A Multi-strategy LSHADE Algorithm and its Applications on Temporal Alignment

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May 24, 2020

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1 Introduction

In general, the approaches which can make DTW [1] faster include abstracting the data, indexing for near neighbors search application, pruning the computation of DTW and reducing the alignment path search space. In this paper, a novel alignment method which is combined with a novel hybrid optimization algorithm is proposed to reduce the calculation cost of alignment. Our contributions can be divided into below several parts:

(i) A multi-strategy LSHADE (MLSHADE) algorithm which combines improved LSHADE with adaptive CMA-ES is presented.

(ii) Combined with multi-strategy LSHADE, DTW based on MLSHADE, called MLDTW, is proposed to reduce the alignment complexity and improve the accuracy of alignment.

(iii) The performance of MLDTW is tested in sinusoidal signal and UCR time series archive, which is compared with other known alignment algorithms.

2 MLSHADE

Based on the ELSHADE-SPACMA, a novel algorithm, called multi-strategy LSHADE, is proposed. The main framework is divided into two phases, which include LSHADE-SPACMA [2] phase and AGDE [3] phase. The main framework is described in [3]. In order to improve the performance of MLSHADE, three strategies are proposed as follows:

(i) Weighted mutation strategy. To enhance the diversity of population, we propose a weighted mutation strategy, called *current-to-pbest-w/1*.

(ii) Inferior solution search strategy. According to fitness values of solutions, the performance rank P_{rank} can distinguish the superior or inferior solutions. For the i^{th} solution, if $P_{rank}\left(i\right) < 0.5$, it is regarded as the superior solution and use the original technique of CMA-ES to generate a new vector. If $P_{rank}\left(i\right) > 0.5$, the individual represents the inferior solution, which can be employed to enhance the exploration ability of CMA-ES method. The inferior solutions can be applied to two different update states. More details are presented as follows: *a).* In state 1, new candidate is generated by superior and inferior solutions in eigen coordinate. *b)*. State 2 updates the shifted mean value by utilizing the difference between the inferior and superior solutions.

(iii) Eigen Gaussian random walk strategy. In the second phase, a Gaussian random walk and the eigen coordinate system are presented to improve the exploitation performance of the AGDE.

$$x_i^{eig,G+1} = Gaussian\left(x_{pbest}^{eig,G}, \sigma\right) + rand_1 \cdot x_{pbest}^{eig,G} - rand_2 \cdot x_r^{eig,G}, \quad rand_1, rand_2 \sim U\left(0,1\right) \tag{15}$$

$$\sigma = \left| x_{pbest}^{eig,G} - x_{pworst}^{eig,G} \right| \tag{16}$$

where $x_r^{eig,G}$ is selected randomly from the middle *NP*-2*(100*p*%) at generation *G* under the eigen coordinate. $x_{pbest}^{eig,G}$ and $x_{pworst}^{eig,G}$ are chosen randomly from the best and worst 100*p*% under eigen coordinate.

3 Temporal Alignment based on MLSHADE

Combined with multi-strategy LSHADE, the DTW based on MLSHADE, called MLDTW, is proposed to reduce the complexity of alignment and improve the accuracy of alignment.

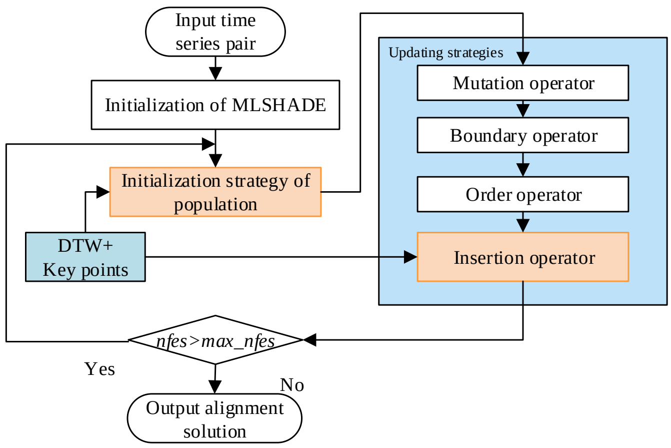


Fig. 1. Flow chart of MLSHADE

(i) As a path optimization problem, the variable length encoding is used by MLDTW.

(ii) In MLDTW, the energy function can be thought as fitness function to minimize the following formula.

$$J\left(p_x, p_y\right) = \left\| X_p W_x - Y_p W_y \right\|_F^2 \tag{19}$$

where $[p_x^T, p_y^T]^T$ is marked as alignment solution.

