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Parameter Free Piecewise Dynamic Time Warping for time series classification

Vanel Steve SIYOU FOTSO ^{*†} Engelbert MEPHU NGUIFO ^{*†} Philippe VASLIN ^{*†}

Abstract

Several improvements have been done in time series classification over the last decade. One of the best solutions is to use the Nearest Neighbour algorithm with Dynamic Time Warping (DTW), as the distance measure. Computing DTW is relatively expensive especially with very large time series. Piecewise Dynamic Time Warping (PDTW) is an efficient variant which consists of segmenting time series into fixed-length segments. However, the choice of the optimal size (or number) of segments remains a difficult challenge for end users. The Brute-force solution, a naive solution, repeats the classification with each segment size, and selects the one with the best accuracy. This solution is not appropriated especially when dealing with massive and large time series data. In this work, we propose a parameter free approach for PDTW, that finds the size (or number) of segments to be used with the Nearest Neighbour algorithm. Our approach is a heuristic that is parameter free since it does not require any domain specific tuning. Several properties of our heuristic are studied, and an extensive experimental comparison demonstrates its efficiency and effectiveness, in terms of accuracy and runtime.

1 Introduction

Time series are ubiquitous in sciences as for example in economics [6], in medicine [7], in finance [18] or in computer science [20]. An important task is time series comparison that can be done in two main ways. Either the comparison method considers that there is no time distortion as in Euclidian distance (ED), or it considers that some small time distortions exist between time axis of time series as in Dynamic Time Warping alignment algorithm (DTW) [28]. Since time distortion often exists between time series, DTW often has better results than the ED [3]. An exhaustive comparison of time series algorithms [1] shows that DTW is among the efficient techniques to be used. However, DTW has two major drawbacks: the comparison of two time series under DTW is time-consuming [21] and DTW sometimes produces pathological alignments [14]. A pathological alignment occurs when, during the comparison of two

time series X and Y , one datapoint of the time series X is compared to a large subsequence of datapoints of Y . A pathological alignment causes a wrong comparison.

Three categories of methods are used to avoid pathological alignments with DTW:

- The first one adds constraints to DTW [22], [27], [2], [23], [10]. The main idea here is to limit the length of the subsequence of a time series that can be compared to a single datapoint of another time series.
- The second one suggests to skip datapoints that produce pathological alignment during the comparison of two time series [17], [9], [19].
- The third one proposes to replace the datapoints of time series by a high level abstraction that captures the local behavior of those time series. A high-level abstraction can be a histogram of values that captures the repartition of time series datapoints in space [28], or a feature that captures the local properties of time series, such as the trend with Derivative DTW (DDTW) [14] or the mean with Piecewise DTW (PDTW) [13].

PDTW has been introduced with the aim to speed up the computation of DTW, which depends on the length of the time series. PDTW suggests to use a compact abstraction of time series instead of the raw data. Indeed, PDTW proposes to split a time series into consecutive fixed-length segments and to compute the mean of each segment. Then, the mean is used instead of the data points in the segment to compare the time series.

In practice, a straightforward way to use PDTW is the brute-force approach that consists in exploring all the possible values for the number of segments. However, this is not feasible with long time series data. So, the question is how to automatically fix this parameter without a considerable decrease of classification accuracy ?

In this paper, we propose a parameter free heuristic to align piecewise aggregate time series with DTW that approximates the optimal value of the number of segments to be considered during the alignment. In

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this heuristic, the number of segments is chosen based on the quality of the alignment, which is evaluated by the classification error on the training set. The best classification algorithm to use for this purpose is one Nearest Neighbor (1NN) that is combined with PDTW. In this case 1NN is the best because its classification error directly depends on the alignment of time series, since it has no other parameters [26].

2 Background and related work

DEFINITION 2.1. A **time series** $X = x_1, \dots, x_n$ is a sequence of numerical values representing the evolution of a specific quantity during the time. x_n is the most recent value.

