249	33.5013	29.6243	54.2266	68.0698
Left	30.5988	0	26.5723	89.9319	46.888	39.8305	78.2258	89.9042
Right	22.0397	26.5723	0	75.5159	37.5828	34.5234	63.7876	80.6848
Forward	66.7249	89.9319	75.5159	0	54.4777	74.299	58.9084	77.4254
Backward	33.5013	46.8808	37.828	54.477	0	44.8455	54.2266	71.3358
Up	29.6243	39.8305	34.5234	74.2499	44.8455	0	51.7068	57.1259
Down	54.9527	78.2258	63.7876	58.4084	54.2266	51.7068	0	47.1963
Stop	68.0698	89.9042	80.6848	77.4254	71.3358	57.1259	47.1963	0

Table III. Results of 2D-DTW with Eight-Command Word Tested with MFCC

		Start	Left	Right	Forward	Backward	Up	Down	Stop
Start	MFCC	0	60.59	42.03	56.72	53.50	59.62	84.22	77.06
	LPCC	0	34.59	52.03	46.72	43.50	89.62	94.22	56.06
Left	MFCC	34.59	0	90.57	98.93	36.88	64.83	38.22	89.90
	LPCC	44.59	0	36.57	79.93	66.88	34.83	88.22	89.90
Right	MFCC	52.03	76.57	0	75.51	77.58	84.52	53.78	60.68
	LPCC	62.01	86.57	0	85.51	57.58	64.52	43.78	50.68
Forward	MFCC	46.72	69.93	35.51	0	44.47	74.29	56.90	77.42
	LPCC	36.72	59.93	45.51	0	34.47	54.29	67.90	57.42
Backw	MFCC	43.50	36.88	56.82	90.47	0	46.84	62.22	85.33

ard	LPCC	34.50	46.88	45.82	89.47	0	35.84	83.22	71.33
Up	MFCC	79.62	72.83	54.52	34.24	54.84	0	81.70	32.12
	LPCC	49.62	63.83	74.52	74.24	34.84	0	89.70	78.12
Down	MFCC	74.95	68.22	23.78	28.40	34.22	61.70	0	98.19
	LPCC	84.95	98.22	33.78	48.40	84.2	62.70	0	67.19
Stop	MFCC	28.06	49.90	30.68	57.4	71.33	37.12	37.19	0
	LPCC	48.06	59.90	70.68	67.42	41.33	27.12	67.19	0

V. CONCLUSION

Speech data were analyzed using DTW. One dimensional speech template of eight command words were considered and taken for evaluation. MFCC and LPCC features of the same set of speech data are extracted, DTW is applied, and then the results were analyzed. Future work should prioritize methods to reduce the computation load and improve the computing speed by optimizing the implementation of the DTW algorithm, and should explore hierarchical or classification techniques to minimize the number of possible matches.

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