(iii) For the novel initialization technique, the key points will be selected to segment the whole alignment path. According to relationship between segmentation points, DTW with short time series segments will be computed.

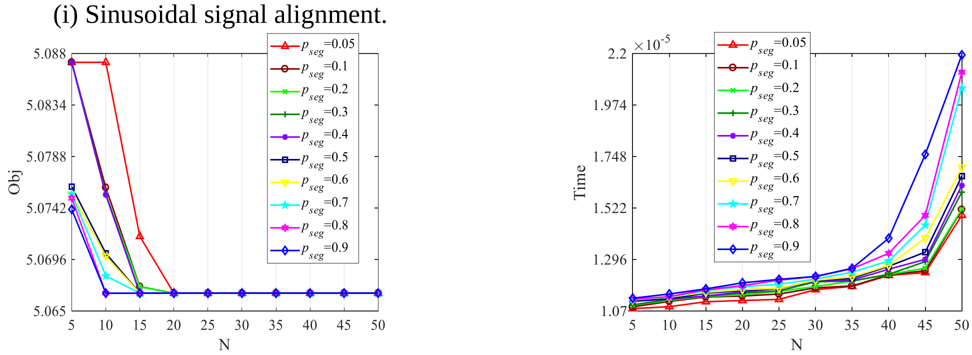
(iv) For individuals with variable length encoding, we propose a variant of mutation operator to overcome the difference. Meanwhile, boundary operator and order operator are proposed to ensure that the solution satisfies boundary condition and monotonicity condition of DTW. Moreover, to meet to continuity condition, the insertion operator is introduced.

Through combining above strategies, MLSHADE can be illustrated in Fig.1.

4 Experiments

This section presents the experiments on temporal alignment based on MLDTW proposed in this paper. For alignment experiments, sinusoidal signal and UCR dataset are utilized.

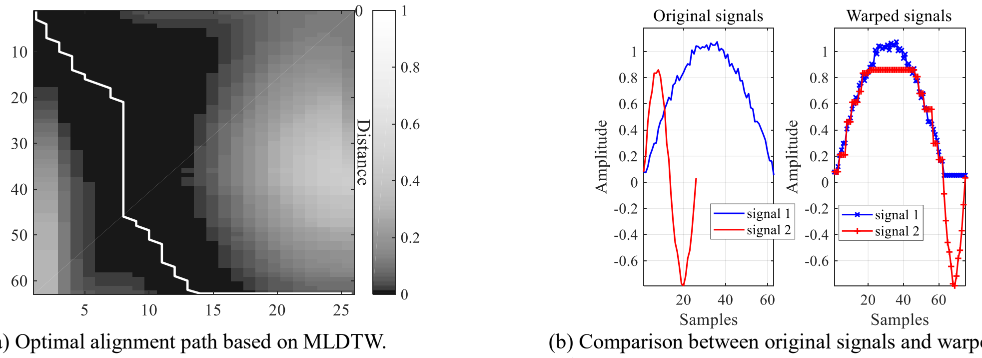
(i) Sinusoidal signal alignment.



(a) Objective function value across different N and P_{seg} levels.

(b) Time results across different N and P_{seg} levels.

Fig.2. Alignment results of proposed method across different N and P_{seg} levels.



(a) Optimal alignment path based on MLDTW.

(b) Comparison between original signals and warped signals.

Fig.3. Optimal alignment paths and warped signals.

To test and verify the availability and robustness of MLDTW, synthetic sinusoidal signal is employed to construct the alignment problem. The two temporal sinusoidal signals generated with zero-mean Gaussian noise can be shown in left of Fig.3(b).

To test the robustness of MLDTW and the sensitivity of parameters, alignment experiments based on MLDTW are carried out on different population size N and segment rate P_{seg} levels. Alignment results of MLDTW across different N and P_{seg} levels are shown in Fig.2. According to the robustness analysis, the appropriate parameters can be selected, including to N=20 and P_{seg}=0.1. Based on suitable parameters, optimal alignment path based on MLDTW is shown in Fig.3(a). According to alignment solution, the warped signals are presented in Fig.3(b).

In order to prove the superiority of MLDTW, the comparison experiments are carried out. The experiment results are shown in Table 5, including objective value mean, SD and average time. As can be seen in Table 5, MLDTW which ranks the first in mean possesses the similar performance as ELDTW and NRO.

Table 1. Experimental results evaluated by compared alignment methods.