2.1 Dynamic Time Warping algorithm. DTW [12] is a time series alignment algorithm that performs a non-linear alignment while minimizing the distance between two time series. To align two time series :

$$X = x_1, x_2, \dots, x_n;$$

$$Y = y_1, y_2, \dots, y_m.$$

the algorithm constructs an $n \times m$ matrix where the cell (i, j) of the matrix corresponds to the squared distance $(x_i - y_j)^2$ that is the alignment between x_i and y_j . To find the best alignment between two time series, it constructs the path that minimizes the sum of squared distances. This path, noted $W = w_1, w_2, \dots, w_k, \dots, w_K$, should respect the following constraints:

- Boundary constraint: $w_1 = (1, 1)$ and $w_K = (n, m)$
- Monotonicity constraint: Given $w_k = (i, j)$, $w_{k+1} = (i', j')$ then $i \leq i'$ and $j \leq j'$
- Continuity constraint: Given $w_k = (i, j)$, $w_{k+1} = (i', j')$ then $i' \leq i + 1$ and $j' \leq j + 1$

The warping path is computed by using an algorithm based on the dynamic programming paradigm that solves the following recurrence:

$$\gamma(i, j) = d(x_i, y_j) + \min\{\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)\},$$

where $d(x_i, y_j)$ is the squared distance contained in the cell (i, j) and $\gamma(i, j)$ is the cumulative distance at the position (i, j) that is computed by the sum of the squared distance at the position (i, j) and the minimal cumulative distance of its three adjacent cells.

DEFINITION 2.2. A **segment** X_i of length l of the time series X of length n ($l < n$) is a sequence constituted by l variables of X starting at the position i and ending at the position $i + l - 1$. We have: $X_i = x_i, x_{i+1}, \dots, x_{i+l-1}$

DEFINITION 2.3. The **arithmetic average** of the data points of a segment X_i of length l is noted \bar{X}_i and is defined by:

$$\bar{X}_i = \frac{1}{l} \sum_{j=0}^{l-1} x_{i+j}$$

DEFINITION 2.4. Let T be the set of time series. The **Piecewise Aggregate Approximation (PAA)** is defined as follows:

$$PAA : T \times \mathbb{N}^* \rightarrow T$$

$$(X, N) \mapsto PAA(X, N) = \begin{cases} \bar{X}_1, \dots, \bar{X}_N \text{ if } N < |X| \\ X \text{ otherwise} \end{cases}$$

Piecewise Dynamic Time Warping Algorithm (PDTW) [13] is the DTW algorithm applied on Piecewise Aggregate time series [11]. Let $N \in \mathbb{N}^*$, X and Y be two time series.

$$PDTW(X, Y, N) = DTW(PAA(X, N), PAA(Y, N)).$$

The number of segments N that one considers greatly influences the quality of the alignment of the time series. However, PDTW does not give any information on the way to choose it. To do so, [4] proposes the Iterative Deepening Dynamic Time Warping Algorithm (IDDTW).

2.2 Iterative Deepening Dynamic Time Warping. IDDTW only considers values for the number of segments that are power of 2 and for each value, computes an error distribution by comparing PDTW with the standard DTW at each level of compression. It takes as input: the query Q , the dataset D , the user's confidence (or tolerance for false dismissals) $user_conf$, and the set of standard deviations $StdDev$ obtained from the error distribution.

- The algorithm starts with applying the classic DTW to the first K candidates from the dataset. The results of the best matches to the query are contained in R , with $|R| = K$. The *best_so_far* is determined from $argmax R$.
- Both the query Q and each subsequent candidate C are approximated using PAA representations with N segments to determine the corresponding PDTW.
- A test is performed to determine whether the candidate C can be pruned off or not. If the result of the test is found to have a probability that it could

be a better match than the current *best_so_far*, a higher resolution of the approximation is required. Then each segment of the candidate is split into two segments to obtain a new candidate.

- The process of approximating Q and C to determine the PDTW should be reapplied and the test is repeated for all levels of approximations until they fail the test or their true distance DTW is determined.

Doing so, IDDTW finds the number of segments that best approximates DTW and speeds up its computation. However, the goal of IDDTW is not the same as ours, which is to find the number of segments that best aligns the time series and speeds-up the computation of DTW. Actually, IDDTW has three main drawbacks:

- It only considers the numbers of segments for PDTW that are power of 2;
- It requires a user-specified tolerance for false dismissals that influences the quality of the approximation, but the algorithm does not give any indication on how to choose the tolerance;
- It considers DTW as a reference while looking for the number of segments that best aligns the time series. However, because of pathological alignments, DTW sometimes fails to align time series properly.

In this paper, we propose a heuristic named parameter Free piecewise DTW (FDTW) that deals with all the drawbacks of IDDTW: it considers all the possible values for the number of segments, it is parameter-free and it finds a number of segments for PDTW based on the quality of the time series alignment namely the classification error. The next section presents a definition of our heuristic.

