Time Series Matching: a Multi-filter Approach

by

Zhihua Wang

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Dennis Shasha

Dedicated to my dear parents Limao Wang, Dejun Zhu
and my lovely wife Nina Liu who blessed and supported me

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Abstract

Data arriving in time order (time series) arises in disciplines ranging from music to meteorology to finance to motion capture data, to name a few. In many cases, a natural way to query the data is what we call time series matching - a user enters a time series by hand, keyboard or voice and the system finds "similar" time series.

Existing time series similarity measures, such as DTW (Dynamic Time Warping), can accommodate certain timing errors in the query and perform with high accuracy on small databases. However, they all have high computational complexity and the accuracy drops dramatically when the data set grows. More importantly, there are types of errors that cannot be captured by a single similarity measure.

Here we present a general **time series matching framework**. This framework can easily optimize, combine and test different features to execute a fast similarity search based on the application's requirements. Basically we use a multi-filter chain and boosting algorithms to compose a ranking algorithm. Each filter is a classifier which removes bad candidates by comparing certain features of the time series data. Some filters use a boosting algorithm to combine a few different weak classifiers into a strong classifier. The final filter will give a ranked list of candidates in the reference data which matches the query data.

The framework is applied to build query algorithms for a Query-by-Humming system. Experiments show that the algorithm has a more accurate similarity measure and its response time increases much more slowly than the pure DTW algorithm when the number of songs in the database increases from 60 to 1400.

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Chapter 1

Introduction

1.1 Motivation

Many applications naturally generate time series data. The research on time series matching is becoming increasingly popular as more and more applications emerge and the sizes of data increase dramatically. For example:

- Millions of traders try to find patterns by tracking similar stocks using the up to 100,000 quotes and trades (ticks) which are generated per second in the United States;
- Meteorologists try to predict weather based on similarities between cloud movements using new satellites (launched last year) which collect 3GB of data every day;
- Many real-time 3D games today need a way to automate a virtual character's transition movement; using a motion-captured animation database, the next motion sequence is selected from the motions whose beginning matches the ending of the current motion.

As the above examples illustrate, the most convenient way to investigate the data is by using existing examples as queries to find similar data.

Existing time series matching similarity measure, such as DTW (Dynamic Time Warping) [37], can accommodate certain timing errors in the query and perform similarity search with high accuracy when matching queries to small databases. However, they all have high computational complexity and the accuracy drops dramatically when the data set grows. In short, they don't scale well. Another problem is that the type and amount of time warping may be different for different applications. There is a need for scalable matching algorithms which can be easily customized for different applications.

1.2 Problem Statement

In summary, there are two major difficulties for the time series matching problem.

- First is the error in the query and the ambiguity of similarity

  There should be either an accurate definition of similarity measure between data or a system that can learn this similarity measure. This way users can find the data they really need.

- Second is the large scale of the database

  The more data, the more difficult it is to discriminate the correct result from other ones and the greater the challenge of giving an accurate definition of similarity. Additionally, the larger the scale, the more computation power needed and the more efficient the query algorithm must be.

This thesis will address both of these challenges. It will discuss how to build fast, accurate and customizable similarity search algorithms for large scale time-series systems that allow for errors in the query.

1.3 Our Contribution

We will present a general **time series matching framework**. This framework can easily optimize, combine and test different features to conduct fast similarity searches based on the requirements of the application. It takes a multi-filter approach plus Boosting [11, 25] to compose a ranking algorithm. Both theoretical discussions and experimental results are presented.

1.4 Thesis Outline

We first review related work and common techniques; this includes the GEMINI indexing framework and the most commonly used template matching algorithm, Dynamic Time Warping (DTW) [20, 37].

Second, we present the time series matching framework. This framework is designed and implemented to address both the ambiguity of the query and the large scale of the database with emphasis on finding the best similarity measure. The idea is to extract and compare different features of the time series data, then configure a composite of features to efficiently measure the similarity between a specific type of the data. The selection of features is based on the time complexity and discriminating power of the different features and the characteristics of the data. This framework can easily optimize the parameters of the new features as well as combine them into comprehensive similarity measure

algorithms.

Third, a concrete application example of a Query-by-Humming system is studied in detail. This music retrieval application is built based on the time series matching framework. A Query-by-Humming system enables the user to find songs by humming part of the tune. In our system, both music and humming are represented as time series data. Thus we can directly use the time series matching framework to build a similarity algorithm with the goal of maximizing the music recognition percentage for the humming we collected.

In this case study, we first review techniques specifically related to music information retrieval; second, we present our algorithm architecture and compare the results with other systems. Finally, we conclude the thesis and discuss possible directions for future work.

Chapter 2

Underlying Technology

2.1 Brief Overview

There are a few important works related to time series matching. Here we provide a brief overview followed by a detailed discussion of each technique.

1. GEMINI framework and related transformations techniques

   GEMINI framework theory[10] essentially transforms the data into a lower-dimension and speeds up the matching process. Various transformation techniques have been developed, mainly for Euclidean distance comparison. Each transformation guarantees *no false negatives* and has a different computational complexity and *tightness of lower-bounding*.

2. DTW and related indexing techniques

   Dynamic Time Warping (DTW) [5] is a similarity matching technique that allows alignment shifting between time series. The DTW distance does not satisfy the *triangle inequality*, so special transformation techniques are developed to speed up the matching process and guarantee no

false negatives. These kinds of transformations act as indexing techniques which reduce comparison computational complexity.

Besides the framework and indexing techniques, **preprocessing techniques** which normalize the data are important to make sure that the comparison makes sense.

2.2 GEMINI framework

Similarity querying for time series databases has been a topic of research in the database community for many years. A lot of work used Euclidean distance between time series as a similarity measure [3, 10, 23, 36, 7, 22, 32, 17, 33, 15, 34]. They can all be applied in the GEMINI framework introduced by Christos Faloutsos, M Ranganathan and Yannis Manolopoulos [10].

The key concept of the GEMINI framework (Figure 2.1) is to first map each time series to a lower dimension, then find similar ones by looking them up in a multidimensional index structure and finally, compare those time series in the original space. The important thing is that the transformations should satisfy the lower-bounding property:

- **Lower-Bounding**

$$D_{index-space}(x, y) \leq D_{true}(x, y) \tag{2.1}$$

Lower-Bounding means the distance between each of the transformed time series should be less than the distance between each of the original time series.

- **No false negatives**

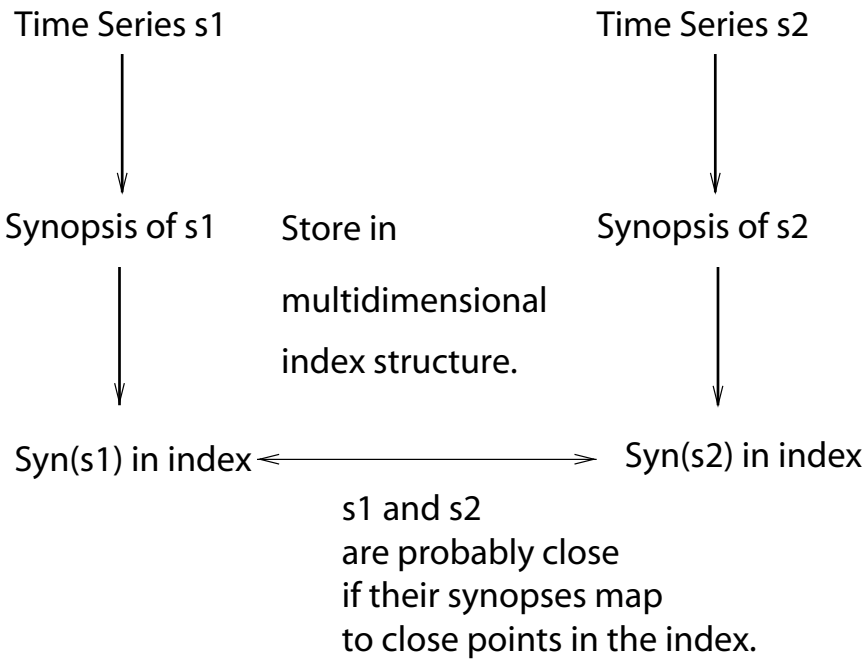


Figure 2.1: GEMINI framework

With the lower-bounding property, the GEMINI framework guarantees *no false negatives*: any time series that is similar to the query in the original space will be selected by the indexing structure. *False negatives* refer to the situation that discards reference data which are actually similar to the query datum; similarly, *true negatives* refer to the discarded reference data that are not similar to the query datum.

- **Tightness of Lower-Bounding**

The differences among the works cited above is that they used different transformations to satisfy the lower-bounding property. The *tightness of lower-bounding* determines the performance of the transformations.

Assume we define:

$$T = \frac{D_{index-space}}{D_{true}}$$

T is in the range of $[0, 1]$ and a larger T gives a tighter bound. The tighter the bound, the better the distance in the transformed space approximates the distance in the original space, thus the better the pruning power of the indexing.

2.3 Dynamic Warping Distance Measure (DTW)

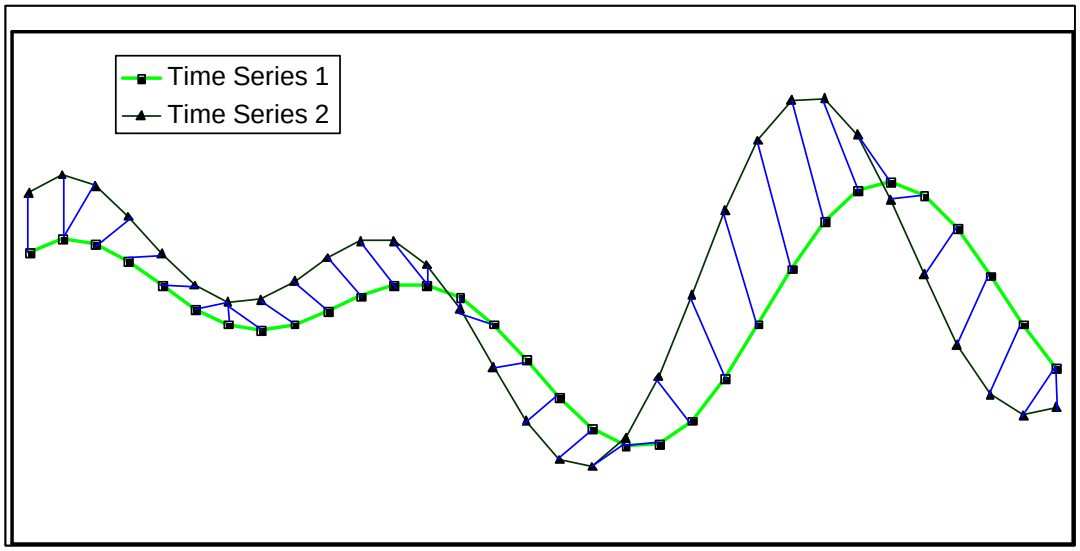


Figure 2.2: Dynamic Time Warping (from [37])

Although the Euclidean distance is used as a similarity measure in a lot of work, it is not suitable for cases where the time series are out of phase in the time axis, see Figure 2.2 for an example. The two time series look similar but they are not close in Euclidean distance. As a solution to this, D. Berndt and J. Clifford [5] introduced DTW into the database community. The Dynamic Time Warping (DTW) distance is a much more robust distance measure for similarity

matching which allows alignment shifting between time series. For the two time series in Figure 2.2, the DTW distance is much smaller than their Euclidean distance.

2.3.1 Definition of DTW Distance

The Dynamic Time Warping distance between two time series x, y is

$$D^2_{DTW}(x,y) = D^2(First(x), First(y)) + min \begin{cases} D^2_{DTW}(x, Rest(y)) \\ D^2_{DTW}(y, Rest(x)) \\ D^2_{DTW}(Rest(x), Rest(y)) \end{cases}$$

where $First(x)$ is the first element of x, and $Rest(x)$ is the remainder of the time series after the $First(x)$ has been removed.

2.3.2 Computation of the DTW Distance

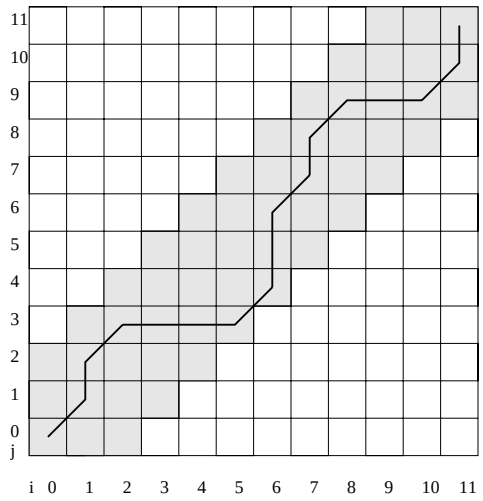


Figure 2.3: DTW distance computation (from [37])

The process of computing the DTW distance can be visualized as a string matching style dynamic program, see Figure 2.3. For time series x of length n and time series y of length m, we use an $n \times m$ matrix M to align them. The cell $M_{i,j}$ corresponds to the alignment of element x_i and y_j. Any monotonic and continuous path P from $M_{0,0}$ to $M_{n-1,m-1}$ forms a particular alignment between x and y:

$$P = p_1, p_2, \ldots, p_l = (p_1^x, p_1^y), (p_2^x, p_2^y), \ldots, (p_l^x, p_l^y)$$

$$max(n, m) \leq l \leq n + m - 1$$

and

- P *is monotonic if* $p_t^x - p_{t-1}^x \geq 0$ *and* $p_t^y - p_{t-1}^y \geq 0$
- P *is continuous if* $p_t^x - p_{t-1}^x \leq 1$ *and* $p_t^y - p_{t-1}^y \leq 1$

If we associate each cell alignment with its corresponding cost, say $D^2(i, j)$, then the sum of the cost along a path represents the cost of the particular alignment. One can prove that the minimum path cost for all possible alignments is the DTW distance between x and y. The minimum-cost path also determines the optimal alignment between x and y.

The time computation cost for DTW distance is $O(mn)$ using Dynamic Programming [37].

2.3.3 Variants of DTW

Usually we add constraints to DTW to avoid too much flexibility in the warping. Two popular global constraints are Sakoe-Chiba Band and Itakura Parallelo-

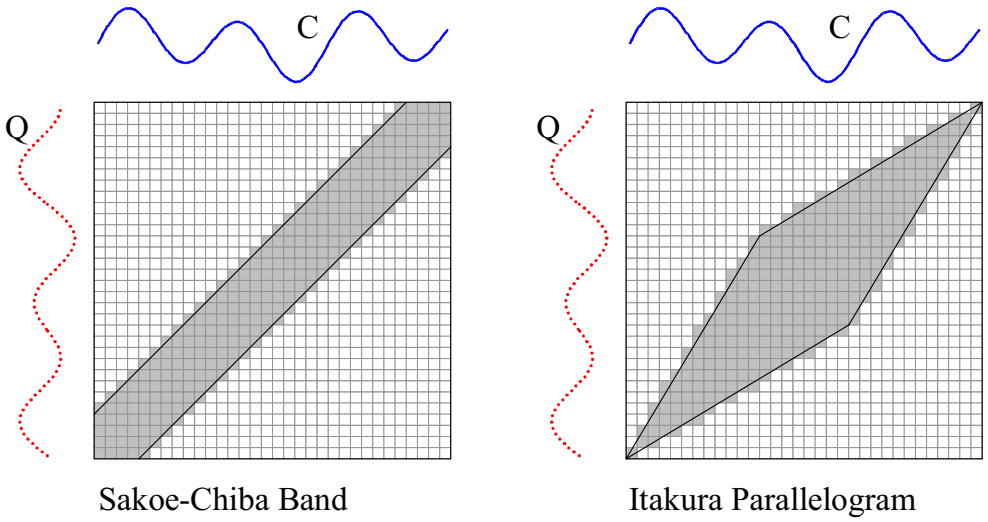


Figure 2.4: DTW distance with global constraints (figure from [14])

gram constraints, illustrated in Figure 2.4. Alignments of cells can be selected only from the shaded area. The Sakoe-Chiba Band constraint is also called k-Local Dynamic Time Warping (k-LDTW). With k-LDTW, the ith element of x can be aligned only to one of the k nearest elements of y.

k-LDTW Distance

The k-LDTW between two time series x, y is

$$D^2_{LDTW(k)}(x,y) = D^2_{constraint(k)}(First(x), First(y))$$

$$+min \begin{cases} D^2_{LDTW(k)}(x, Rest(y)) \\ D^2_{LDTW(k)}(y, Rest(x)) \\ D^2_{LDTW(k)}(Rest(x), Rest(y)) \end{cases} \tag{2.2}$$

where

$$D^2_{constraint(k)}(x_i, y_j) = \begin{cases} D^2(x_i, y_j) & if\ |i-j| \leq k \\ \infty & if\ |i-j| > k \end{cases}$$

α%-LDTW Distance

The α%-LDTW distance of x and y is equivalent to the k-LDTW distance where k is the production of the α% and the larger value between the x and y's lengths.