	DTW	ELDTW	iLSHDTW	jSODTW	GEDGWODTW	NRODTW	MLDTW
Mean	4.9995	**4.8988**	5.8309	6.1630	5.5078	**4.8988**	**4.8988**
SD	0.3952	0.4246	0.8793	3.8249	0.6151	**0.3735**	**0.3735**
Mean rank	4	3	6	**7**	5	**1**	**1**
Average Time/s	2.45e-04	1.84e-05	1.46e-05	**1.32e-05**	3.49e-05	2.33e-05	1.33e-05
Time rank	7	4	3	**1**	6	5	2

(ii) Temporal alignment on UCR dataset

To further highlight the effectiveness of proposed alignment measure, the 6 datasets from UCR time series database using the one-nearest-neighbor (1-NN) error rate are employed. Based on parameters obtained from above section, MLDTW is compared against the DTW, ELDTW, iLSHDTW, jSODTW, GEDGWODTW and NRODTW using 1-NN error rate in Fig.8. It is clear that MLDTW outperforms the other alignment methods.

Additionally, the statistical results evaluated by compared alignment methods on UCR database are given in Table 6. The statistical results show that Error Rate (ER) and mean time of MLDTW rank the first and second, respectively.

5 Conclusions

As a novel alignment technique, MLDTW using multi-strategy LSHADE and DTW is described. MLSHADE is a novel optimization algorithm, which employs weighted mutation strategy, inferior solution search strategy and Eigen Gaussian random walk strategy at the framework of ELSHADE-SPACMA. In order to improve the efficiency of DTW, a novel alignment approach is proposed by using MLSHADE operators. The analysis of MLDTW is based on sinusoidal signal and six datasets of UCR time series. The statistical results show that MLDTW exerts the characteristics of high accuracy and efficiency compared with other alignment techniques.

Future work can address two points. First, MLDTW should be applied to specific real-world applications. Second, MLDTW can be extended to multi-dimensional time series alignment problems.

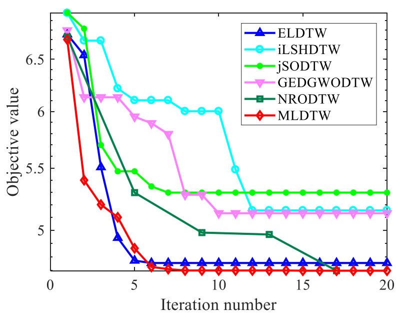


Fig.7. Fitness curves of compared methods.

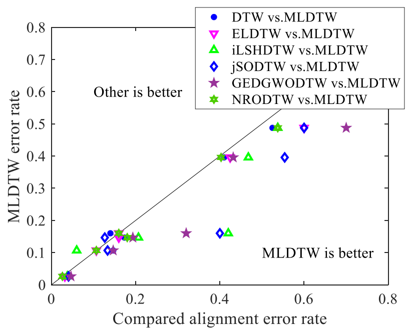


Fig.8. 1NN error rates of proposed different alignment measures on UCR database.

Table 2. Experimental results evaluated by compared alignment methods on UCR database.

Type		DTW	ELDTW	iLSHDTW	jSODTW	GEDGWODTW	NRODTW	MLDTW
BME	ER	0.1467	0.1067	**0.0600**	0.1333	0.1467	0.1067	0.1067
	Time	2.82e-04	7.13e-05	1.45e-04	**5.17e-05**	7.78e-05	6.40e-05	6.01e-05
Chinatown	ER	0.0435	0.0319	0.0377	0.0406	0.0467	**0.0261**	**0.0261**
	Time	4.19e-05	8.05e-06	1.40e-05	**5.95e-06**	7.31e-06	6.87e-06	6.39e-06
DistalPhalanxTW	ER	0.4101	0.4245	0.4676	0.5540	0.4317	0.4029	**0.3957**
	Time	7.56e-05	2.97e-05	5.96e-05	**2.44e-05**	3.28e-05	2.58e-05	2.32e-05
DodgerLoopDay	ER	0.5250	0.6000	0.5375	0.6000	0.7000	0.5375	**0.4875**
	Time	1.43e-03	3.57e-04	7.56e-04	**2.42e-04**	3.36e-04	3.28e-04	3.10e-04
ShakeGestureWiimoteZ	ER	**0.1400**	0.1600	0.4200	0.4000	0.3200	0.1600	0.1600
	Time	4.95e-04	1.62e-04	3.44e-04	**1.07e-04**	1.54e-04	1.46e-04	1.40e-04
SmoothSubspace	ER	0.1733	0.1600	0.2067	**0.1267**	0.1933	0.1800	0.1467
	Time	3.88e-05	5.67e-06	8.36e-06	**3.64e-06**	4.22e-06	3.88e-06	4.73e-06
Ranks	ER	4	3	5	6	7	2	**1**
	Time	7	5	6	**1**	4	3	2

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