3 Heuristic search of the number of segments

3.1 Problem definition. Let $D = \{d_i\}$ be a set of datasets composed of time series. We note $|d_i|$ the number of time series of the dataset d_i .

Let $X \in d_i$ be a time series of the dataset d_i ; we note $|X| = n$ the length of the time series X . For simplicity of notation we suppose that all the time series of d_i have the same length.

DEFINITION 3.1.

$$1NNDTW : D \rightarrow [0, 1]$$

$$d_i \mapsto 1NNDTW(d_i)$$

$1NNDTW(d_i)$ is the classification error of one Nearest Neighbour with Dynamic Time Warping on the dataset d_i .

DEFINITION 3.2. Let $d \subseteq T$ be a subset of time series, $N \in \mathbb{N}^*$, $PAAset(d, N) = \{PAA(X, N), \forall X \in d\}$

DEFINITION 3.3.

$$1NNPDTW : D \times \{1 \dots n\} \rightarrow [0, 1]$$

$$(d_i, N) \mapsto 1NNPDTW(d_i, N) =$$

$$= 1NNDTW \circ PAAset(d_i, N)$$

$1NNPDTW(d_i, N)$ is the classification error of 1-NN with PDTW using N segments on d_i .

Our goal is to find the number of segments that allows PDTW to best align time series. PDTW gives a good alignment when its classification error with 1NN is low [21]. Our problem is then to find the number of segments N that minimizes $1NNPDTW(d_i, N)$.

Formaly, **given a dataset d_i , we look for the number of segments $N \in \{1 \dots n\}$ such that**

$$1NNPDTW(d_i, N) = \min_{1 \leq \alpha \leq n} \{1NNPDTW(d_i, \alpha)\}.$$

3.2 Brute-force search. The simplest way to find the value for the number of segments that minimized the classification error is to test all the possible values. Obviously, this method is time consuming as we have to test n values to find the one that has the minimal classification error. The time complexity of this process is :

$$O\left(\left(\frac{|trainingset|}{2}\right)^2 \times \sum_{N \in C} N^2\right), |C| = n,$$

where C is the set of values for the number of segments.

To reduce the time of the search, the heuristic proposes to look for the number of segments with the minimal classification error without testing all the possible values.

3.3 Parameter free heuristic. The idea of our heuristic is the following:

1. We choose N_c candidates distributed in the space of possible values to ensure that we are going to have small, medium and large values as candidates. The candidates values are: $n, n - \lfloor \frac{n}{N_c} \rfloor, n - 2 \times \lfloor \frac{n}{N_c} \rfloor, \dots, n - N_c \times \lfloor \frac{n}{N_c} \rfloor$. For instance, if the length of time series is $n = 12$ and the number of candidates is $N_c = 4$, we are going to select the candidates 12, 9, 6, 3.

$$1, 2, [3], 4, 5, [6], 7, 8, [9], 10, 11, [12]$$

2. We evaluate the classification error with 1NNPDTW for each candidate that we have previously chosen and we select the candidate that has the minimal classification error: it is the best candidate. In our example, we may suppose that we get the minimal value with the candidate 6 it is thus the best candidate at this step.

1, 2, 3, 4, 5, [6], 7, 8, 9, 10, 11, 12

3. We respectively look between the predecessor (i.e., 3 here) and successor (i.e., 9 here) of the best candidate for a number of segments with a lower classification error. This number of segments corresponds to a local minimum. In our example, we are going to test the values 4, 5, 7 and 8 to see if there is a local minimum.

4. We restart at step one, while choosing different candidates during each iteration to ensure that we return a good local minimum. We fix the number of iterations to $\lfloor \log(n) \rfloor$. At each iteration the first candidate is $n - (\text{number_of_iteration} - 1)$.

In short, in the worst case, we test the N_c first candidates to find the best one. Then, we test $\frac{2n}{N_c}$ other candidates to find the local minimum. We finally perform $nb(N_c) = N_c + \frac{2n}{N_c}$ tests. The number of tests that we have to perform is a function of the number of candidates. How many candidates should we consider to reduce the number of tests? The first derivative of the function nb vanishes when $N_c = \sqrt{2n}$ and the second derivative is positive so the minimal number of tests is done when the number of candidates $N_c = \sqrt{2n}$. Algorithm 1 presents the details of the heuristic.

