Parameter Free Piecewise Dynamic Time Warping for time series classification
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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
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 $X = x_1, \ldots, x_n$ 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:

$$X = x_1, x_2, \ldots, x_n;$$
$$Y = y_1, y_2, \ldots, y_m.$$

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 $W = w_1, w_2, \ldots, w_K$, 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: $X_i = x_i, x_{i+1}, \ldots, x_{i+l-1}$

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:

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

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


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

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.**

\[
1NN\text{DTW} : D \to [0, 1] \quad d_i \mapsto 1NN\text{DTW}(d_i)
\]

\(1NN\text{DTW}(d_i)\) 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, \( N \in \mathbb{N}^* \), \( \text{PAAset}(d, N) = \{\text{PAA}(X, N), \forall X \in d\} \)

**Definition 3.3.**

\[
1NNPDTW : D \times \{1 \ldots n\} \to [0, 1] \quad (d_i, N) \mapsto 1NNPDTW(d_i, N) = 1NN\text{DTW} \circ \text{PAAset}(d_i, N)
\]

\(1NNPDTW(d_i, N)\) 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 \( N \in \{1 \ldots n\} \) 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:

\[
O\left(\frac{||\text{training set}||^2}{2} \times \sum_{N \in C} N^2\right), |C| = n,
\]

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: \( n, n - \left\lfloor \frac{n}{N_c} \right\rfloor, n - 2 \times \left\lfloor \frac{n}{N_c} \right\rfloor, \ldots, n - N_c \times \left\lfloor \frac{n}{N_c} \right\rfloor \). 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 \([\log(n)]\). At each iteration the first candidate is \(n - (\text{number of iterations} - 1)\).

In short, in the worst case, we test the \(N_c\) first candidates to find the best one. Then, we test \(\frac{2N_c}{N}\) other candidates to find the local minimum. We finally perform \(nb(N_c) = N_c + \frac{2n}{N}\) 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

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

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 \(|C| = \sum_{i=0}^{\log(n)-1} 8\sqrt{n} - 1\).

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

**Proof.** \(1\text{NNDTW}(d_i) = 1\text{NNPDTW}(d_i, n)\). \(1\text{NNDTW}(d_i)\) is then one of the candidate considered by the heuristic \(\text{FDTW}\). Since \(\text{FDTW}\) returns the minimal classification error from all candidates, the classification error of \(1\text{NNDTW}\) is always greater than or equal to \(\text{FDTW}\).

**Algorithm 1**

\begin{verbatim}
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 ← (n - i)
        l ← floor(n/sqrt(2 * n))
        tab_N_candids ← seq(from = n, to = 1, by = -l)

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

        # Mark candidates already used to not reuse
        for (i in tab_N_candids) 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
\end{verbatim}

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: \(acc_{\text{max}}(d_i) = 1 - \min_{1 \leq \alpha \leq n} \{1\text{NNPDTW}(d_i, \alpha)\}\) is the maximal accuracy for the dataset \(d_i\), \(acc_{\text{DTW}} = 1 - 1\text{NNDTW}(d_i)\) is the accuracy with \(d_i\) and \(1\text{NNDTW}\) and \(acc_{\text{FDTW}} = 1 - \text{FDTW}(d_i)\) is the accuracy of our heuristic.
To ensure the quality of our heuristic FDTW, Proposition 3.1 assume that 1NN DTW 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 \( \text{acc}_{\text{DTW}} \geq \frac{1}{c_i} \) then \( \frac{1}{c_i} \times \text{acc}_{\max} \leq \text{acc}_{\text{FDTW}} \leq \text{acc}_{\max} \)

Proof. By definition, \( \text{acc}_{\text{FDTW}} \leq \text{acc}_{\max} \) We look for \( k \in \mathbb{N} \) such that \( \frac{1}{k} \times \text{acc}_{\max} \leq \text{acc}_{\text{FDTW}} \)

\[
\frac{1}{k} \times \text{acc}_{\max} \leq \text{acc}_{\text{FDTW}}
\]

i.e.

\[
\frac{\text{acc}_{\max}}{\text{acc}_{\text{FDTW}}} \leq k
\]

\[
\frac{\text{acc}_{\max}}{\text{acc}_{\text{FDTW}}} \leq \frac{1}{\text{acc}_{\text{DTW}}}
\]

because \( \text{acc}_{\max} \leq 1 \) and

\[
\frac{1}{\text{acc}_{\text{FDTW}}} \leq \frac{1}{\text{acc}_{\text{DTW}}}
\]

because \( \text{acc}_{\text{DTW}} \leq \text{acc}_{\text{FDTW}} \)

\[
\frac{1}{\text{acc}_{\text{DTW}}} \leq c_i
\]

because \( \frac{1}{c_i} \leq \text{acc}_{\text{DTW}} \) by hypotesis

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 find 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.

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20 Haptics 5 155 308 1092
21 InlineSkate 7 100 550 1882
22 Italy 2 67 1029 24
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
27 Phalanx 6 154 399 80
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
33 ShapeletSim 2 20 180 500
34 SonyAIBO 2 20 601 70
35 SonyAIBO 2 27 953 65
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 memory 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.](image)

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

[1] A. Bagnall, E. Keogh, J. Lines, A. Bostrom, and J. Large, Time Se-
### Our experiments

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**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 \( \lfloor \frac{n}{N} \rfloor \).