Other variants of DTW have been introduced to accommodate different situations. Selina Chu, Eamonn Keogh, David Hart and Michael Pazzani [9] introduced an iterative deepening DTW which automatically adjusts the warping parameter based on user specified tolerance for the probability of false dismissal.

C. A. Ratanamahatana and E. Keogh [24] added a machine learning technique to DTW, so that each datum in the database had a learned constraint to be applied during the DTW distance computation. In this way, both the accuracy and efficiency are improved, although the learning process is computationally expensive. This method generally requires a large number of training samples, so it has limited applications.

More general variants of DTW are discussed in Sergios Theodoridis and Konstantinos Koutroumbas's book *Pattern Recognition* [29]. These include applying different local or global constraints and allowing the omission or insertion of data elements.

2.3.4 Advantages and Disadvantages

One advantage of DTW is that the DTW distance measure is less sensitive to local time shift distortion than the Euclidean distance measure. Also, it can handle time series of various lengths while the Euclidean distance measure can compare only equal length time series.

However, the cost of the DTW distance computation is much higher than

that of the Euclidean distance computation, which is $O(n)$ if both time series are of length n. Secondly, the DTW distance does not obey the triangle inequality and it is difficult to index precisely.

Triangle Inequality

A distance measure D satisfies triangle inequality if:

$$D(x, y) \leq D(x, z) + D(y, z), \ for\ any\ data\ x, y, z$$

"Virtually all techniques to index data require the triangle inequality to hold." [13]

A very simple example that DTW distance does not obey the triangle inequality is as follows:

Suppose there are three time series data x, y, z where

$x = 1, 1, 1, 2, 2, 2$

$y = 1, 1, 2, 2, 2, 2$

$z = 1, 1, 1, 1, 2, 2$

The local DTW distances between them with 5%-warping are $D(x, y) = 0$, $D(x, z) = 0$ and $D(y, z) = \sqrt{2}$. Thus $D(y, z) > D(x, y) + D(x, z)$ where it does not obey the triangle inequality.

2.4 Indexing the DTW distance

Despite the fact that DTW distance still does not satisfy the triangle inequality, Keogh's paper [14] proposed a novel indexing technique by introducing envelope filtering and transformed envelope filtering to exactly index the DTW distance.

Y. Zhu, D. Shasha, X. Zhao [37] further generalized the idea into a GEMINI framework for the DTW distance measure by introducing the container-invariant property of the transformations. They also improved the pruning power of the indexing by introducing a transformation which gives a tighter lower-bounding.

2.4.1 Envelope Filter

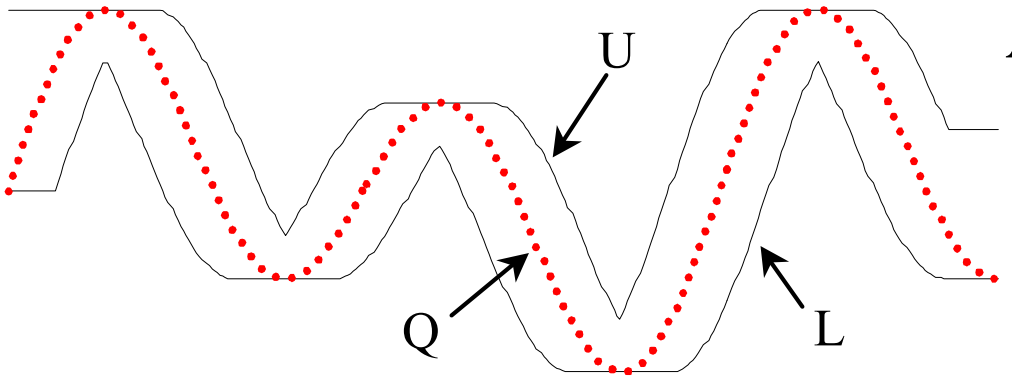


Figure 2.5: Envelope of a time series (figure from [14])

An envelope time series $E = (\underline{E}, \overline{E})$ contains two time series: the lower envelope $\underline{E}$ and upper envelope $\overline{E}$ where each element of upper envelope has a larger value than the corresponding element of the lower envelope.

k-Envelope

The k-Envelope of a time series x of length n is

$$Env_k(x) = (\underline{x}, \overline{x}) \tag{2.3}$$

where $\underline{x}$ *and* $\overline{x}$ *are the upper and lower* k*-envelope of* x *respectively:*

$$\underline{x}_i = min\{x_{i-k}, x_{i-k+1}, \ldots, x_{i+k-1}, x_{i+k}\} \quad for \quad i = 1, 2, \ldots, n$$

$$\overline{x}_i = max\{x_{i-k}, x_{i-k+1}, \ldots, x_{i+k-1}, x_{i+k}\} \quad for \quad i = 1, 2, \ldots, n$$

See Figure 2.5 for an example.

k-Envelope Distance

The k*-envelope distance between time series* x *and* y *is*

$$\begin{aligned} D_{Env_k}(x, y) &= D_{toEnv}(x, Env_k(y)) \\ &= D_{toEnv}(x, (\underline{y}, \overline{y})) \\ &= \sqrt{\sum_{i=1}^{n} \begin{cases} (x_i - \underline{y}_i)^2 & if \ x_i < \underline{y}_i \\ (x_i - \overline{y}_i)^2 & if \ x_i > \overline{y}_i \\ 0 & otherwise \end{cases}} \end{aligned}$$

We say $x \in Env(y)$ if $D_{Env}(x, y) = 0$, which is the case that x is contained within $Env(y)$. Note that this envelope distance is not necessarily symmetric:

$$D_{Env_k}(x, y) \neq D_{Env_k}(y, x)$$

However, this is not a problem for a similarity query since all the comparisons refer to the time series used as query.

Lower-bounding Property of Envelope Distance

Keogh proved that k-envelope distance is a distance metric which lower-bounds the k-LDTW distance [14].

$$D_{Env_k}(x, y) \leq D_{k-LDTW}(x, y) \tag{2.4}$$

One thing to note is that if we use absolute element distance instead of squared element distance in k-LDTW distance and k-envelope distance computation, the same property still holds.

k-LDTW Distance with absolute element distance

The k-LDTW between two time series x, y is

$$D_{LDTW(k)}(x,y) = D_{constraint(k)}(First(x), First(y))$$

$$+min \begin{cases} D_{LDTW(k)}(x, Rest(y)) \\ D_{LDTW(k)}(y, Rest(x)) \\ D_{LDTW(k)}(Rest(x), Rest(y)) \end{cases} \tag{2.5}$$

where

$$D_{constraint(k)}(x_i, y_j) = \begin{cases} |D(x_i, y_j)| & if |i-j| \leq k \\ \infty & if |i-j| > k \end{cases}$$

and $|x|$ is the absolute value of x.

Envelope Filter

We can use envelope distance as a filter to quickly weed out bad candidates at a computation cost lower than that of the DTW distance. More importantly, with this lower-bounding property, we can make slight modifications to the transformations in the GEMINI framework to achieve the indexing of the DTW distance.

2.4.2 Transformed Envelope Filter

Container-Invariant Envelope Transform

Suppose a transformation Γ *of an envelope* $Env(x)$ *is still an evenlope* $\Gamma(Env(x))$*,* $Env(x)$ *it is container-invariant if:*

$$\forall y, if\ y \in Env(x)\ then\ \Gamma(y) \in \Gamma(Env(x))$$

Lower-bounding Property of Envelope Distance

It is easy to prove that the transformed envelope distance lower-bounds the envelope distance if the transformation of the envelope is container-invariant [37].

$$D_{toEnv}(\Gamma(x), \Gamma(Env(y))) \leq D_{Env_k}(x, y) \tag{2.6}$$

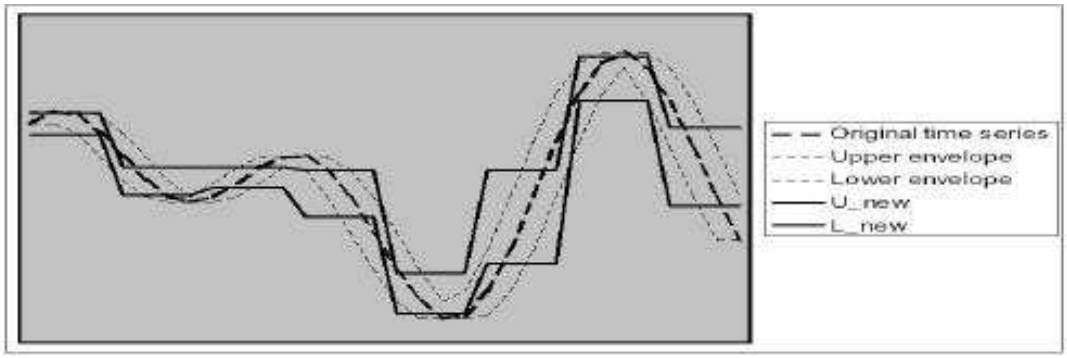


Figure 2.6: Transformed Envelope of a time series (figure from [37])

Transformed Envelope Filter

It is with the above properties that we use the transformed envelope distance as a filter to eliminate bad candidates at a lower computation cost than that of computing the envelope distance.

2.4.3 Adaptive Multi-level Filter Algorithm

From equation 2.4 and 2.6, we have:

$$D_{toEnv}(\Gamma(x), \Gamma(Env(y))) \leq D_{Env_k}(x, y) \leq D_{k-LDTW}(x, y)$$

Let:

$$transformedEnvDis(x, y) = D_{toEnv}(\Gamma(x), \Gamma(Env(y)))$$

$$envDis(x, y) = D_{Env_k}(x, y)$$

$$DTWDis(x, y) = D_{k-LDTW}(x, y)$$

We have:

$$transformedEnvDis(x, y) \leq envDis(x, y) \leq DTWDis(x, y)$$

Given this hierarchical lower-bounding property, we have the following *Adaptive Multi-level Filter Algorithm* in pseudo-code for nearest neighbor query:

```
Given a query time series q
1       //set minimum distance to infinity
2       minDis=infinity
3       for all candidates x in database
4       {       disLevelOne = transformedEnvDis(q,x)
5               //transformed envelope filter check
6               if (disLevelOne < minDis)
7               {       disLevelTwo = envDis(q,x)
8                       //envelope filter check
9                       if (disLevelTwo < minDis)
10                      {       disLastLevel = DTWDis(q,x)
11                              //true DTW distance check
12                              if (disLastLevel < minDis)
13                              {       //found a better match
14                                      bestMatch = x
15                                      //update the minimum distance
16                                      minDis = disLastLevel
17                              }//if at last level
18                      }//if at level two
19              }//if at level one
20      }//for
```

This algorithm guarantees no false negatives and can be easily modified to handle k-nearest neighbor query.

2.4.4 Piecewise Aggregate Approximation Based Transformation

The envelope transformation which was constructed based on Piecewise Aggregate Approximation (PAA) has proven to be a good transformation for the multi-level filter Algorithm [37]. The following gives its definition.

- **Piecewise Aggregate Approximation (PAA)**

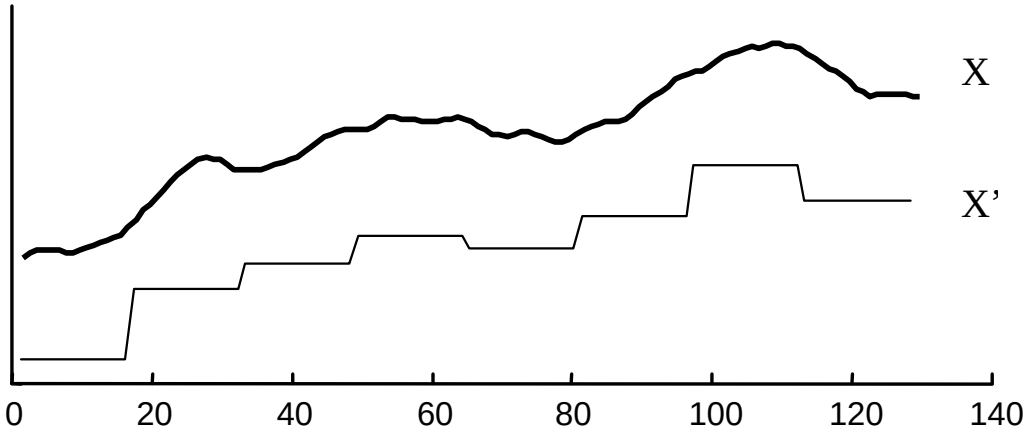


Figure 2.7: The PAA transformation (figure from [16])

PAA was proposed independently by B. K. Yi and C. Faloutsos [33] and E. Keogh, K. Chakrabarti, M. Pazzani and S. Mehrotra [16]. It is a data reduction method which divides a time series of length n into N segments of equal length, see Figure 2.7.

A time series x of length n can be approximated in N space by a vector $X = X_1, X_2, \ldots, X_N$:

$$X_i = \frac{N}{n} \sum_{j=\lfloor \frac{n}{N} * (i-1) \rfloor + 1}^{\lfloor \frac{n}{N} * i \rfloor} x_j \tag{2.7}$$

where $\lfloor x \rfloor$ is called the floor function which returns the maximum integer that is not greater than x.

The time complexity is $O(N+n) = O(n)$ [16].

- **PAA Envelope Transformation**

  The PAA envelope transformation is constructed as follows:

$$\underline{E}_i = \frac{N}{n} \sum_{j=\lfloor \frac{n}{N}*(i-1) \rfloor + 1}^{\lfloor \frac{n}{N}*i \rfloor} \underline{x}_j \ , \ \overline{E}_i = \frac{N}{n} \sum_{j=\lfloor \frac{n}{N}*(i-1) \rfloor + 1}^{\lfloor \frac{n}{N}*i \rfloor} \overline{x}_j \tag{2.8}$$

  It can be proven that the PAA envelope transformation is container invariant. Suppose that there is a time series $y = y_1, y_2, ..., y_n$ and an envelope time series $Env(x) = (\underline{x}, \overline{x})$ and $y \in Env(x)$, we know $\underline{x_j} \leq y_j \leq \overline{x_j}$ for all $j = 1, 2, ..., n$

  Consider applying the PAA transformation on y and the PAA envelope transformation on $Env(x)$, then for $i = 1, 2, ..., N$,

$$\underline{E}_i = \frac{N}{n} \sum_{j=\lfloor \frac{n}{N}*(i-1) \rfloor + 1}^{\lfloor \frac{n}{N}*i \rfloor} \underline{x}_j \leq \frac{N}{n} \sum_{j=\lfloor \frac{n}{N}*(i-1) \rfloor + 1}^{\lfloor \frac{n}{N}*i \rfloor} y_j = \Gamma(y)_i$$

  Similarly $\Gamma(y)_j \leq \overline{E}_j$. So $\Gamma(y) \in \Gamma(Env(x))$. Therefore, the PAA transformation is container invariant and the PAA transformed envelope distance lower-bounds the envelope distance.

2.5 Data Preparation

In most cases, a good similarity measure allows various distortions of the time series. Otherwise the time series need to be normalized before the actual sim-

ilarity measure. The following is a list of distortions and the corresponding solutions to eliminate the distortions.

- Amplitude Shifting Distortion:

  An (amplitude) shifting by δ on a time series $x = (x_1, x_2, ..., x_n)$ is $Shift(x, \delta) = x + \delta = (x_1 + \delta, x_2 + \delta, ..., x_n + \delta)$.

  This distortion can be eliminated by subtracting the average of each time series from the values in the time series. In this way, every time series is normalized to have an average 0. Let $\delta = avg(x) = \sum_{i=1}^{n} x_i$, the time series x after normalization is $Shift(x, -\delta)$.

- Amplitude Scaling Distortion:

  An (amplitude) scaling by β on a time series $x = (x_1, x_2, ..., x_n)$ is $Scale(x, \beta) = \beta x = (\beta x_1, \beta x_2, ..., \beta x_n)$.

  This distortion can be eliminated by first subtracting the average value and then dividing by the resultant time series's standard deviation. In this way, every time series is normalized to have the average 0 and the same standard deviation value 1. Let $\beta = std(x) = \sqrt{\sum_{i=1}^{n}(x_i - avg(x))^2}$; the time series x after normalization is $Scale(Shift(x - avg(x)), 1/\beta)$.

- Global Time Scaling Distortion:

  A global time scaling on a time series uniformly squeezes or stretches the time series on the time axis.

  A w-up-scaling of a time series x of length n is $U^w(x) = y$ of length nw, where $y_i = x_{\lfloor i/w \rfloor}, i = 0, 1, ..., nw - 1$;

A w-down-scaling of a time series x of length n is $D^w(x) = z$ of length $\lfloor n/w \rfloor$, where $z_i = x_{iw}, i = 0, 1, ..., \lfloor n/w \rfloor - 1$.

This distortion can be eliminated by up-scaling or down-scaling each time series to a uniform length.