Time complexity: We use the training set to find the number of segments that should be considered with PDTW. To do so, we applied 1NN on the training set that costs

$$O\left(\left(\frac{|\text{trainingset}|}{2}\right)^2 \times \sum_{N \in C} N^2\right), |C| = \sum_{i=0}^{\log(n)-1} 8\sqrt{n-i}.$$

where $\left(\frac{|\text{trainingset}|}{2}\right)^2$ comes from 1NN algorithm and $\sum_{N \in C} N^2$ comes from PDTW with N being one value of the number of segments, and C being the set of values for the number of segments. At each iteration, the heuristic tests $nb(\sqrt{2n}) = 8\sqrt{n}$ number of segments.

We have $\log(n)$ iterations so $|C| = \sum_{i=0}^{\log(n)-1} 8\sqrt{n-i}$

LEMMA 3.1. *For a given a dataset d_i $FDTW(d_i) \leq 1NNDTW(d_i)$. The quality of the alignment of our heuristic is better than that of DTW.*

Proof. $1NNDTW(d_i) = 1NNPDTW(d_i, n)$. $1NNDTW(d_i)$ is then one of the candidate considered by the heuristic $FDTW$. Since $FDTW$

returns the minimal classification error from all candidates, the classification error of 1NNDTW is always greater than or equal to $FDTW$.

Algorithm 1 FDTW(training_set, test_set, n, nb_rep=log(n))

```

# Look for a good value of the number of segments
N
# using the training set
for (i in 0 : (nb_rep - 1)) do
  tab_N ← 1 : (n - i)
  l ← floor(n/sqrt(2 * n))
  tab_N_candidats ← seq(from = n, to = 1, by = -l)

# Parallel execution of 1NNPDTW
mat_r ← 1NNPDTW(training_set,
  tab_N_candidats)

# Mark candidates already used to not reuse
for (i in tab_candidats) do
  tab_N[i] ← -1
end for

# Search for the best candidate with the minimal error
min ← minimum(mat_r)

# look for the local minimum near of the best candidate
result[[i + 1]] ← localMinimum(min.N_min,
  min.error_min, training_set, tab_N)
end for

# The best local minimal error
m ← minimum(result)
return m

```

A heuristic does not always give the optimal value. To ensure that it gives a result not far from the optimal value, one approach is to guarantee that the result of the heuristic always lies in an interval with respect to the optimal value [8].

In our case, we are looking for the number of segments that allows a good alignment of time series. The alignment is good when the classification error with 1NN is minimal or when the accuracy is maximal.

Let d_i be a dataset: $acc_{max}(d_i) = 1 - \min_{1 \leq \alpha \leq n} \{1NNPDTW(d_i, \alpha)\}$ is the maximal accuracy for the dataset d_i , $acc_{DTW} = 1 - 1NNDTW(d_i)$ is the accuracy with d_i and 1NNDTW and $acc_{FDTW} = 1 - FDTW(d_i)$ is the accuracy of our heuristic.

To ensure the quality of our heuristic FDTW, Proposition 3.1 assume that 1NNDTW is better than the baseline classifier Zero Rule. Zero rule classifier is a simple classifier that predicts the majority class of test data (if nominal) or average value (if numeric). Zero rule is often used as baseline classifier [5]. The minimal value of the accuracy of Zero rule is $\frac{1}{c}$ where c is the number of classes of the dataset.

PROPOSITION 3.1. *For a given dataset d_i that has c_i classes, $c_i \in \mathbb{N}^*$,*

if $acc_{DTW} \geq \frac{1}{c_i}$ then $\frac{1}{c_i} \times acc_{max} \leq acc_{FDTW} \leq acc_{max}$

Proof. By definition, $acc_{FDTW} \leq acc_{max}$ We look for $k \in \mathbb{N}$ such that $\frac{1}{k} \times acc_{max} \leq acc_{FDTW}$

$$\frac{1}{k} \times acc_{max} \leq acc_{FDTW}$$

$$i.e. \frac{acc_{max}}{acc_{FDTW}} \leq k \text{ or}$$

$$\frac{acc_{max}}{acc_{FDTW}} \leq \frac{1}{acc_{FDTW}}$$

because $acc_{max} \leq 1$ and

$$\frac{1}{acc_{FDTW}} \leq \frac{1}{acc_{DTW}}$$

because $acc_{DTW} \leq acc_{FDTW}$

$$\frac{1}{acc_{DTW}} \leq c_i$$

because $\frac{1}{c_i} \leq acc_{DTW}$ by hypothesis

We take $k = c_i$

4 Experiments and discussion

4.1 Datasets. The performance of FDTW has been tested on 45 datasets of the UCR time series datamining archive [3], which provides a large collection of datasets that cover various domains (Table 1). Each dataset is divided into a training set and a testing set. The 45 datasets possess between 2 and 50 classes, the length of the time series varies from 24 to 1882, the training sets contain between 20 and 1000 time series and the testing sets contain between 28 and 6164 time series. An implementation of BF, IDDTW and FDTW is available online [24]

