Supplementary materials

The similarity search of time series is usually transformed into a time series classification problem. To verify the effectiveness of the proposed method in this article, comparative experiments were conducted with the performance of existing DTW, DDTW, and CTW methods. The algorithm uses the 1-NN method, which is a commonly used classification technique [27]. The experiment was conducted on Intel (R) Core (TM) i7-9750H CPU @ 2.60GHz 2.59 GHz, 8GB of memory, and Microsoft Windows 10 operating system. All programs required for this study were written using Python 3.9 software

S1 Evaluation methods

This article uses classification accuracy and uses system runtime T to measure the accuracy of time series algorithms. Assuming the time series experimental dataset is $D(D_1, D_n)$ and the total number is *n*, where the correct number of classifications is n_r, the formula for classification accuracy is n_r/n.

S2 Datasets

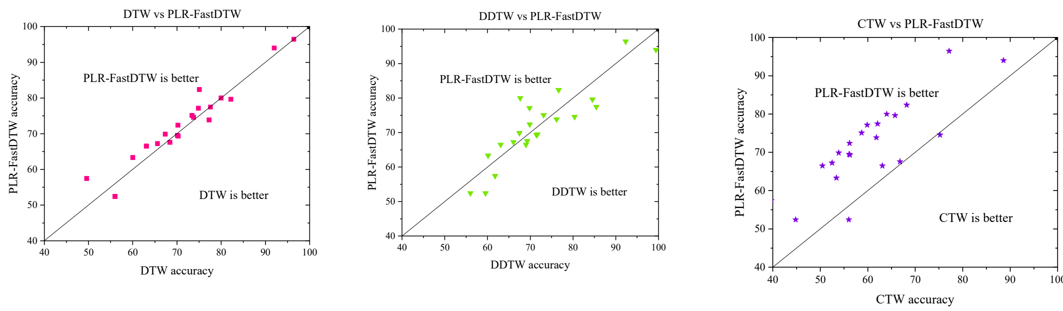
The experimental data used in this article is from open UCR standard time series data. The performance of PLR-FastDTW was tested on the UCR time series data mining archive (*https://www.cs.ucr.edu/~eamonn/time_series_data/*), which has the most comprehensive and extensive testing dataset. It covers various real-time sequence datasets collected from different fields, such as computer vision, medicine, meteorology, and video trajectory recognition. A total of 20 datasets were tested to demonstrate the speed and accuracy of PLR-FastDTW in processing different time series.

In addition, the proposed PLR-FastDTW algorithm was also applied to analyze a flight maneuver recognition dataset from a specific organization in this study. The dataset consists of time series data related to aircraft flight maneuvers and was specifically collected for the purpose of evaluating the performance of PLR-FastDTW in this application domain. The analysis of this dataset aimed to assess the effectiveness of PLR-FastDTW in accurately classifying and recognizing different flight maneuvers based on the recorded time series data.

S3 Alignment experiments

S 3.1 Alignment using UCR time series data sets

To further highlight the effectiveness of the proposed method, 20 datasets from the UCR time series database were used with a 1-NN accuracy. Compare the accuracy of FsatDTW with DTW, DDTW, and CTW using 1-NN. Obviously, as shown in the accuracy results of 1-NN **(Figure S1)**, most of the points are located in areas with good FastDTW.



(a) (b) (c)

Figure S1 1-NN accuracy of proposed different alignment measures on UCR datasets.

What is shown in **Table S1** provides a comprehensive comparative analysis of the PLR-FastDTW method in relation to DTW, DDTW, and CTW techniques on 20 UCR datasets. Results show that PLR-FastDTW achieves a higher average analysis accuracy of 73.31% compared to DTW (72.16%) and CTW (60.57%), with a minimal difference to DDTW (73.59%). Moreover, PLR-FastDTW demonstrates significant improvement in average analysis time, outperforming DTW, DDTW, and CTW by reducing the computation time to 1069.17, 53.01%, 52.83%, and 73.05% respectively. These findings highlight the superior accuracy and efficiency of PLR-FastDTW for time series analysis.