- Global Time Shifting Distortion:

  A global time shifting by i (which can be negative) on a time series $x = (x_1, x_2, ..., x_n)$ is $TShift(x, i) = (x'_1, x'_2, ..., x'_n)$, where $x'_j = x_{j+i}$ for $0 < j \leq n$ and $x_{j+i} = x_1$ if $j + i < 1$(when i is negative) and $x_{j+i} = x_n$ if $j + i > n$(when i is positive).

  This distortion, also called lag, can be detected and eliminated by applying a lagged distance measure or a time warping distance measure, which allows for extra or missing elements at the beginning or end.

- Local Time Shifting Distortion:

  For local time shifting, the shifting happens locally and non-uniformly.

  This distortion can be solved by applying a distance measure that allows time warping.

- Background Noise:

  Sometimes the query or data contains unavoidable random noise data. This noise is comparable to the low-pitch or high-pitch background noise in a recording or the disturbance in a radio broadcast.

  This noise can be removed by applying signal processing techniques such as low- or high-band-filtering.

For more detailed information about related work on time series matching, see D. Gunopulos and G. Das[12] and Keogh [13]; both gave a tutorial on time series similarity search which covered the topics of similarity measures and indexing. Shasha and Zhu's book [28] is also a valuable tutorial on time series techniques with case studies.

2.6 Summary

This chapter reviewed a few important techniques related to time series matching: the GEMINI framework, the DTW and related indexing techniques such as the envelope filter and the tranformed envelope filter. The next chapter will present our time series matching framework.

Chapter 3

Time Series Matching Framework

Here we present our *time series matching framework*. It is a framework to easily optimize, combine and test different features to perform fast similarity searches based on the application requirements. The framework can be easily extended and it provides a collection of simple and easy-to-use tools. For example, there is a tool analyze feature measure and generate distribution charts; there is a tool to combine a few feature measures into a feature measure; there is tool to generate algorithm which is written tersely in the configuration file.

We will first formalize the problem, then present the functionality and structure of the framework and finally give explanatory examples. In the following we discuss time series, but the framework works on any ordered array data.

3.1 Formal Problem Statement

Our goal is to build a time series matching algorithm which can be customized for any application. It can be formalized as follows:

Given any training data for an application, there is a set of time series data pairs:

$$S = \{(q_1, r_1), (q_2, r_2), ...(q_n, r_n)\}$$

where

- Each $r_i = \{r_i(0), r_i(1), \ldots, r_i(l_i)\}$ is a time series reference data of some finite length l_i; $\mathbf{r} = \cup r_i$ for $i = 1, 2, \ldots n$,
- Each $q_i = \{q_i(0), q_i(1), \ldots, q_i(h_i)\}$ is a time series query data of some finite length h_i; $\mathbf{q} = \cup q_i$ for $i = 1, 2, \ldots n$,
- The r_i is considered the best match to q_i

Let us say that for each query q there is a function *correctmatch* such that $correctmatch(q)$ is the best match for q in the database. (The criterion for "best" depends on the application, e.g. the song the most closely corresponds to a humming as far as the user is concerned.) Here we assume all the correct match r_i for q_i are in the database.

If G is an algorithm for matching and we have a threshold k, then $G(q_i) = p_1, p_2, ..., p_k$. We say G is correct on q_i if r_i belongs to $G(q_i)$. We want to find the G that maximize the number of q_i for which G is correct.

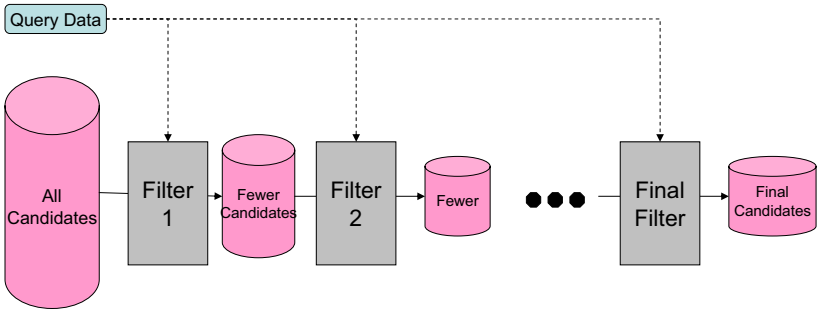


Figure 3.1: Multi-filter algorithm structure

3.2 Framework Overview

Given any application training data, the framework can be used to build a multi-filter algorithm as shown in Figure 3.1. At each filter level, the algorithm compares certain features of the query and reference data and filters out bad candidates; the number of candidates becomes smaller and smaller; finally the algorithm gets a list of candidates which are similar to the query data. The last filter will rank the results.

A filter can be very simple and compare only a simple feature of the query and candidates; or it can be very complicated and by itself be a ranking algorithm; or it can be a boosted set of filters. We will discuss *Boosted Filters* in

detail later in the thesis.

Unlike the GEMINI framework where the similarity measure is defined beforehand, the framework "learns" the best similarity measure on the training data. The best similarity measure with the correct goal is not explicitly defined before training and it may not match all the query data to the correct reference data. Thus it is hard to define "guarantee no false negatives". Each filter simply maximizes the correctness of the labeling on good candidates.

3.3 Functionalities

The major functionalities of the framework are analyzing features, building matching algorithms, boosting filters, benchmarking and validating algorithms.

3.3.1 Feature Analysis

The framework helps analyze any specific feature of the time series data. Technically, it is analyzing different feature parameters or comparison methods for any particular feature. The user defines how to compute a particular feature and how to compare two feature values; the framework automatically computes the features for all the training data, compares them and outputs an analysis; based on the analysis, the user can decide whether or not, and how, to use the feature to build a filter in the algorithm.

3.3.2 Building an Algorithm

The framework can be used to build a similarity matching algorithm. The user simply defines the filters in a text configuration file. Each filter is a line of text

which consists of the name of the feature comparison function and the condition test. The framework will read the configuration file and dynamically generate a multi-filter algorithm for the similarity measure. The order of the filters in the text file is the order of the filters in the algorithm.

The filters to be used in the algorithm are selected based on both the feature analysis and on the benchmark results. The configuration for building the algorithm can be easily altered to change the order and the parameters of each filter.

In some cases, a simple filter may not work well, such as when it has a high percentage of false negatives . Then a more sophisticated filter should be used, such as boosted filters as described next.

3.3.3 Boosted Filters

Boosting [11, 26, 25] is an algorithm for constructing a 'stronger' classifier using only a training set and a set of 'weak' classifiers. We can use it to combine simple filters into a more discriminating filter.

Figure 3.2 is an example of simple boosting. $W1, W2, W3$ are three weak classifiers, each of which has above 50% but much less than 100% probability to correctly classify a datum. Each datum can be classified as one of two classes: *black* or *white*.

Suppose A, B, C are three data each respectively belonging to the class *black*, *white* and *black*. $W1$ will label A, B, C as *black*, *white* and *white* respectively; $W2$ will label A, B, C as all *black*; $W3$ will label A, B, C as *white*, *white* and *black* respectively. We can construct a stronger classifier S which is a linear combination of $W1, W2, W3$. By assigning appropriate weights to $W1, W2, W3$

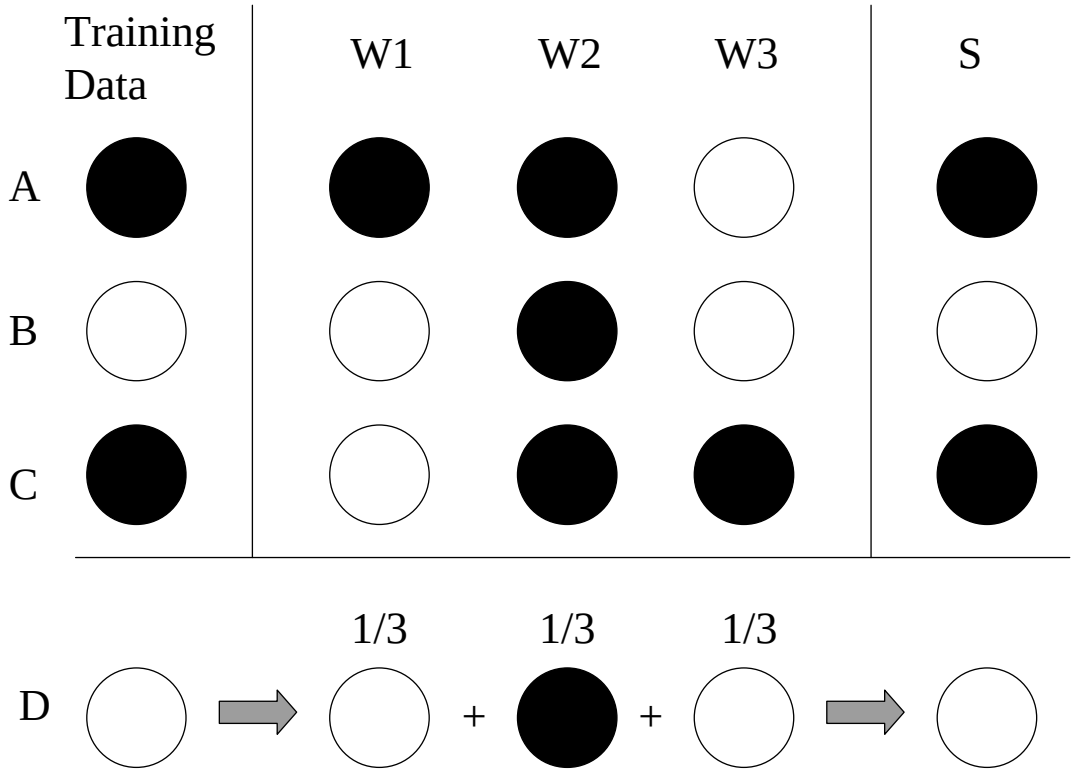


Figure 3.2: Ada boosting

(1/3 each), S will treat A as $\frac{1}{3}$ $black + \frac{1}{3}black + \frac{1}{3}white$, and by rounding it to the majority decision, it will correctly classify A as *black*. Also, S will correctly classify B and C. The probability to correctly classify a datum for S is 100%. As proven in [11], for reasonable distributions, for any other datum D, it is highly likely that S will classify it correctly. The process of computing the appropriate weights for weak classifiers is called **boosting**.

Our framework is using a specific version of the boosting algorithm called **AdaBoost.MR**: a multiclass, multi-label version of AdaBoost based on ranking loss. More details can be found in Appendix A.

It is suggested in [29] that the **decision tree algorithm** is a good algorithm

to detect weak classifiers as good candidates for boosting [26]. So the framework also supplies a tool to build decision trees.

3.3.4 Algorithm Assessment

Benchmark

Once an algorithm is built, the framework can be used to benchmark and validate the algorithm. By selecting different testing data sets, the benchmark result will show whether the algorithm is general enough to cover not only the training data but also the testing data.

Cross-validation

The simplest and most widely used method for estimating prediction error is **k-fold cross-validation** [30]. Basically, given the training data, we randomly divide them into k roughly equal-sized parts; picking the i-th part, we train the algorithm with the other $k-1$ parts and test the result on the i-th part; we do this for each i in $1 \ldots k$. We usually choose 10 as k based on the general observation that 10 is a good value.

If the training error and testing error do not change more than 5% as i changes, it means that the algorithm is general enough with regards to the data selection. If the testing error is much bigger than the training error, it means that the algorithm has an overfitting problem, indicating that a different parameter setting should be used.

The framework uses 10-fold cross-validation to assess the generality of the parameters, such as the condition test value for the simple filters and the weights for the boosting filters.

Scalability Test

By increasing the size of the reference database step by step, the framework can assess the scalability of the algorithm it builds.

For each scale level of the reference database, we need to make sure the prediction error estimate is accurate. So **Bootstrapping** [30] is used to make sure the data selected for testing is general enough that our prediction error for this scale level is reasonable.

Suppose:

- The scale we want to test is a reference database R' of m time series;
- The whole reference data space is R of size n ($m < n$);
- The current testing data are k ($k < m$) pair of time series

$$S = \{(q_1, r_1), (q_2, r_2), ...(q_k, r_k)\}$$

and

$R_T = \cup r_i$, $R_T \subset R$ for $i = 1, 2, \ldots k$

where

1. the r_i is considered the best match to q_i.

Bootstrapping:

For about $C = 1000$ times (a customary number),

- Select $m - k$ time series data uniformly with replacements from R to form a set R_S;

- Use $R' = R_T \cup R_S$ as a benchmark reference database and compute the prediction error

Output the C prediction errors and the average prediction error.

If the C prediction errors have low standard deviation, then the algorithm does not depend much on the selection of data. The average prediction error gives a good idea of what the prediction error is in the general case.

3.4 Framework Components

3.4.1 Overview

The framework consists of the following major components from bottom to top:

- Transformation Functions
- Comparison Functions
- Features
- Feature Measures
- Conditions
- Filters
- Algorithms

The relationship between the different components is shown in Figure 3.3. A more detailed explanation can be found in the following subsections.

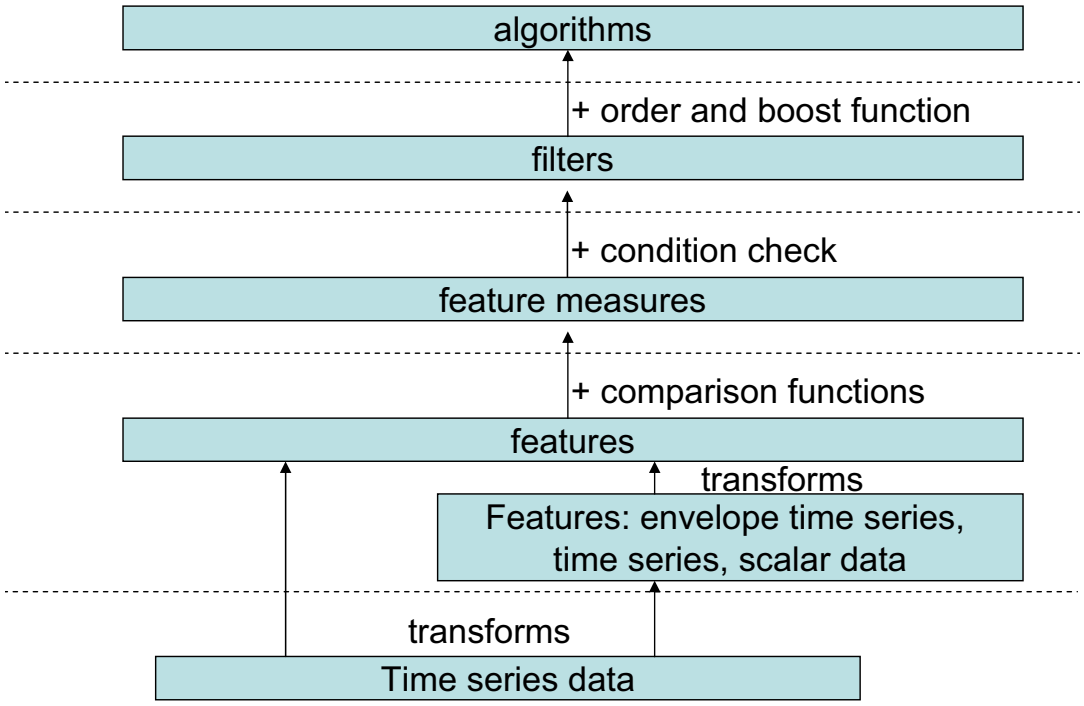


Figure 3.3: Framework components from bottom to top

3.4.2 Transformation Functions

Transformation functions are primitive functions that transform data from one form to another, such as the Discrete Fourier Transform (DFT) [28] that transforms data from the time domain to the frequency domain.

Currently there are three data forms in the framework: *scalar*, *time series* and *envelope time series*.

- Scalar

  A single real value.

- Time Series

  A real value sequence with finite length.

- Envelope Time Series

  A set of two finite length real number value sequences. In the case that each element's value in the first number sequence is greater than the corresponding element in the second number sequence, we call the first number sequence a higher envelope and the other a lower envelope.

3.4.3 Comparison Functions

Comparison functions are functions that compare two data items and return a scalar value. The scalar value is 0 when two data are considered equal. It *can be* negative; a positive value means the first datum is "bigger" in the measure's sense and a negative value means the first datum is smaller.

The comparison function is *often reflexive and symmetric*. It *might* either *be transitive* or *satisfy the triangle inequality*. Currenly we don't make use of these properties. But they can served as meta information in case we want to automate the framework process in the future. The two data items could be of the same or of different form; the restriction on the function is very loose. The maintainer of the framework needs to understand the functions to use them.

Suppose F is the comparison function and q, r are two data inputs. It may satisfy the following properties. These properties may be used to automate the process to create new feature measures.

- Reflexive

  $$F(q, q) = 0$$

  This property does not usually hold when F applies only to two data of different forms with a special order such as envelope distance measure.

- Symmetric (on absolute value)

  $$|F(q,r)| = |F(r,q)|$$

  under the condition that $F(q,r)$,$F(r,q)$ can be computed.