4.2 Results. Firstly, to evaluate the quality of our heuristic FDTW, we compared its classification errors with that of IDDTW (Figure 4) and the minimal one (Figure 3). The classification error was calculated based on the holdout model evaluation and the minimal one was found by applying Brute-force search (BF) on both training set and testing set. FDTW and IDDTW used the training set to find the number of segments N using 3 fold cross validation. IDDTW tested all the values of N that were equal to a power of two and kept the one that had a minimum classification error. We also compared FDTW to BF and IDDTW in terms of number of tested values (Figure 1), running time (Figure 2) and compression ratio.

Then, we compared FDTW to other classification methods reported in the literature. The comparison was based on the classification error calculated using the hold out evaluation model. The smallest classification error reported on each dataset and the 1NN classification error of Euclidean distance, DTW without a warping window and DTW with best warping window have been published by previous researchers [3] [1]. In this paper we report the 1NN classification error of Brute-force search, IDDTW and FDTW.

N°	Dataset	classes	Size of training set	Size of testing set	Time series length
1	50Words	50	450	455	270
2	Adiac	37	390	391	176
3	Beef	5	30	30	470
4	Car	4	60	60	577
5	CBF	3	30	900	128
6	Coffee	2	28	28	286
7	Cricket_X	12	390	390	300
8	Cricket_Y	12	390	390	300
9	Cricket_Z	12	390	390	300
10	Distal Phalanx OutlineAge Group	3	139	400	80
11	Distal Phalanx TW	6	139	400	80
12	Earthquakes	2	139	322	512
13	ECG	2	100	100	96
14	ECGFiveDays	2	23	861	136
15	Face (all)	14	560	1690	131
16	Face (four)	4	24	88	350

17	Fish	7	175	175	463
18	Gun-point	2	50	150	150
19	Ham	2	109	105	431
20	Haptics	5	155	308	1092
21	InlineSkate	7	100	550	1882
22	Italy	2	67	1029	24
	PowerDemand				
23	Lightning-2	2	60	61	637
24	Lightning-7	7	70	73	319
25	MedicalImages	10	381	760	99
26	Middle	3	154	400	80
	Phalanx				
	OutlineAgeGroup				
27	Middle	6	154	399	80
	PhalanxTW				
28	MoteStrain	2	20	1252	84
29	OliveOil	4	30	30	570
30	OSU leaf	6	200	242	427
31	Plane	7	105	105	144
32	Proximal	6	205	400	80
	PhalanxTW				
33	ShapeletSim	2	20	180	500
34	SonyAIBO	2	20	601	70
	Robot Surface				
35	SonyAIBO	2	27	953	65
	Robot SurfaceII				
36	Swedish leaf	15	500	625	128
37	Symbols	6	25	995	398
38	Synthetic control	6	300	300	60
39	Trace	4	100	100	275
40	Two patterns	4	1000	4000	128
41	TwoLeadECG	2	23	1139	82
42	Wafer	2	1000	6164	152
43	Wine	2	57	54	234
44	WordsSynonyms	25	267	638	270
45	Yoga	2	300	3000	426

Table 1: Detailed information about the datasets

4.3 Discussions. Comparing FDTW and BF approaches (Figure 1) clearly shows that the number of candidates in BF is considerably reduced in FDTW by a factor at least greater than 2.5. This number is exponentially correlated to the time series length, for example FDTW tested 0.08% less candidates than BF with the dataset ItalyPowerDemand that has the shortest time series length of our sample (24 data points) and 76% less candidates than BF with dataset Inlineskate that has the longest time series of our sample (1882 data points). Actually, the number of candidates to be tested ranges from 1 to n , n being the length of time series. This demonstrates an advantage of FDTW in terms of space exploration and thus indirectly in terms of mem-

ory usage and execution time. However, FDTW tested more candidates than IDDTW, which tested in average 96% less candidates than Brute-force search (Figure 1).