Table **S1** Comparison of accuracy and time

UCR dataset	Accuracy (%)				Time (s)			
	DTW	D-DTW	CTW	PLR-FastDTW	DTW	DDTW	CTW	PLR-FastDTW
50Words	63.08	69.00	50.46	66.50	10765.20	11841.72	17088.00	5733.95
Adiac	56.01	59.53	44.81	52.43	3125.77	3438.35	9636.42	1798.26
ArrowHead	65.60	66.09	52.48	67.24	273.80	296.56	517.76	133.54
Beef	60.00	60.13	53.40	63.33	129.73	142.70	145.00	73.55
Coffee	96.43	92.32	77.14	96.43	42.68	46.95	73.79	21.12
Cricket_X	68.40	69.28	66.80	67.56	4352.62	4700.36	6752.51	1354.86
Cricket_Y	70.10	71.69	56.08	69.51	4526.55	4979.21	7521.23	1453.25
Cricket_Z	70.30	71.45	56.24	69.33	3956.13	3998.25	5425.56	1442.34
ECGFiveDays	77.58	85.46	62.06	77.47	288.75	317.63	881.68	161.91
Face (all)	73.40	73.13	58.72	75.10	348.35	365.56	442.89	164.58
Face (four)	77.27	76.15	61.82	73.86	174.60	192.06	269.06	84.86
Fish	74.86	69.83	59.89	77.14	4078.81	4486.69	4408.49	2364.89
Gun-point	92.00	99.40	88.60	94.00	251.49	276.64	359.47	165.36
Medicallmages	67.37	67.46	53.90	69.87	3642.74	4007.01	8375.01	1622.20
MoteStrain	82.19	84.55	65.75	79.63	139.19	153.11	691.62	82.23
OliveOil	80.00	67.64	64.00	80.00	182.13	200.34	159.01	99.56
OSU leaf	49.59	61.76	39.67	57.44	5409.71	5950.68	7067.09	2675.80
SonyAIBORobot Surfacell	70.22	69.88	56.18	72.38	45.60	50.16	217.61	29.33
Swedish leaf	73.76	80.39	75.21	74.56	3598.38	3958.22	8727.88	1845.22
TwoLeadECG	75.07	76.65	68.20	82.35	132.25	145.48	550.42	76.50
Average	72.16	73.59	60.57	73.31	2273.22	2477.38	3965.53	1069.17

S 3.2 Alignment using flight maneuver data sets

In order to further validate the effectiveness of the proposed alignment method, recognition experiments were conducted on the fighter flight maneuver dataset using a 1-NN pursuit rate. Based on the parameters learned above, using the accuracy of 1-NN, compare FastDTW and MADCTW with 1-NN to DTW, DDTW, and CTW. The accuracy results of 1-NN are shown in **Figure S2**. It is easy to see that most points are located in areas with good FastDTW. Although the accuracy of DDTW is slightly better than FastDTW, FastDTW has better recognition performance than DDTW. The accuracy and time of aircraft maneuvering data recognition are shown in **Table S2**. Overall, FastDTW can greatly improve recognition efficiency compared to other comparison measures while ensuring recognition accuracy. Therefore, FastDTW based on 1-NN has higher recognition efficiency for fighter flight maneuver datasets.

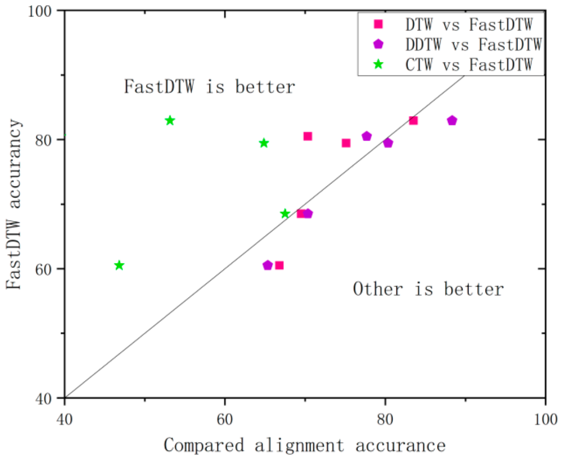


Figure S2 1-NN error of proposed different alignment measures compared with FastDTW.

Table S2 Comparison of accuracy and time

Maneuver classifiction	Accuracy (%)				Time(s)			
	DTW	DDTW	CTW	PLR-FastDTW	DTW	DDTW	CTW	PLR-FastDTW
Level	83.51	88.34	53.15	82.94	2010.91	2171.56	3119.66	625.94
Climb	75.12	80.36	64.86	79.45	2091.27	2300.39	3474.81	671.40
Descend	70.34	77.69	39.54	80.51	1827.73	1847.19	2506.61	666.36
Turn	69.51	70.35	67.51	68.51	1884.41	2072.85	2036.72	1092.57
Turn and ascend	66.79	65.35	46.82	60.51	1682.95	1851.24	3869.26	749.45
Turn and descend	72.52	77.67	68.51	78.33	2161.77	2377.94	2336.49	1253.39
Average	72.97	76.63	56.73	75.04	1979.20	2067.50	2890.59	843.19