  This property does not usually hold when F only applies to two data of different forms with a special order such as envelope distance.

- Transitive

  $$F(q,r_2) = F(q,r_1) + F(r_1,r_2)$$

  when q, r_1, r_2 are of the same data form and $F(q,r)$ could return a negative value.

  This property does not usually hold when F only applies to two data of different forms with a special order such as dynamic warping distance measure.

- Triangle Inequality (on absolute value)

  $$|F(q,r_2)| \leq |F(q,r_1)| + |F(r_1,r_2)|$$

  when q, r_1, r_2 are of the same data form and $F(q,r)$ returns a negative value.

3.4.4 Features

Transformation functions compute feature data from the original time series data or other feature data, as in Figure 3.1.

3.4.5 Feature Measures

The comparison functions, together with the feature data, comprise feature measures, as in Figure 3.1. A comparison function can apply to different feature data to construct different feature measures.

3.4.6 Conditions

The condition functions, together with the feature measures, construct filters. A feature measure having different condition thresholds forms different filters, one for each threshold.

3.4.7 Filters

As we mentioned earlier, we built a multi-filter algorithm based on the filters. At each filter level, the algorithm uses one or more feature measures to compare certain features of the query and reference data and filters out some bad reference candidates.

Consider a classifier which labels each candidate 'good' or 'bad'. If it always gives the correct answer, it is considered a *perfect classifier* which can be directly used as one filter in the multi-filter chain; if it gives the correct answer much more than 50% of the time, it is called a *strong classifier*; if it gives the correct answer slightly more than 50% of the time, then it is called a *weak classifier*, which can be combined with other weak classifiers to create a boosted strong classifier. Each filter in the multi-filter chain of the algorithm should be at least a strong classifier if not a perfect classifer.

3.5 Component Examples

In this chapter we will show how easy it is to create components with $K[1]$ example codes. A long list of the example framework components are in Appendix B. Here we present only a few examples, which will be helpful in understanding Section 3.6.

3.5.1 Example Transformation Functions

Each transformation function component has 3 APIs: **name, description** and **compute**, where the API function **compute** is required and the other two are helpers for the purpose of debugging or display.

For $K[1]$ code implementation, each transformation function has an entry in the dictionary **.transform**.

- Remove Average(**deavg**):

  Subtract the average value from each element in the time series.

  K code:

  $\backslash d$ **.transform.deavg**

  name*:"Subtract the Average"*

  description*:"Subtract the average value from each element in the time series"*

  compute*:{[x] :x-(+/x)%x}*

- Zero Crossing Rate(**zcr**):

  Compute how many times the time series data cross the average line.

K code:

\d **.transform.zcr**

name*:"Zero Crossing Rate"*

description*:"Compute how many times the time series cross the average line"*

compute*:{[x] x:***.transform.deavg.compute***[x]*

/rest of the implementation omitted}

This transformation reuses the **deavg** tranformation to preprocess input data.

- Direction Change Count(**dcc**):

  Compute how many times the time series data changes direction, either up or down.

  K code:

  \d **.transform.dcc**

  name*:"Direction Change Count"*

  description*:"Compute how many times the time series data changes up or down direction"*

  compute*:{[x] /implementation omitted}*

3.5.2 Example Comparison Functions

Each comparison function component has 3 APIs: **name, description, compare**, where the API function **compare** is required and the other two are

helpers for the purpose of debugging or display. API **compare** takes two values as input. The forms of the two input values may be different and the order of input usually matters.

For the $K[1]$ code implementation, each comparison function has an entry in the dictionary **.measure**.

- Subtraction(**subtraction**)

  $C(q, r) = r - q$, where q, r are both scalars or both time series of the same length.

  It is reflexive, symmetric on absolute value and transitive. It satisfies the triangle inequality on absolute value when both input are scalars.

  K code:

  $\backslash d$ **.measure.subtraction**
  name*: "subtraction"*
  description*: "Subtraction of the first datum from the second"*
  input*: `ts*
  compare*:{[q;r]:r-q}*
  /note that the order of the subtraction is important

- α%-Local Dynamic Time Warping(**ldtw**)

  It computes the k-local dynamic time warping distance between two time series q, r where $k = 1 + n * \alpha\%$ and n is the length of q. It is reflexive.

3.5.3 Example Feature

Each feature component has 4 APIs: **name, description, input and compute** where the API functions **input and compute** are required and the other two are helpers for the purpose of debugging or display.

For the $K[1]$ code implementation, each feature has an entry in the dictionary **.segts_features**.

- Relative offset of the time series(**ts_rel**):

  For each consecutive pair in the time series, subtract the two values in the pair and we get a new time series.

  K code:

  $\backslash d$ **.segts_features.ts_rel**
  name: *'ts_rel*
  description: *"Relative offset of the time series"*
  input: *'ts*
  compute: {*[x]:-':x*}

  The above code assumes the time series data feature **'ts** is defined at **.segts_features.ts**. Its **input** API refers to **'ts**, meaning that the feature **'ts_rel** can be computed from feature **'ts** using its **compute** API.

3.5.4 Example Feature Measures

Each feature measure component has 5 APIs: **name, description, opl, opr** and **op**, where the API functions **opl, opr** and **op** are required and the other

two are helpers for the purpose of debugging or display. **op** is the operater and **opl opr** are the left and right operands respectively. **opl** may be different from **opr**, depending on the **op**'s requirement on the input.

For the $K[1]$ code implementation, each feature has an entry in the dictionary **.segts_measures**.

- Zero-crossing rate difference(**ts_zcr**):

  Compute the difference of the zero-crossing rate of two time series.

  K code:

  $\backslash d$ **.segts_measures.ts_zcr**

  name*: 'ts_zcr*

  description*: "Subtract the value of the zero-crossing rate of two time series"*

  opl:opr*:.segts_features.ts_zcr.name*

  op*:.measure.subtraction.compare*

  The above code assumes the time series data feature **'ts_zcr** is defined at **.segts_features.ts_zcr**. Its **opl,opr** API both refer to **'ts_zcr**, meaning that the measure is based on feature **'ts_zcr**.

  The **.segts_measures** and **.segts_feature** appear to be duplicated and redundant. However, for the same feature, we can apply different comparison functions to create different feature measures. It does not look useful in this simple case but will be useful when we create complicated feature measures.

More importantly, the result of a feature measure is a monotonic scalar value which we can analyze and determine a parameter to create filters.

In a way similar to creating the feature measure **.segts_measures.ts_zcr**, we can create the feature measure **.segts_measures.ts_dcc** using feature **.segts_features.ts_dcc** and comparison function **.measure.subtraction**. We will compare these two feature measures **ts_zcr, ts_dcc** later in section 3.6.

3.5.5 Example Conditions

The condition keywords are used in the algorithm builder configuration file to create filters. Some examples are as follows.

- **e**: Feature value is equal
- **le**: Measure value equal to or less than
- **ge**: Measure value equal to or greater than
- **in**: Measure value is in a range
- **rank**: Rank of measure value among all reference data in DB

3.5.6 Example Filters

We will show how easy it is to use a configuration file to prototype algorithm and how easy to make changes to an algorithm.

Each line in the algorithm builder configuration file defines a filter. The format is 'condition, feature measure, condition value'. To add a new filter, simply add a new line; to remove a filter, simply remove or comment out the line.

The framework can load the new configuration file and generate the algorithm for matching. Each algorithm can be stored in a separate terse text file which makes it very easy to maintain.

For example, suppose the query datum is q, a reference datum is r, and $\mathcal{M}$ is a feature measure for q, r.

- **e,ts_zcr,1**

$$\mathcal{M}(q,r) = ts\_zcr(r,q) = \begin{cases} 1 & if\ (r_{ts\_zcr} == q_{ts\_zcr}) \\ 0 & otherwise \end{cases}$$

where r_{ts_zcr} and q_{ts_zcr} are the ts_zcr feature of q and r respectively.

This filter will consider r as a good candidate only if

$$\mathcal{M}(q,r) == 1$$

In this example, the feature measure ts_zcr incidentally has the same name as the feature name ts_zcr it used to test the condition.

- **le,ts_dcc,3**

$$\mathcal{M}(q,r) = ts\_dcc(r,q) = r_{ts\_dcc} \ - \ q_{ts\_dcc}$$

where r_{ts_dcc} and q_{ts_dcc} are the ts_dcc feature of q and r respectively.

Since we specify the threshold as 3, this filter will consider r a good candidate only if

$$\mathcal{M}(q,r) \leq 3$$

In this example, the feature measure ts_dcc incidentally has the same name as the feature name ts_dcc it used to test the condition.

- **rank,ts_ldtw5,15**

  Here **ts_ldtw5** is the feature measure that computes the 5% local dynamic time warping distance between the query datum and reference datum,

  $$\mathcal{M}(q, r) = ts\_ldtw5(r, q) = ldtw(q, r)$$

  where the warping parameter $\alpha\%$ is the default 5%.

  This filter will consider r as a good candidate only if its 5% local dynamic time warping distance to q is one of the 15 smallest values among all the reference data's 5% local dynamic time warping distances to q.

3.5.7 Example Boosted-Filter

In the algorithm builder configuration file, a boosted filter is represented as a few text lines as follows:

1. The first line is "**boost{** *weights*" where a "**{**" separates keyword "**boost**" and the *weights* for the combining filters. The weights are a list of numbers separated by "**,**";

2. Each line of the following lines defines a filter as in Section 3.5.6. The i-th filter's weight is the i-th number in the number list;

3. The boosted filter ends with "**}**".

Suppose the boosting algorithm suggests that three filters **(e,ts_zcr,1)**, **(le,ts_dcc,3)**, **(rank,ts_ldtw5,15)** can be combined with equal weights 0.33, 0.33, 0.33 to create a stronger filter. It can be represented as:

Config file text:

boost{1,1,1

e,ts_zcr,1

le,ts_dcc,3

rank,ts_ldtw5,15

}

The weights in the example are 1,1,1 which will be automatically normalized.

3.6 Usage Examples

3.6.1 Feature Measure Analysis

The framework can generate a report for *any* distance feature measure $\mathcal{M}$ for further analysis. This makes it convenient to analyze and experiment new feature measures.

For any training data $S = \{(q_1, r_1), (q_2, r_2), ...(q_n, r_n)\}$ where r_i is the correct match for q_i, $\mathcal{M}(q_i, r_j)$ will be computed for all i from 1 to n and all $r_j \in R$.

We look at two distributions:

- **The distribution of $\mathcal{M}(q_i, r_i)$ for all i, (P):**

  It gives information about whether the $\mathcal{M}$ gives a distance value close to zero for correct matches.

- **The distribution of $\mathcal{M}(q_i, r_j)$ for a fixed i and all $r_j \in R$, (Q_i)**:

  It gives information about whether the $\mathcal{M}$ can distinguish the correct matches from the incorrect ones.

Situations:

- If $\mathcal{M}$ is consistantly low for correct matches and consistantly high for incorrect ones, then $\mathcal{M}$ is a good feature measure.

- In other cases, $\mathcal{M}$ might be used as weak classifier. Since a weak classifier only needs to have slightly higher than 50% correctness probability, if it is worse than 50% probability, then the reverse would be a weak classifier. The only case where a measure is useless is when the correctness probability is 50%.

For example, usually **Direction Change Count** is not a good feature measure for data with even small noise.

Considering a time series datum 1, 2, 2, 2, 1 as the reference data, the direction change count is 1. If there is some noise in the query data, say 1.0, 2.0, 1.9, 2.0, 1.0, the direction change count in the query data is 3!

3.7 Summary

This chapter explained the structure and functions of the time series matching framework. Given any application training data, the framework can be used to build a multi-filter algorithm to perform an accurate and efficient similarity search. In the next chapter, we will study a case of a music retrieval system. We will apply this time series matching framework to analyze music data and build a similarity search algorithm to match people's humming to music melodies.

Chapter 4

Case Study: Query-by-humming

A Query by Humming (QbH) system allows the user to find a song by humming part of the tune. The idea is simple: the user hums into the microphone; the computer records the humming and extracts certain melody and rhythm features; then it compares these features to those of the songs in the database; finally it returns a ranked list of the songs or song segments most similar to the humming. There are several applications for this technology, such as music search engines, cell phone ring-tone searches, karaoke scoring and music learning software.

Usually the evaluation of a query-by-humming system is based on human judgment. We say a hummed tune is *human recognizable* if any person who knows the song being hummed can recognize the song from the humming. We say a hummed tune is *top-K system recognizable* if the song name is in the system's top K list (K is usually small, 1, 5 or 10). Given a set of hummed tunes, the percentage of hummed tunes that are recognizable by the system is called the *hit rate*. The higher the hit rate, the higher the accuracy.

$$Top_K hitrate = \frac{the\ number\ of\ TopK\ system\ recognizable}{the\ number\ of\ human\ recognizable}$$

My goal is to build a fast and accurate system with thousands and eventually millions of songs. I will first compare related work on QbH systems, then propose an approach to improve one of them, and finally show some experimental results.

4.1 Related Work Review

Currently there are several Query-by-Humming systems being built and various techniques have been applied.

1. String-represented note sequence matching

   Alexandra Uitdenboderd and Justin Zobel [31] at RMIT University used strings to represent the note sequence of music so that many fast and mature string-matching algorithms could be directly used. For example, each interval between two notes is represented as a letter "S" if the interval is close to 0. However, it is very hard for a human to hum exact music notes; so humming cannot be represented accurately by symbolic sequences of music notes. As a result the accuracy of the system is not satisfactory.

   The New Zealand Digital Library MELody inDEX developed by Rodger J. McNab, Lloyd A. Smith, David Bainbridge and Ian H. Witten [21] also used stringsa to represent music. They applied an approximate string matching technique which is basically Dynamic Time Warped string matching. As a result, the extended time taken to perform the approximate matching in large databases was still a problem. "The system con-

tains 9,400 folk songs and a 20-note search pattern requires approximately 21 seconds." The bigger problem is that the returned list contains too many entries and does not have a high top-K hit-rate for small K. An online version of the system recently become available [2].

W. Archer's [4] string editing matching algorithm is another variant of the DTW string matching technique which allows missing of notes in the humming.

Another novel idea is to not only dynamically match note values but also dynamically match duration values.

2. Time Normalization and Partial Tone Transition

   N. Kosugi, Y. Nishihara, T. Sakata, M. Yamamuro and K. Kushima's Large Music Database [19] "holds over 10,000 songs but the retrieval time is about one second. And it is able to recognize the song and rank it within the first 5 places on the list for about 70% of hummed tunes that are recognizable to human beings as a part of a song". Although this performance is far from perfect, it is very good considering the scale of the system. Also, it is a system that supports sub-sequence matching. However, the system requires the user to hum with the syllable 'ta' and requires the user to hum following the beats of a metronome.

   Their system uses the music notes information from MIDI files. The duration of the notes in a song are normalized based on the most frequent duration among all the notes. Then the song is segmented into subsequences with equal duration lengths. The subsequence may be segmented into subsubsequence if the most frequent duration among the notes in the sub-

sequence is smaller than the one among all the song notes; the subsequence may be merged if the most frequent duration is bigger. Then the tone-transition (relative note offset) feature is computed for each subsequence. The partial tone-transition feature are extracted from the tone-transition starting from a high note in the subsequence. Then the features are used to compare query and reference candidates. Some indexing techniques are used to speed up the system.

3. Melody slope matching

   Y. Zhu, M. S. Kankanhalli and C. Xu [35] matched music based on the music's melody slope. For example, several adjacent notes are approximated by a line and the slope of the line will be treated as a feature. This method is not equipped to handle a bad humming query, and thus will not have high accuracy. However, this method may be used as one filter to quickly remove bad candidates.

4. Dynamic Time Warping (DTW) on pitch contour time series

   D. Mazzoni and R. B. Dannenberg [20] proposed a subsequence matching algorithm which uses local time-warped distance measure to match music. Although the precision is better than Euclidean distance, the response time is not ideal because no indexing on DTW distance is applied.

   Y. Zhu, D. Shasha and X. Zhao [37] used DTW distance measure and the GEMINI framework with PAA-based envelope transforms. The songs in the database were chopped into song segments based on melody and transcribed into pitch contour. The query is compared to each song segment in the system using the adaptive multi-level filter algorithm. Both

the efficiency and precision results are very good on a small demo system with 53 Beatles songs.

5. Survey

   The survey paper on audio fingerprinting by Pedro Cano, Eloi Batlle, Ton Kalker and Jaap Haitsma [6] is a significant paper on audio retrieval-by-content algorithms. It gives a general framework with a list of algorithm design requirements and a long list of algorithms. It also discusses different distance metrics and different indexing methods.

Conclusion

From the survey and our experimental results, we can summarize the related work as follows:

1. Warped distance is more robust

   Generally, similarity measures that allow time warping have higher accuracy than those which use Euclidean distance or exact string matching.