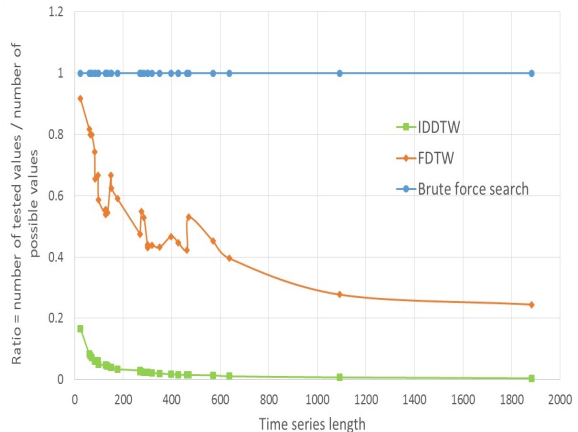


Figure 1: Comparison of the number of tested values of the parameter, number of segments with the Brute-force search algorithm, FDTW and IDDTW. x-axis datasets are sorted according to the length of the time series.

Nevertheless, the values of the number of segments are evaluated on the training set. To take into account the cost of classification performed on the testing set, we also compare the methods FDTW, IDDTW and Brute-force search based on their execution time on the training and the testing sets.

Generally, FDTW is 8 times faster than Brute-force search with an average execution time of 176 minutes against 1386 minutes for Brute-force search. IDDTW is 7 times faster than FDTW and remains the fastest with an average execution time of 24 minutes. The execution time increases with the length of the time series (Figure 2). The increase of Brute-force search execution time is faster than that of FDTW and IDDTW. This can be seen on the dataset Lightning-2 whose time series have a length equal to 637 data points.

As regard in the compression ratio, the heuristic uses a compact representation for time series whose length contains in average 44% data points less than the initial time series against 63% for IDDTW.

The experiments show that IDDTW is faster and test fewer candidates. However, FDTW have better performance. Actually, FDTW resulted in a lower classification error than IDDTW on 22 datasets and the same classification error than IDDTW on 8 datasets (Figure 4). They also show that the classification error of Brute-force search (BF) is smaller than the smallest classification error reported in the literature on six datasets and is equal to the smallest classification error

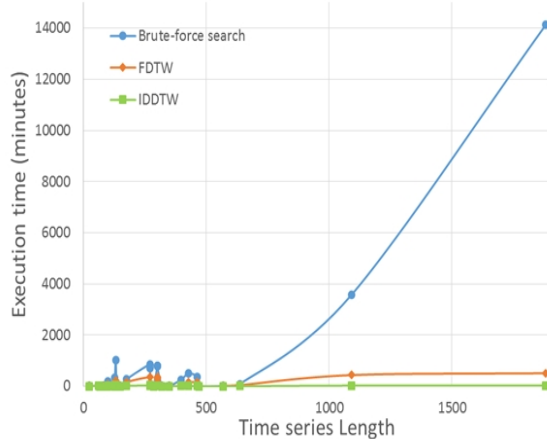


Figure 2: Comparison of the execution time of the Brute-force search algorithm, FDTW and IDDTW.

reported on four datasets. Moreover, In average, BF is better than the other algorithms of Table 4.3 with a classification error of 0.175. In other words, it is a good strategy to piecewise aggregate time series before classifying them if we know a good number of segment to use.

Our heuristic FDTW managed to find the minimum error for 9 datasets (Coffee, ECGFiveDays, Gun-point, ItalyPowerDemand, OliveOil, Plane, Synthetic control, Trace, Two patterns). It also outperforms the smallest classification error reported in the literature on dataset CBF ($N^{\circ}5$). The methods of the literature are

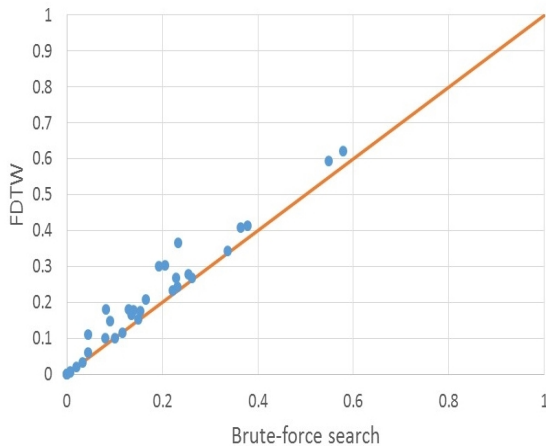


Figure 3: Comparison of the classification error of the Brute-force search algorithm in x-axis and FDTW in y-axis.