2. Need to scale up

   The computational complexity of time-warped matching is still prohibitive. A real large scale system with millions of songs needs a better indexing method and a more discriminative similarity measure.

3. Difficulty of performance comparison

   Although there are successful works on query-by-humming systems, it is hard to compare the results for the following reasons:

   - No standard for evaluation

(a) The data set and testing set are different.

The music collection and the size of the database varies greatly. The testing sets are generally too small to be statistically meaningful. Also, the selection of the testing will affect the result. For example, some melodies are more distinguishable than others.

(b) The definition of accuracy is not reliable

The hit-rate definition is based on human's recognition of humming, which is not reliable. For example, a human can recognize a hummed tune by recognizing the most distinguishable part even if other parts may be out of tune. Also, a human who knows only a few songs might more easily recognize more hummed tunes than a human who knows a lot of songs, who may not recognize a hummed tune because it is similar to many tunes. So a human may mistakenly label a hummed tune because of their personal knowledge.

- No easy access to the system

  Only two of above systems have online interfaces, one of which was not accessible until very recently.

Since I am continuing my work based on Yunyue Zhu's system [37], I will use that system as a benchmark reference. The evalution process is to first have more than 3 people verify each humming. Only hummings that can be recognized by at least 3 people are used for the system training. Also, the reference database for training contains only songs of the training hummings to avoid influence of other song data.

4.2 Our Query-by-humming System

Our system uses the time series matching framework to learn the measure instead of relying purely on a single distance measure.

4.2.1 New Workflow

The workflow of the new system is an extension of the old system from [37], see Figure 4.1. We will first give a query work flow example here and then discuss the key ideas in detail.

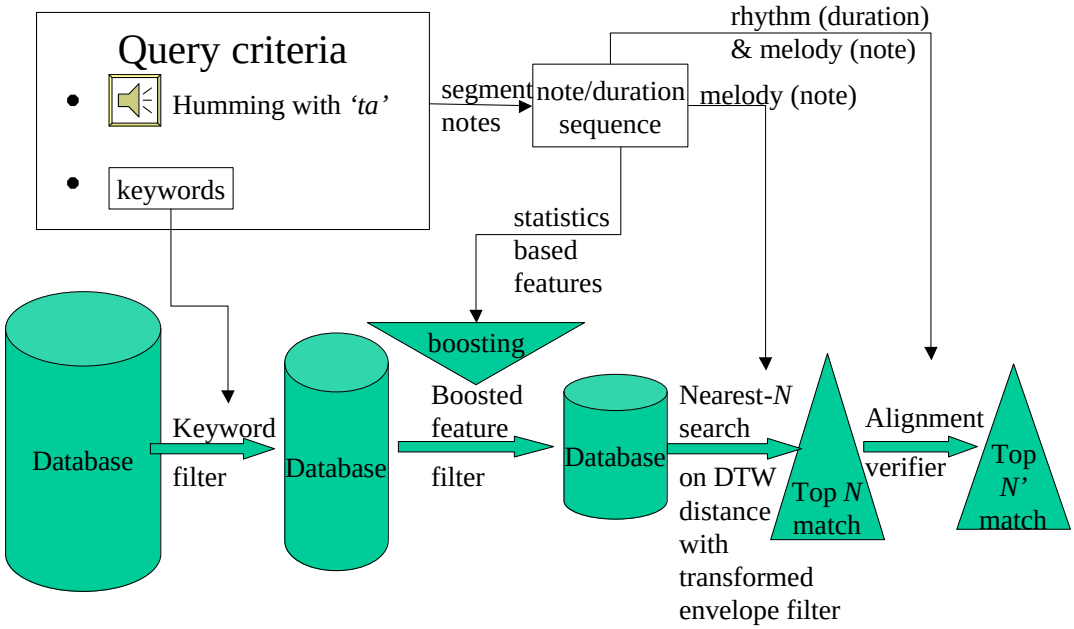


Figure 4.1: New Query-by-humming System

Given a query,

1. Preprocessing

The humming is transcribed into pitch contours and extracted as a note value sequence and duration value sequence.

2. Keyword filter

   The candidate set is first filtered using the keyword if any keyword is supplied.

3. Multiple Statistical Feature Filters

   The candidate set is further filtered based on a multi-filter chain, some of which are boosted filters.

4. Adaptive multi-level DTW filters

   The melody (note-sequence) information is used as a query to obtain a top-K list. This step uses the same adaptive multi-level filter algorithm as Yunyue Zhu's framework except that note-sequences are used instead of pitch-contours.

5. Alignment verifiers

   For each candidate in the top-K list, the alignment between it and the query is verified based on both the melody (note-sequence) and rhythm (duration-sequence) information.

4.2.2 Key Idea: 'ta'-based humming

Kosugi et al [19] showed that humming with only the syllable 'ta' can be easily segmented into note-sequences; experiments also show the same result. Figure 4.2 shows two hummings of the same song segment. Unlike humming using 'la',

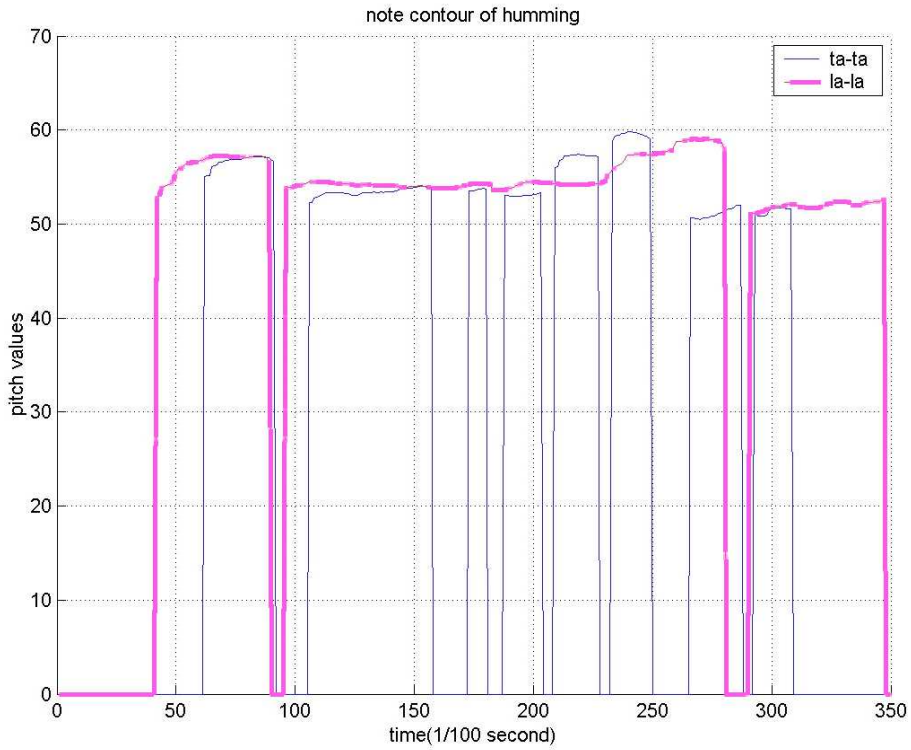


Figure 4.2: Compare humming using 'ta' and 'la'

the humming using 'ta' has obvious rests between music notes which may be because of the hard, short sound 't'.

By using 'ta'-based humming, we can reduce the length of the time series by orders of magnitude (from hundreds to less than 30). Then we can still use DTW distance measure to compute the similarity. This preserves the flexibility of warping while reducing the computational complexity.

The difference between our system and Kosugi's system is that we don't require the user to hum with the aid of a metronome because a metronome is usually not available and that requirement is not natural for a common user.

4.2.3 Key Idea: Low-Computation-Cost Filters

If a (boosted) filter has a lower computation cost than the DTW distance measure, then the system can use it as a filter to quickly weed out bad candidates, thus improving the speed of the system. Many statistical feature measures, if we set the condition loosely, can yield good filters.

Some features that the new framework currently uses to build filters are: standard deviation of note value, zero crossing rate of note value, number of local minima/maxima of note value, and a histogram of notes.

For example, based on the feature analysis, if the standard deviation of the query note-sequence's note value is 3.0, a standard-deviation-based weak classifier may be defined as follows: any candidate whose standard deviation is not between 1.5 and 4.5 is labeled "not similar" to the query.

Also, many statistical features are weak classifiers and usually computation is fast. They can be combined into a boosted strong classifier.

Note that although a boosted classifier does not guarantee no false negatives, it gives a high probability guarantee if we set parameters appropriately.

4.2.4 Key Idea: Alignment Verifiers

Whenever we compute a minimum DTW distance between two time series, we get a particular alignment between them. It is wise to verify the alignment.

If two time series align well to each other globally (have a low DTW distance) but align badly locally (the aligned elements have huge distance), we should not consider it a good match. Figure 4.3 is such an example, the two time series do not match. They align well globally but align badly at the $12, 13, 14$th elements. The 13th element of the upper time series is aligned to the 12th element of the

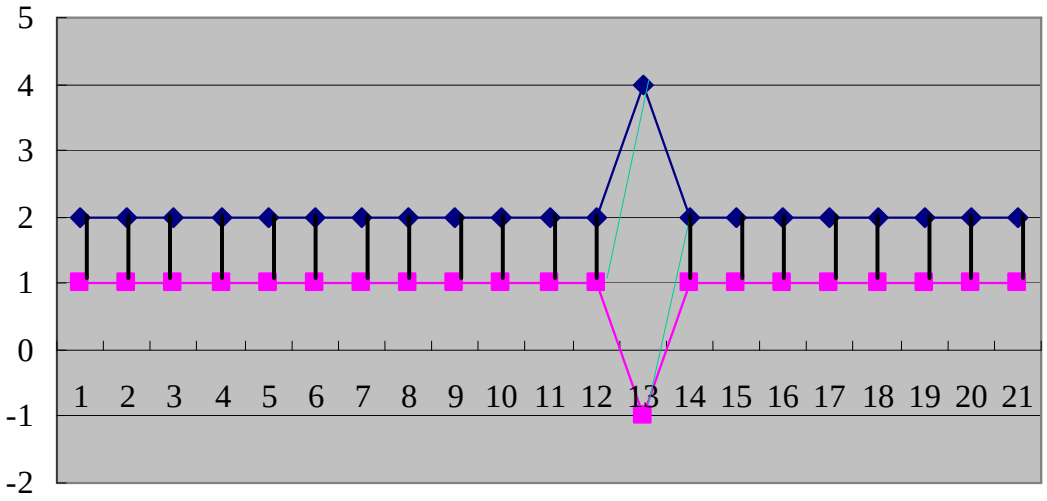


Figure 4.3: Good global alignment, bad local alignment

lower time series; the 14th element of the upper time series is aligned to the 13th element of the lower time series.

In our framework, the DTW distance is computed based solely on the melody information. It is also wise to verify that the alignment is a reasonable alignment for rhythm. Note that we cannot verify the rhythm alignment unless we know which notes in the query correspond to which notes in the reference because of the possibile note add/delete error. Several consecutive notes in the query may correspond to one note in the reference or vice versa. After we determine the time alignment based on the DTW distance computation, we can verify the rhythm alignment.

4.3 Building the algorithm

4.3.1 Order of filters

Since speed is an important concern, the initial filters in the multi-filters chain are better if they have a low computation cost. Here we assume that all the features for the reference and query data are pre-computed, so the computation cost for a filter mostly depends on the comparison function.

If a filter is based on a lower computation cost comparison function than other filters, then it should be used first in the filter chain; on the other hand, if a filter can largely reduce the size of the reference database, thus reducing the full-scan cost for the next level, it should be used first as long as its computation cost is not too high. The trade-off depends on how much of the full scan cost the filter can save in the next level and how much the filter will cost for the current level.

In our experiments, a filter based on the number of musical notes can be computed quickly and effectively reduces the reference database set of candidates. Suppose the query has k_q notes, this filter computes the reference candidate melody's music note number, say k_r, if k_q/k_r is not in $(1-a, 1+b)$ (a, b are trained parameters with positive value), then the reference candidate is not a match for the query with very high probability (99.9%), and the filter can usually reduce the reference database size by about 25%. So this filter is placed at the beginning of the algorithm filter chain.

Some filters have dependence on other filters such that they must be placed after those prerequisite filters. For example, the duration alignment verifier can be placed only after the DTW algorithm determines the alignment of notes,

because comparing the duration size is meaningful only if they correspond to the same note.

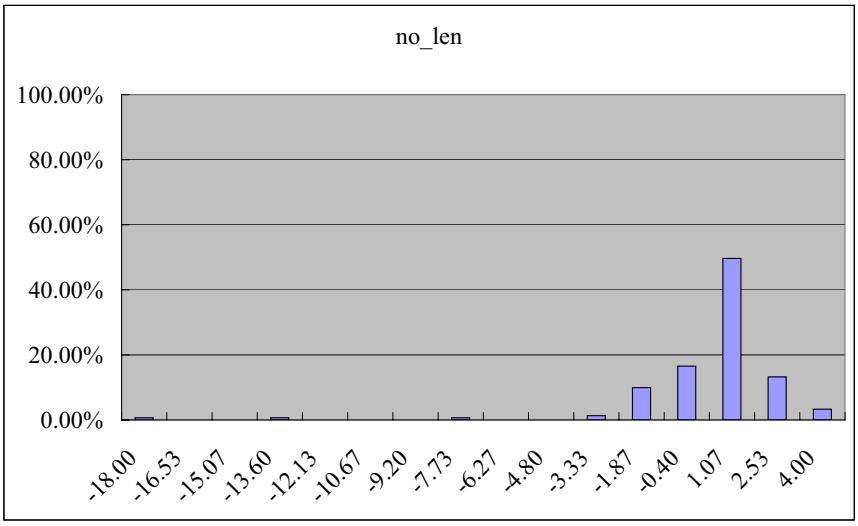
4.3.2 Feature Analysis and Selection

For each feature, we can create different feature measures using different comparison functions. Then we can analyze the output of the comparison function between the query datum's feature and other reference data's feature, as described in section 3.6.1. The analysis will also give insights about the errors people tend to make when they hum.

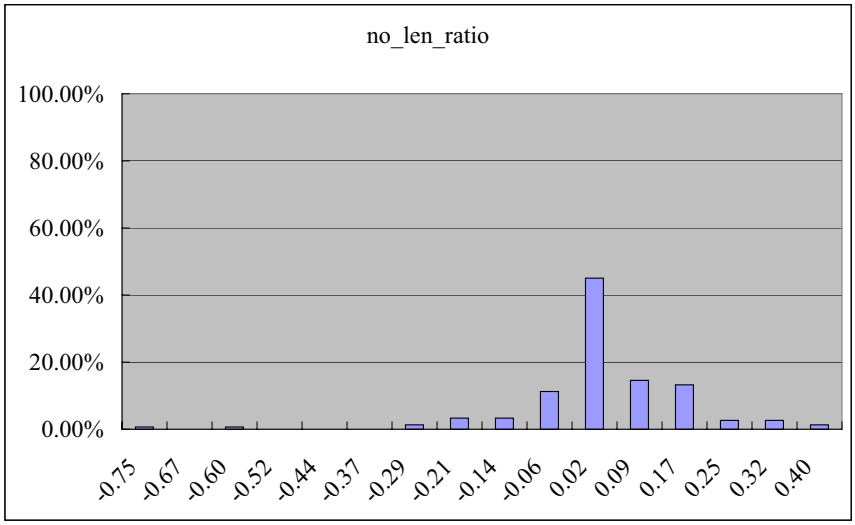
1. **Number of Notes:** Subtraction vs. Ratio

   In our system, the songs are segmented into melody phases so we know exactly the number of notes in each melody phases. For the training data, the analysis shows the distribution for all the differences of the number of notes between all the training (q_i, r_i) pairs. For example, given a query q_i and its matching reference r_i, suppose the note number of query q_i is $len(q_i)$ and the note number of r_i is $len(r_i)$; the distribution of the difference $len(q_i) - len(r_i)$ over i is what we are analyzing. If we use the difference between the query and reference data's number of notes to check whether the reference data is a possible good match for the query, it would be a good estimate since the distribution is condensed around a small region with only a few exceptions, as shown in Figure 4.4(a).

   Using the ratio betwen the number of notes is more intuitive since the note number can be very small or big but the number of notes people add in the humming may be proportional to the length of the melody. Figure 4.4(b) shows the distribution of $len(q_i)/len(r_i) - 1$ for all i. Although



(a) Subtraction of number of notes



(b) Ratio of number of notes

Figure 4.4: The distribution of the measures based on the number of notes

it is only a little more condensed than Figure 4.4(a), here training data are mostly short queries. More longer queries in the training data should show a bigger difference.

2. **Note value sequence's standard deviation:** Subtraction vs. Ratio

   For the same reason, we chose to use the ratio between the query and the reference data's standard deviation of note value sequence rather than the difference as a feature measure to build a filter. See Figure 4.5 for the distribution of the subtraction/ratio between queries and the matching songs' standard deviation of the note value sequence.