1NN associated with Euclidean distance, DTW without warping windows, DTW with warping windows. FDTW outperforms 1NN associated with Euclidean distance

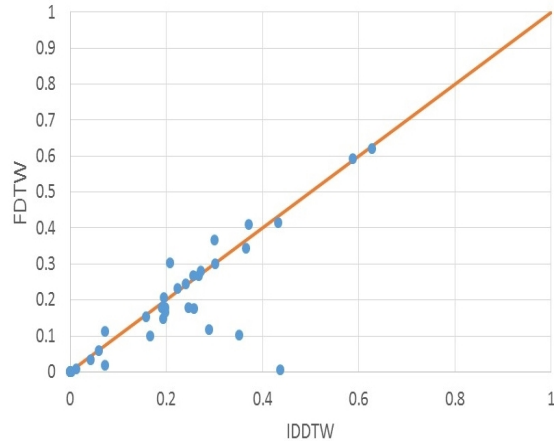


Figure 4: Comparison of the classification error of IDDTW in x-axis and FDTW in y-axis. The points below the diagonal represent the datasets for which FDTW is better than IDDTW.

ED on 33, they are equal on 1 dataset. FDTW outperforms 1NN associated with DTW on 19 datasets, they are equal on 11 datasets. FDTW outperforms 1NN associated with DTW with warping windows on 19 datasets they are equal on 2 datasets.

5 Conclusion

Our problem was to choose a good number of segments for Piecewise Dynamic Time Warping. To answer this question, we proposed a heuristic approach called Parameter Free Piecewise Dynamic Time Warping (FDTW) that proposes an approximation of the best number of segments to be used during times series classification based on DTW. FDTW has been experimented on 45 data sets on a classification task. In average, it returned a classification error lower than the one of IDDTW. Our approach is a heuristic that is parameter free since it does not require any domain specific tuning. This work allows to reduce the storage space and the processing time of time series classification without decreasing the quality of the alignment. As a perspective, we plan to use piecewise aggregate time series with other variants of DTW to improve the classification. Using the same strategy presented in FDTW, we plan to find the number of segments to be considered for symbolic representations of time series like SAX [15], ESAX [16], SAX-TD [25].