3. **Direction change count vs. Zero-crossing-rate**

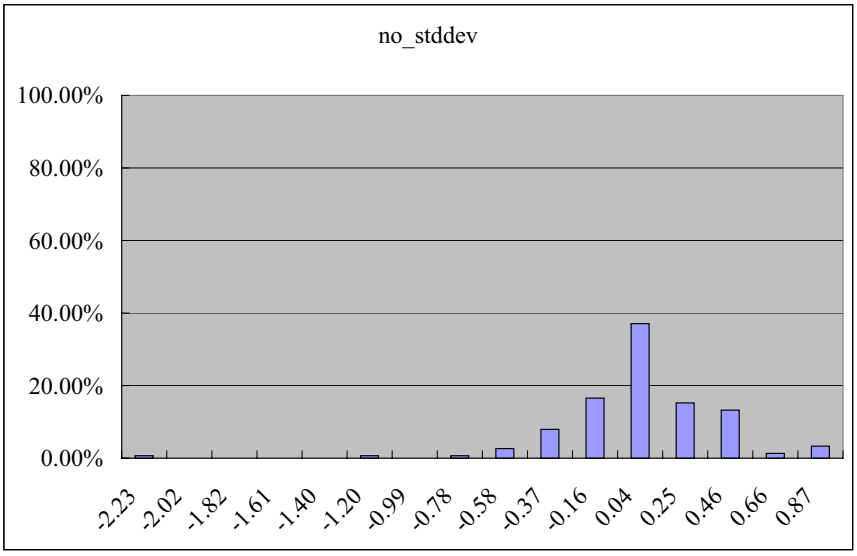
   In our experiments, we find that the direction change count is not a good filter, as shown in Figure 4.6(a). Slight noise in the data sequence dramatically changes the direction change count feature as in the example below, which we have already seen:

   Consider a time series datum 1, 2, 2, 2, 1 as the reference data, its direction change count is 1. If there is some noise in the query data, say 1.0, 2.0, 1.9, 2.0, 1.0, the direction change count in the query data is 3! Each data distortion might introduce two new direction changes.

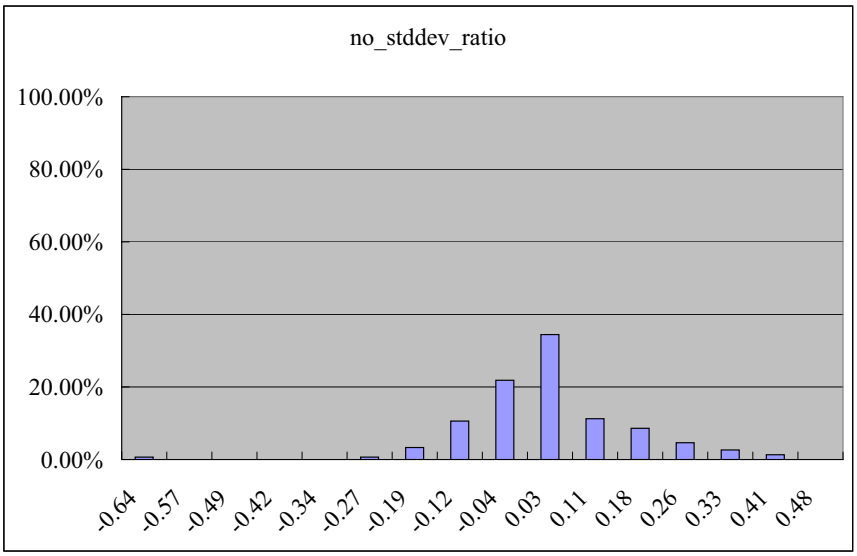
   Zero-crossing-rate tends to be a better measure, however, it is not stable either, see Figure 4.6(b). So we will use the zero-crossing-rate measure to build one of the filters to be boosted.

4. **Relative note offset vs. Note value**

   There have been arguments about whether or not people will change bases while humming. If so, then the relative note offsets between consecutive

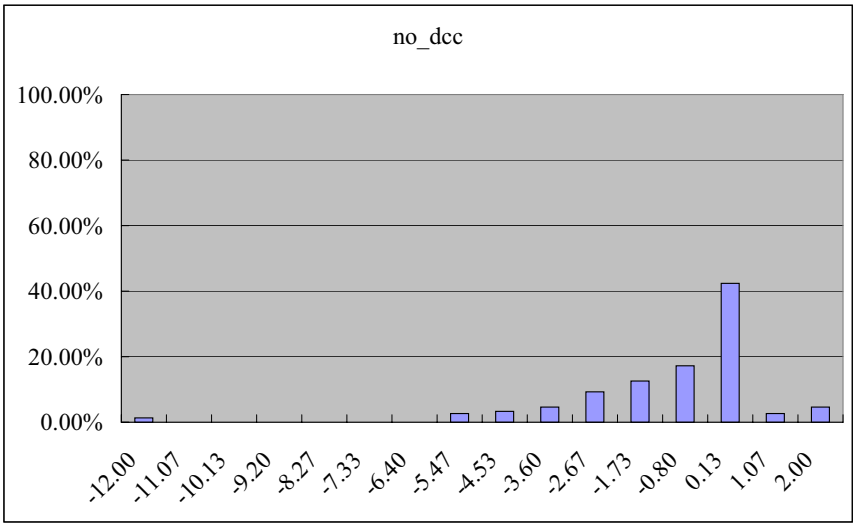


(a) Subtraction based

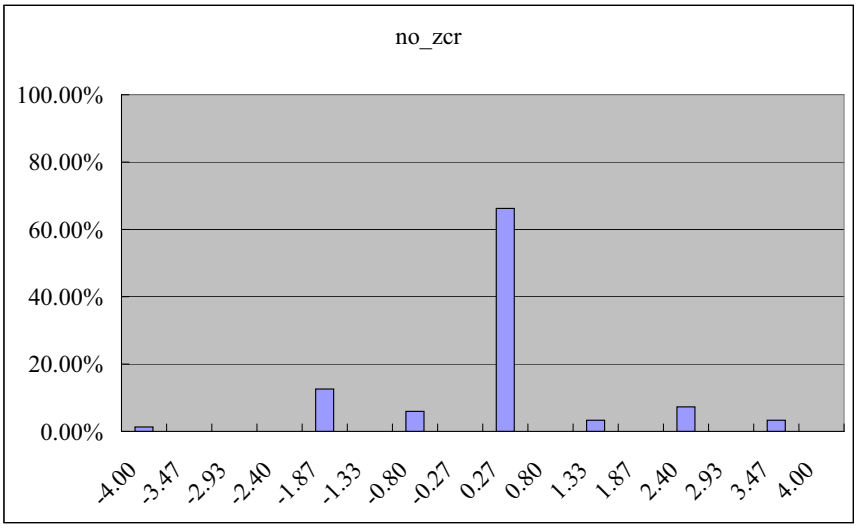


(b) Ratio based

Figure 4.5: The distribution of note values' standard deviation



(a) Ratio of Direction Change Count



(b) Ratio of Zero Crossing Rate

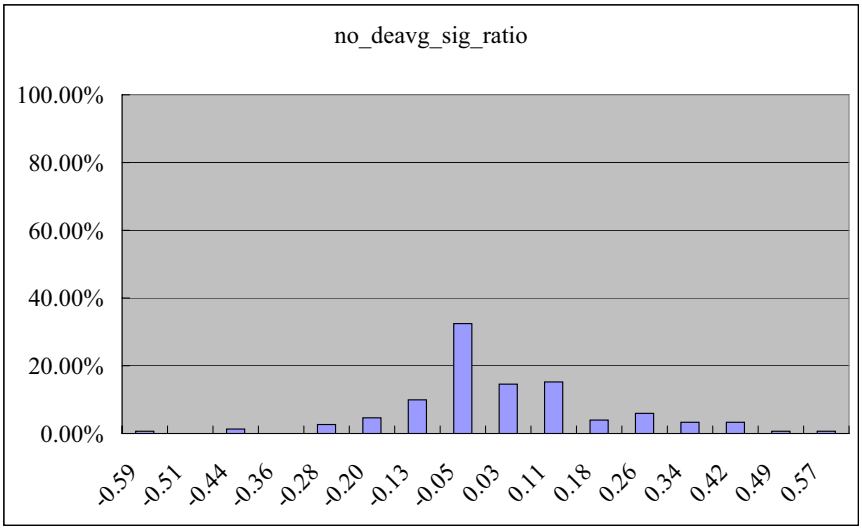
Figure 4.6: Compare the direction change count and zero-crossing rate

note pairs form a better representation of the humming; otherwise the absolute note values relative to the average captures the more accurate information. Here we analyze and compare different feature measures based on both relative consecutive note offset sequences and absolute note sequences.

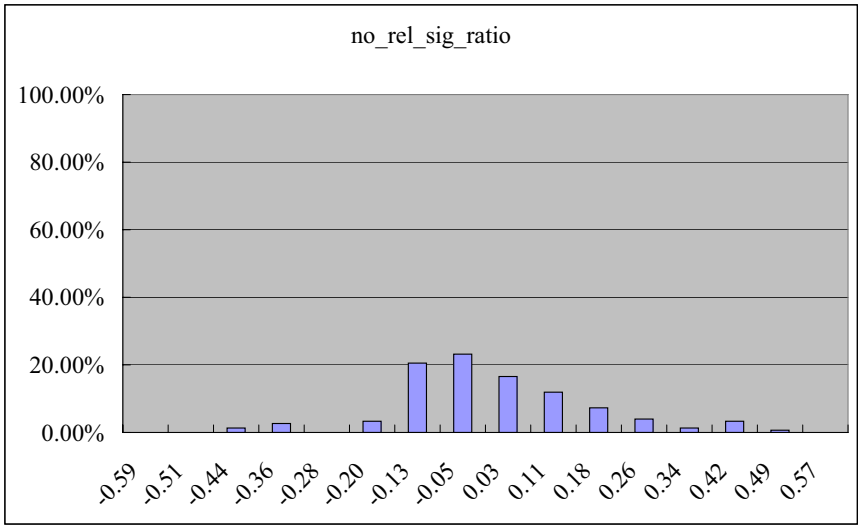
For each feature measure related to the note value sequence, a similar feature measure is built based on the relative note sequence. For example, one feature measure compares the most significant value (biggest absolute value) of the mean-removed note sequence of the query and the reference candidate. A similar feature measure compares the most significant value of the relative consecutive note offsets sequence of the query and the reference candidate.

The experimental results do not strongly favor one over the other in most cases. If we use the most significant absolute value in the mean-removed note sequence as a feature, the ratios between the query and reference pairs have a distribution similar to that if we use the most significant absolute value in the relative note offset sequence, as in Figure 4.7. In our algorithm, we use the former feature to build one of the filters to be boosted.

If a feature is based on the difference between the maximum and minimum values in the note sequence, the ratios between the query and reference pairs' feature have a distribution slightly more condensed than that if we use the most significant absolute value in the relative note offset sequence, as in Figure 4.8. In our algorithm, we use the former feature to build one of the filters to be boosted.

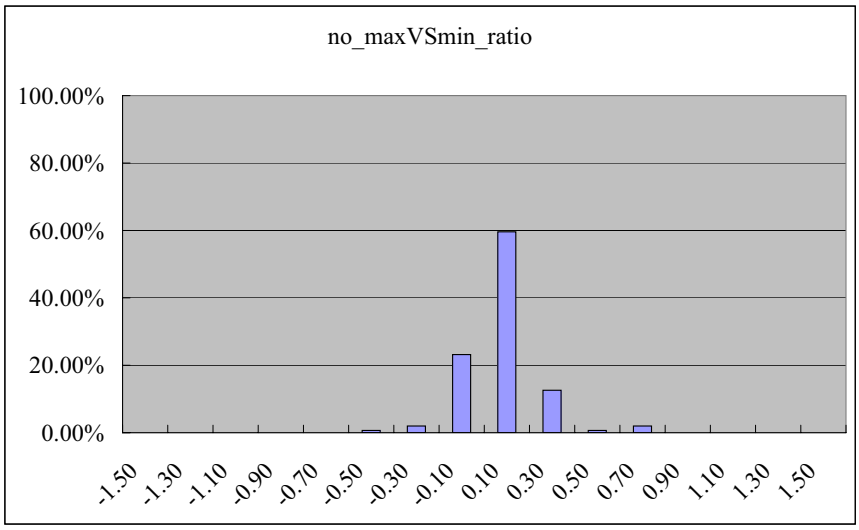


(a) For note sequence

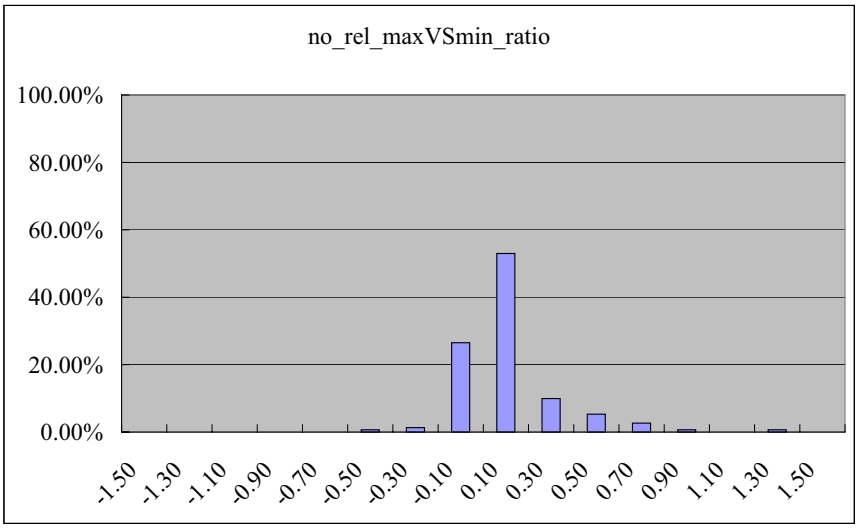


(b) For relative note offsets

Figure 4.7: The distribution of the ratio of most significant value

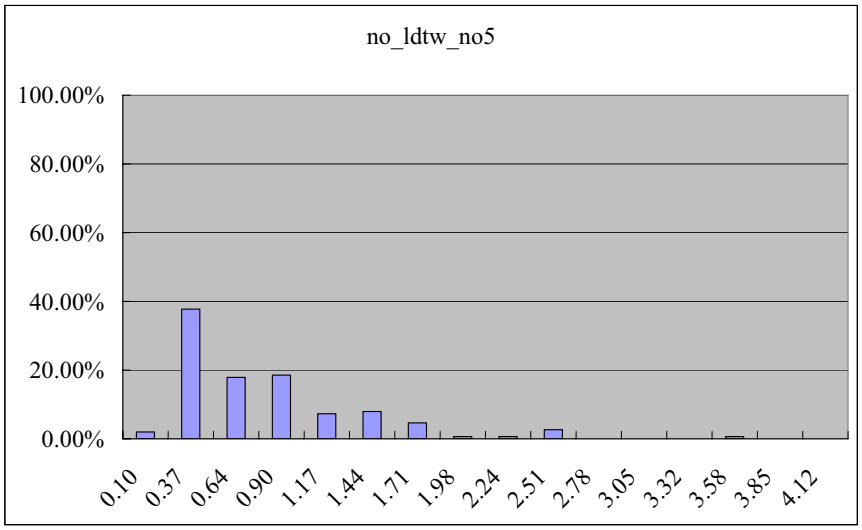


(a) For note sequence

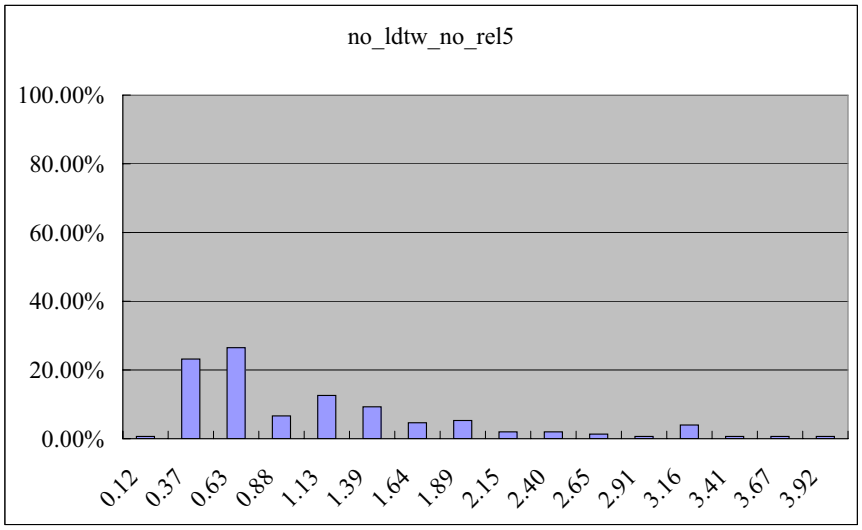


(b) For relative note offsets

Figure 4.8: The distribution of the max-min value difference



(a) For note sequence



(b) For relative note offsets

Figure 4.9: The distribution of the LDTW measure on the first 5 values

If a feature is based on the local dynamic time warping (DTW) distance of the first 5 elements' values in the mean-removed note sequence, the ratios between the query and reference pairs' feature have a distribution that is more condensed than that if we use the local dynamic time warping distance of the first 5 elements in the relative note sequence, as in Figure 4.9. This is easily explained: if there is some note added into or deleted from a few consecutive notes with similar values in the note sequence, the relative note sequence would have errors that cannot be handled by the dynamic time warping measure. For example, suppose the song melody is 55, 62, 62, 55, 58, ... where the durations are 4, 1, 1, 4, 4, ..., the query may merge two short notes of value 62 into one longer note, such as 55, 62, 55, 58, ... The DTW distance measure will give a small distance between the query and reference note sequence. But for the relative note sequence feature, the query becomes 7, -7, 3, ... and the reference becomes 7, 0, -7, 3, ... and the DTW distance measure will give a big distance between them. In our algorithm, we use the local dynamic time warping distance of the first 5 elements' values in the mean-removed note sequence as a feature to build one of the filters to be boosted. No duration information is used though.

5. **Which to use as measure reference:** humming vs. music

   Some measures, such as envelope distance and dynamic time warping distance, are non-symmetric. This begs the question of whether we should measure the humming against music or vice versa. It looks more intuitive to measure the humming against music because humming is a distorted version of its corresponding music. The experiment shows the same result,

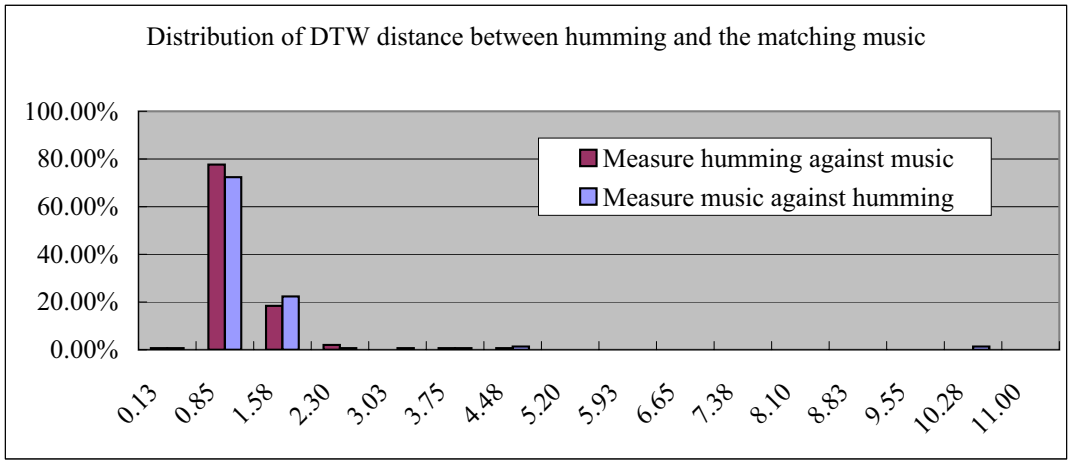


Figure 4.10: The distribution of the LDTW measures using different order

as illustrated in Figure 4.10.

What's interesting is that some humming can be recognized in the top list if we measure the humming against music but cannot be recognized if we measure music against humming. So it may be a good idea to combine both results to get a better result than using either one alone.

An example configuration file for the algorithm we built follows:

Configuration File:

/good filters

/based on note length

in,no_len_ratio,-0.50,0.50

/based on note value's variance

in,no_stddev_ratio,-0.50,0.50

/based on the difference between maximum and minimum note value

in,no_maxVSmin_ratio,-0.50,0.50

/based on the the most significant note value

in,no_deavg_sig_ratio,-0.50,0.50

/based on the the envelope distance of uniform length note values

le,no_uni128_env5percent_paa8,1.50

/based on the the moving average's auto-correlation's parameter number

in,no_MArank,-4,4

/based on the the LDTW distance between the first 5 notes

le,no_ldtw_no5,4.0

/boosted filter, each weak classifier has same weight

boost{1,1,1,0,0,0

/based on the note length

in,no_len,-1,2

/based on the note value variance

in,no_stddev,-1.0,1.0

/based on the zero-crossing rate

in,no_zcr,-3,3

}

/final ranker, based DTW distance

rank,no_ldtw_5percent,5

4.4 Evaluating the algorithm

4.4.1 Setup

- Training Data
  - Label confirmed by at least 3 people

    230 hummed tunes from 66 songs were collected from all over the world. They were labeled by the person who contributed the hummings, the thesis author and a few amateur musicians.
  - Labeled by the contributor him/herself

    In addition to the above hummed tunes, 167 hummed tunes from 29 songs are collected from all over the world, labeled by the person who contributed the hummings.
  - Song pool

    The hummed tunes are from 1400 songs including 123 Beatles MIDI files, 937 pop song MIDI files and 340 ringtones. The ringtones include selections from the following categories: anthems, arcade, cartoons, children's songs, christmas, classical, entertainment, military, soccer, TV and films. Each song is segmented based on the melody, merged (if appropriate) and organized into 40891 melody segments.
- Computing Environment

  Pentium III 1.0G Hz CPU and 384M memory. Not all the data in the database can be loaded into the memory but the system is first "warmed up" using a few sample tests before doing performance measurements. The queries are preprocessed into pitch-contour representations without

any normalization. The query-handling server is written in the array-processing-language K which processes sequential data very efficiently.

- Scalibility test

  For the same set of testing query data, the algorithm is benchmarked against a few different scales of the reference database. The reference database at the minimum scale includes only the songs to which the testing query data corresponds. Then the size doubles and triples by randomly selecting other songs in the song pool. The size increases until it reaches the full size of the song pool.

4.4.2 Observations

Multi-filter outperforms pure DTW

Experiments show that if only the DTW distance is used to measure the similarity between the humming and music, the top-5 and top-10 hit rate is about 5% less than using multi-filters, as shown in Figure 4.11. 167 hummings are tested on a reference database with 540 melody segments of 25 songs. (Note that the size of the reference database is quite small here.)

The multi-filters algorithm for this experiment is a chain of 3 simple statistics based filters with the DTW distance measure at the end of the chain. The three simple filters are based on the length, the standard deviation and the zero-crossing-rate of the note sequence. This demonstrates that pure DTW distance measure is not good enough to measure the similarity and that the time series matching framework is helpful in identifying better similarity measure.

Not only can the hit-rate can be improved, but the response time can also

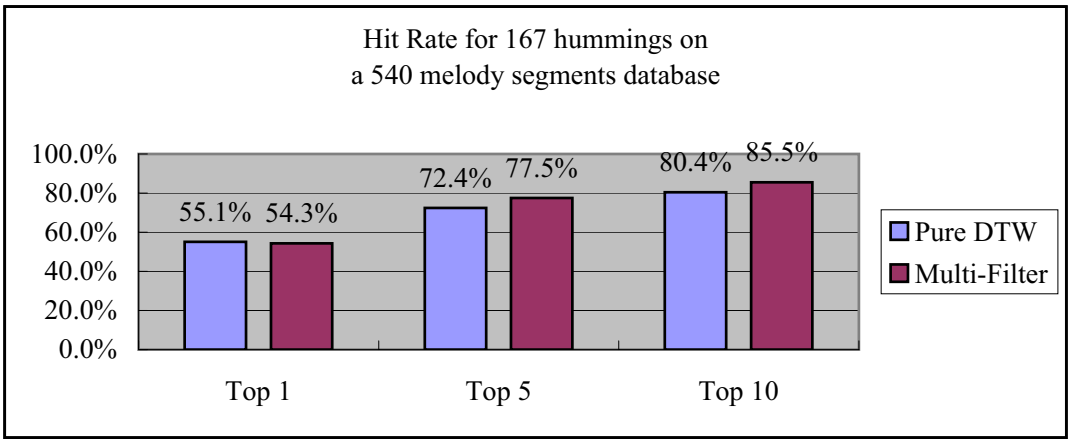


Figure 4.11: Compares the hit-rate to pure DTW distance measure

be improved as well, as shown in Figure 4.12. Later in the section, we will show that the response time for the new system scales much better than for the old system.

Scalability of the algorithm

Here we study the scalability of the proposed multi-filter system and compare it to the old system [37].

The benchmark used 230 hummings from 66 randomly chosen songs, each verified by at least 3 people. The database at each test scale respectively contains 66, 317, 819, 1323 songs; each including the 66 hummed songs. The number of melody segments in the database for each test scale is respectively

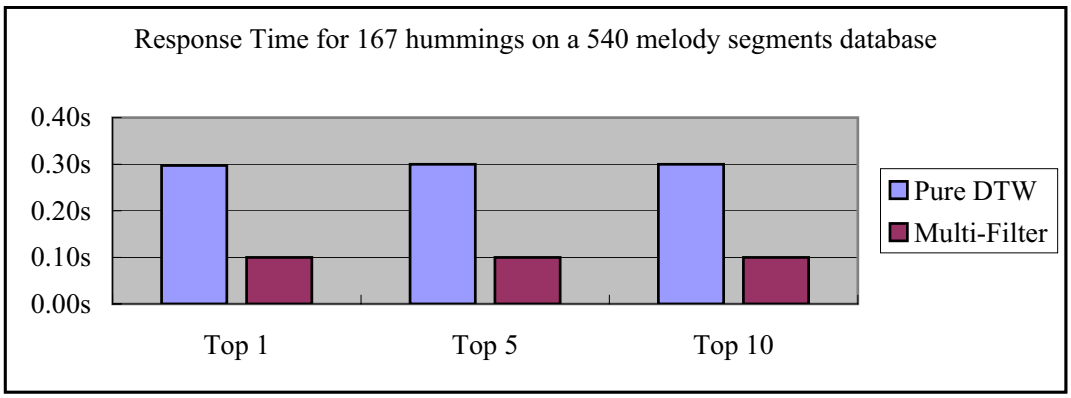


Figure 4.12: Compares the response time to pure DTW distance measure

1363, 9398, 24804, 40891, which is the number of references the algorithm needs to measure similarity against. The more melody segments in the database, the greater the discriminating power needed to find the correct match, and the greater the computation cost.

Figure 4.13 shows the top-10 hit-rate for the algorithm in the old system [37] and the top-1, top-5 and top-10 hit-rate for the multi-filter based algorithm we use in the new system. The old system uses DTW distance measure on pitch contours along with envelope filter and transformed envelope filters. It is clear that even the top-1 hit rate of the multi-filter algorithm is better than the top-10 hit rate of the old system. And the multi-filter algorithm's hit rate's scalability has a similar pattern.

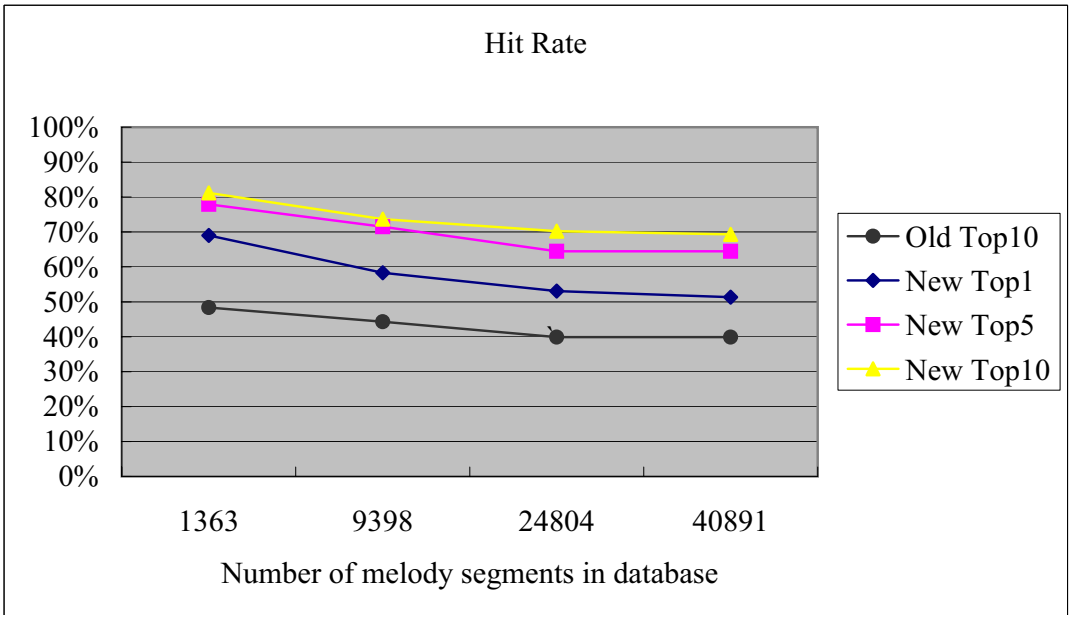


Figure 4.13: Compare the hit-rate's scalability

Figure 4.14 compares the top-10 response time of the old system and the new system. It is clear that the multi-filter algorithm's response time scales much better.

Overall, the scalability of the multi-filter algorithm is much better.

4.4.3 System Demo and User Feedback

The system is available online at **http://querybyhum.cs.nyu.edu**. It has an easy web interface (see Figure C.4) to upload wave files of hummings to query the database. Also, a Java-based GUI client can be downloaded to support more interaction, (see Figure C.5). The GUI client is also used to collect hummings from fans and label them automatically. This helps a lot in the data collection

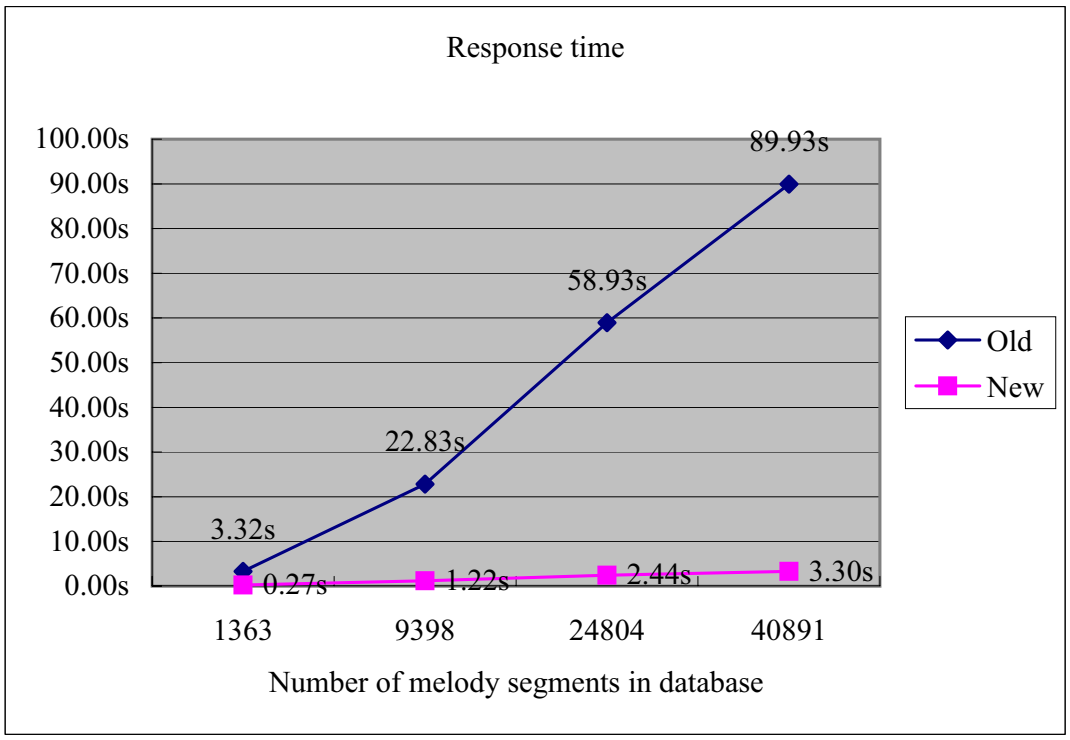


Figure 4.14: Compare the response time's scalability

process and in improving our system, because the key to getting an accurate analysis of the hummings is to get enough data from a variety of users for a variety of songs.

The efforts of the team members of the query-by-humming project has resulted in our project page being ranked in the top result list by major search engines if a user searches keywords such as "query by humming", "whats that song" and "humming"[1]. Please see Appendix C for some example snapshots.

We participated in a Tech-Show hosted by the Swiss Broadcasting Company to demostrate the power of query-by-humming and the demo "was a big success" according to the organizer. More detailed feedback can be found in Appendix

[1]As of the written month of this thesis: December 2005.

C.

Also, many websites and blogs discovered us and some users say it "works like a dream ...".

4.5 Future Work

There are some techniques developed in related recent work that we can integrate into our framework.