References

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Results reported in [3][1]					Our experiments					
N°	1NN Eucli dean distance	1NN DTW	1-NN DTW (r)	Smallest known error	Brute force search	N(ℓ)	IDDTW	N(ℓ)	FDTW	N(ℓ)
1	0.369	0.310	0.242 (6)	<i>0.179</i>	0.262	251(1)	0.268	256(1)	0.268	258(1)
2	0.389	0.396	0.391 (3)	<i>0.190</i>	0.379	162(1)	0.432	128(1)	0.414	143(1)
3	0.333	0.367	0.333 (0)	<i>0.181</i>	0.233	286(2)	0.3	8(59)	0.367	94(5)
4	0.267	0.267	0.233 (1)	<i>0.098</i>	0.183	52(11)	0.367	8(72)	0.367	377(1)
5	0.148	0.003	0.004 (11)	0.002	<i>0</i>	118(1)	0.003	128(1)	0.001	128(1)
6	0.000	0.000	0.000 (0)	<i>0</i>	<i>0</i>	13(22)	0	64(4)	0.000	286(1)
7	0.423	0.246	0.228 (10)	<i>0.186</i>	0.228	142(2)	0.256	256(1)	0.269	84(4)
8	0.433	0.256	0.238 (17)	<i>0.185</i>	0.231	271(1)	0.241	256(1)	0.244	294(1)
9	0.413	0.246	0.254 (5)	<i>0.173</i>	0.221	249(1)	0.223	256(1)	0.233	276(1)
10	0.218	0.208	0.228 (1)	<i>0.171</i>	0.2	78(1)	0.225	16(5)	0.223	80(1)
11	0.273	0.29	0.272 (0)	<i>0.272</i>	<i>0.263</i>	35(2)	0.288	16(5)	0.278	80(1)
12	0.326	0.258	0.258 (22)	0.241	<i>0.198</i>	176(2)	0.258	512(1)	0.276	101(5)
13	0.120	0.230	0.120 (0)	<i>0.110</i>	0.13	38(3)	0.19	8(12)	0.180	11(9)
14	0.203	0.232	0.203 (0)	<i>0.014</i>	0.117	11(12)	0.289	32(4)	0.117	11(12)
15	0.286	0.192	0.192 (3)	<i>0.010</i>	0.091	79(2)	0.194	128(1)	0.148	99(1)
16	0.216	0.170	0.114 (2)	<i>0.004</i>	0.08	107(3)	0.352	32(11)	0.102	140(3)
17	0.217	0.177	0.154(4)	<i>0.026</i>	0.154	149(3)	0.257	16(29)	0.177	27(17)
18	0.087	0.093	0.087 (0)	<i>0.001</i>	0.02	38(4)	0.073	32(5)	0.020	38(4)
19	0.4	0.533	0.400 (0)	<i>0.164</i>	0.343	21(20)	0.026	32(13)	0.432	32(13)
20	0.630	0.623	0.588 (2)	<i>0.483</i>	0.549	328(3)	0.588	64(17)	0.594	948(1)
21	0.658	0.616	0.613 (14)	<i>0.448</i>	0.578	1770(1)	0.627	64(29)	0.622	171(11)
22	0.045	0.050	0.045 (0)	<i>0.030</i>	0.033	20(1)	0.043	8(3)	0.033	24(1)
23	0.246	0.131	0.131 (6)	0.131	<i>0.082</i>	70(9)	0.246	16(40)	0.180	524(1)
24	0.425	0.274	0.288 (5)	0.201	<i>0.192</i>	150(2)	0.301	64(5)	0.301	51(6)
25	0.316	0.263	0.253 (20)	<i>0.215</i>	0.255	95(1)	0.271	64(2)	0.280	34(3)
26	0.26	0.25	0.253 (5)	<i>0.178</i>	0.233	27(2)	0.283	2(40)	0.283	2(40)
27	0.439	0.416	0.419 (2)	0.413	<i>0.398</i>	27(2)	0.414	32(2)	0.416	80(1)
28	0.121	0.165	0.134 (1)	<i>0.083</i>	0.135	14(6)	0.197	16(5)	0.165	84(31)
29	0.133	0.167	0.133 (0)	<i>0.099</i>	0.1	191(3)	0.167	32(18)	0.100	234(2)
30	0.479	0.409	0.388 (7)	<i>0.033</i>	0.364	31(14)	0.372	32(13)	0.409	35(12)
31	0.038	0	0.000 (6)	<i>0</i>	<i>0</i>	35(4)	0	128(1)	0	135(1)
32	0.292	0.263	0.263 (6)	<i>0.185</i>	0.24	75(1)	0.288	4(20)	0.288	4(20)
33	0.461	0.35	0.300 (3)	<i>0</i>	0.083	54(9)	0.239	64(7)	0.122	48(10)
34	0.305	0.275	0.305 (0)	<i>0.082</i>	0.206	37(2)	0.208	16(4)	0.304	26(3)
35	0.141	0.169	0.141 (0)	<i>0.04</i>	0.14	5(13)	0.197	16(4)	0.178	45(1)
36	0.211	0.208	0.154 (2)	<i>0.033</i>	0.165	59(2)	0.195	64(2)	0.208	55(2)
37	0.100	0.050	0.062 (8)	<i>0.037</i>	0.044	376(1)	0.059	32(12)	0.060	34(12)
38	0.120	0.007	0.017 (6)	<i>0.001</i>	0.007	60(1)	0.437	2(30)	0.007	60(1)
39	0.240	0.000	0.010 (3)	<i>0</i>	<i>0</i>	47(6)	0	64(4)	0.000	275(1)
40	0.090	0.000	0.002 (4)	<i>0</i>	<i>0</i>	21(6)	0	64(2)	0.000	128(1)
41	0.253	0.096	0.132 (5)	<i>0.006</i>	0.045	55(1)	0.073	32(3)	0.112	70(1)
42	0.005	0.020	0.005 (1)	<i>0</i>	0.007	109(1)	0.013	8(19)	0.008	95(2)
43	0.389	0.426	0.389 (0)	<i>0.074</i>	0.204	3(78)	0.463	20(11)	0.37	128(1)
44	0.382	0.351	0.252 (8)	<i>0.222</i>	0.337	133(2)	0.365	64(4)	0.343	135(2)
45	0.170	0.164	0.155 (2)	<i>0.090</i>	0.149	117(4)	0.158	128(3)	0.154	384(1)
\bar{X}	0.268	0.227	0.242		0.175		0.214		0.232	

Table 2: Comparison of classification errors. In **italics**, the smallest classification error. In **bold**, the smallest classification error between IDDTW and FDTW. N is the number of segments selected and ℓ is the number of data points in a segment which is equal to $\lfloor \frac{n}{N} \rfloor$.

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