For example, a VLDB 2005 paper "Scaling and Time Warping in Time Series Querying" [8] by Ada Wai-chee Fu, Eamonn Keogh, Leo Yung Hang Lau and Chotirat Ann Ratanamahatana proposes a technique to exactly index both the DTW and uniform scaling. This technique would be useful to speed up partial sub-sequence matching where the query time series data may match the leading portion of the reference time series data with some time-scaling.

Naoko Kosugi's thesis [18] includes updated information about her group's music retrieval system: **SoundCompass**. Their extensive study of people's humming behavior can be used to build better preprocessing components in our framework. For example, the most frequent note duration in each melody segment in SoundCompass is used as the time-domain unit length for the segment. Each note's duration is then represented as the discrete ratio to the unit length, thus each melody segment's length in terms of the unit can be determined. If the query's length is represented the same way, we can quickly filter out reference melody segments which have much larger or smaller length. This length-based filter takes into account the duration information, thus it may be better than a filter based on the numbers of notes.

"QBH2- A Query by Humming Retrieval System Based On Polyphonic

Karaoke Music Database" [27] is a recent work that discusses various indepth issues dealing with polyphonic music retrieval. Engineering effort and low-level data analysis are the highlights. The authors have a good idea about music theory and the paper is heavy on music signal processing. The insight corcerning music data and the signal processing techniques may be useful in building databases from polyphonic music data and in building better filters.

Building a large content-based commercial music retrieval system is quite difficult because of the nature of the problem. The human humming input accuracy is hard to predict; different people's perception of the same music might be quite different and the existence of many similar songs make them hard to distinguish. Techniques that immitate human's perception of the music, such as machine learning, may have great potential to solve these problems. Besides, processing the large amount of data requires greater computation power than usual text information. More efficient data structures or algorithms are in demand. Even with all of the recent work, a lot of work needs to be done on this topic.

Chapter 5

Conclusion

Our experiments on the query-by-humming system show that the multi-filter based time series matching framework is useful in identifying and building fast and accurate similarity measures between time series data.

If the process to select the features and tune the parameters can be automated using some generic algorithm, that would improve the process even more. Future work may follow in that direction to adapt more machine learning techniques and generic algorithms to further automate the system.

Appendix A

Boosting Algorithm

• AdaBoost.MR

Given a problem in which the goal is to find a hypothesis which ranks the labels with the hope that the correct labels will receive the highest ranks, the problem can be formalized in the following (quoted from [26]):

"We seek a hypothesis of the form $f : \mathcal{X} \times \mathcal{Y} \to \mathbb{R}$ with the interpretation that, for a given instance x, the labels in $\mathcal{Y}$ should be ordered according to $f(x, \cdot)$. That is, a label l_1 is considered to be ranked higher than l_2 if $f(x, l_1) > f(x, l_2)$. With respect to an observation (x, Y), we care only about the relative ordering of the *crucial pairs* l_0, l_1 for which $l_0 \notin Y$ and $l_1 \in Y$. We say that f *misorders* a crucial pair l_0, l_1 if $f(x, l_1) \leq f(x, l_0)$ so that f fails to rank l_1 above l_0. Our goal is to find a function f with a small number of misorderings so that the labels in Y are ranked above the labels not in Y.

Our goal then is to minimize the expected fraction of crucial pairs which are misordered. This quantity is called the *ranking loss*, and, with respect to a

distribution D over observation, it is defined to be

$$E_{(x,Y)\sim D}\left[\frac{|\{(l_0,l_1)\in(\mathcal{Y}-Y)\times Y\ :\ f(x,l_1)\leq f(x,l_0)\}|}{|Y|\cdot|\mathcal{Y}-Y|}\right]$$

We denote this measure $rloss_D(f)$. Note that we assume that Y is never empty nor equal to all of $\mathcal{Y}$ for any observation since there is no ranking problem to be solved in this case."

The **AdaBoost.MR** algorithm follows:

Given: $(x_1,Y_1),\ldots,(x_m,Y_m)$ where $x_i\in\mathcal{X}, Y_i\subset\mathcal{Y}$

Initialize

$$D_1(i,l_0,l_1)=\begin{cases}\frac{1}{m\cdot|Y_i|\cdot|\mathcal{Y}-Y_i|} & x\ if\ l_0\notin Y_i\ and\ l_1\in Y_i\\ 0 & else\end{cases}$$

For $t=1,\ldots,T$:

1. Train weak learner if necessary using distribution D_t
2. Get weak hypothesis $h_t:\mathcal{X}\times\mathcal{Y}\to\mathbb{R}$
3. Choose $\alpha_t\in\mathbb{R}$
4. Update:

$$D_{t+1}(i,l_0,l_1)=\frac{D_t(i,l_0,l_1)exp(\frac{1}{2}\alpha_t(h_t(x_i,l_0)-h_t(x_i,l_1)))}{Z_t}$$

   where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution: non-negative, sum is 1).

Output the final hypothesis:

$$f(x,l)=\sum t=1^T\alpha_t h_t(x,l)$$

Appendix B

Components Examples

- ## Example Transformation Functions

  The actual code implementation name of each example component is in the bracket.

  1. Average (**avg**):

     Compute the average value of a time series.

  2. Remove Average (**deavg**):

     Subtract the average value from each element in the time series.

  3. Length (**len**):

     Compute the number of elements in a time series.

  4. Standard Deviation (**stddev**):

     Compute the standard deviation of a time series.

  5. Zero Crossing Rate (**zcr**):

     Compute how many times the time series crosses the average line.

  6. Direction Change Count (**dcc**):

Compute how many times the time series changes direction, either up or down.

7. Map to Uniform Axis (**uni128**):

   Map the time series to a uniform length (default is 128). It is the same as the global time scaling function in Section Underlying Technology 2 except that it up-scales the data when the original size is less than the uniform length and down-scales the data otherwise.

8. Envelope with α%-Warping (**env5percent**):

   Compute the k-Envelope (see Equation 2.3) of the time series where k is $\alpha\% * n$, where n is the length of the time series. By default, $\alpha = 5$.

9. n-PAA: Piecewise Aggregate Approximation (**paa8**):

   Divide the time series into n equal length pieces and average the value by piece (see Equation 2.7). The result is a time series of length n. By default, $n = 8$.

   If the input is an envelope time series, the result is still an envelope where the resulting higher (lower) envelope is the n-PAA of the original higher (lower) envelope.

10. k-DFT: Discrete Fourier Transform (**dft8**):

    Compute the first k real-part coefficients of the Discrete Fourier Transform of the time series, see reference [28]. By default, $k = 8$.

11. k-db2-DWT: Discrete Wavelet Transform (**db2dwt8**):

    Compute the first k co-efficient of the **db2 Discrete Wavelet Transform** (see reference [28]) of the time series. By default, $k = 8$.

12. k-offset filter (**noisefilter**):

    Low/high-pass filter: delete any element if its value v satisfies $|v - \bar{v}| \geq k$ where $\bar{v}$ is the average value of the time series. It also resets any value less than 0 as 0.

13. Transform value-duration pair sequence to value sequence (**nd2ts**):

    Given a value-duration pair sequence, $X = [(v_1, d_1), (v_2, d_2), \ldots, (v_n, d_n)]$ where v_i is a real number, d_i is a positive integer for any i, this transformation function T outputs a real-value time series where v_i is padded d_i times. E.g. $T([(3, 2), (5, 1), (4, 3)]) = [3, 3, 5, 4, 4, 4]$.

14. Transform zero-separated value sequence into value-duration pair sequence (**segts2nd**):

    Given a zero-separated value sequence $X = [V_1, 0, V_2, 0, \ldots, V_n]$, where $V_i = [V_i(1), V_i(2), \ldots, V_i(k_i)]$, $k_i > 0$ for each i,$V_i(j_i)$ is a real number for any $1 \leq j_i \leq k_i$, this transformation function T outputs a value-duration pair sequence $Y = [(\bar{V_1}, k_1), (\bar{V_2}, k_2), \ldots, (\bar{V_n}, k_n)]$ where $\bar{V_i}$ is the average of all the values in V_i. E.g. $T([3, 3, 0, 5, 0, 4, 4, 4] = [(3, 2), (5, 1), (4, 3)]$.

- # Example Comparison Functions

1. Subtraction (**subtraction**)

   $C(q, r) = q - r$, where q, r are both scalars or both time series of the same length.

   It is reflexive and transitive; its absolute value is symmetric and satisfies triangle inequality when both input are scalars.

2. Ratio (**ratio**)

$C(q,r) = \frac{q}{r} - 1$

It is reflexive.

3. Normalized Manhattan Distance (**manhattan_dis**)

   $C(q,r) = \frac{\sum_i^n |q_i - r_i|}{n}$, where q, r are both time series of the length n and q_i, r_i is respectively the i-th element of q, r.

   It is reflexive, symmetric, transitive and satisfies triangle inequality.

4. Normalized Euclidean Distance (**euclidean**)

   $C(q,r) = \frac{\sum_i^n \sqrt{(q_i - r_i)^2}}{n}$, where q, r are both time series of the length n and $q_i(r_i)$ is the i-th element of $q(r)$.

   It is reflexive, symmetric, transitive and satisfies triangle inequality.

5. Normalized Envelope distance (**env_dis**)

$$C(q, env) = \frac{\sum_i^n env_D(q_i - env_i)}{n}$$

   where q is a time series of length n, env is an envelope time series of the length n and q_i/env_i is the i-th element of q/env.

   and

$$env_D(q_i, env_i) = \begin{cases} 0 & if\ b_i \leq q_i \leq t_i \\ q_i - t_i & if\ q_i > t_i \\ b_i - q_i & if\ q_i < b_i \end{cases}$$

   where t_i, b_i are the i-th element of the top/bottom envelope of env.

   It is non-reflexive, non-symmetric, non-transitive and does not satisfy triangle inequality.

6. α%-Local Dynamic Time Warping (**ldtw**)

It computes the k-local dynamic time warping distance between two time series q, r where $k = 1 + n * \alpha\%$ and n is the length of q. See Equation 2.5. It is reflexive.

Appendix C

Feedback on the system

Figure C.1: Google search result top-1 with keywords "query by humming"

The efforts of the team members of the query-by-humming project have

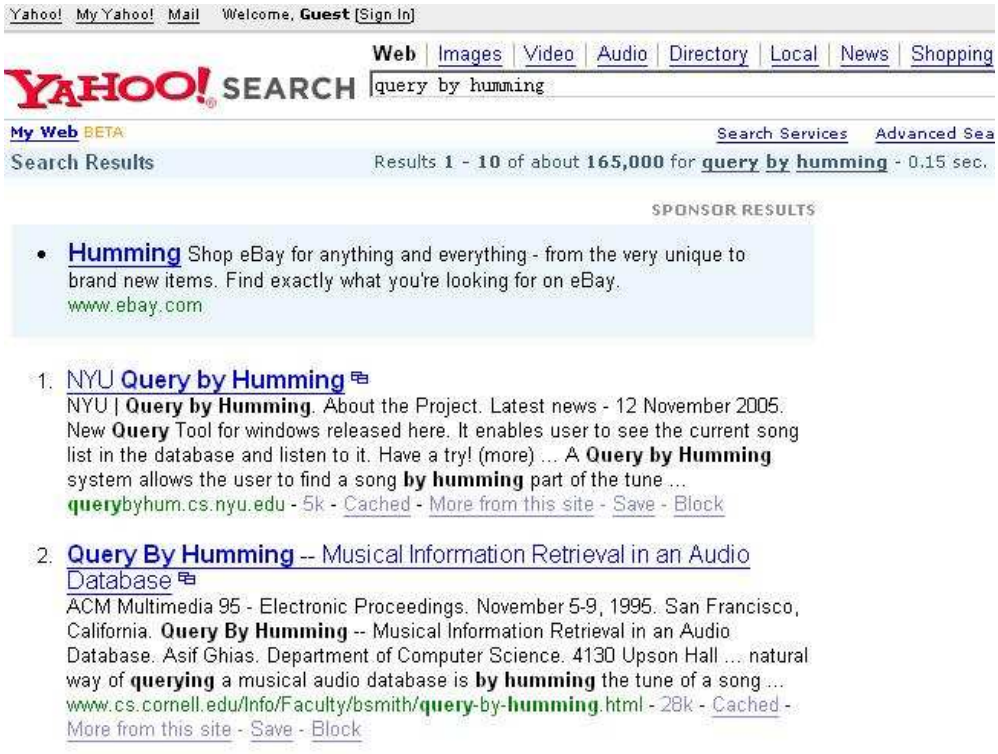


Figure C.2: Yahoo search result top-1 with keywords "query by humming"

resulted in our project page being ranked in the top result list by major search engines if a user searches keywords such as "query by humming", "whats that song" and "humming". See Figure C.1, C.2 and C.3.

Besides the website, our team also participated a tech-show event. "The demo was a big success. There were more 'hummers' than we expected and there was a lot of enthusiasm and amazement. I prepared mp3-files for the 25 selected titles in the database and so the attendees had the possibility to listen to the audio-file before humming. Result was much better, when the hummer listened to the midi-sequence instead of the audio-file before humming. It seems that for some titles it's hard to filter a simple melody from a complex title in mp3 format. But for 70% of the hummers the matching score was very high

Figure C.3: MSN search result top-1 with keywords "query by humming"

(ranking 1 or 2) and there were about two persons with bad matching, but not everyone is really an apt hummer... Sometimes it was very noisy in the demo room and it seemed to me that this also has had an influence on the matching score." — Swiss Broadcasting Company

" Works like a dream... " — a user on www.digg.com's post about us

Figure C.4: Screenshot of the web demo

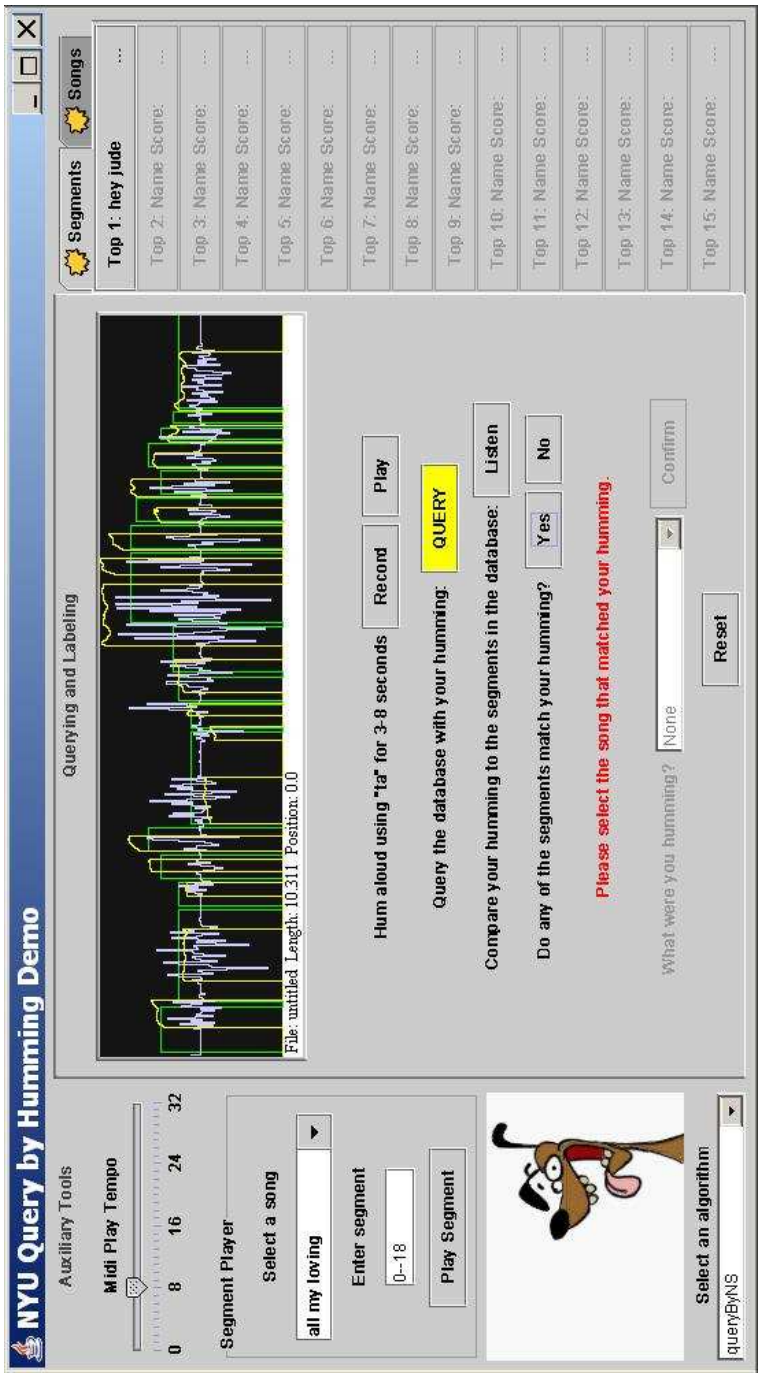


Figure C.5: Screenshot of the Java GUI client

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