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STGA-CBR: A Case-Based Reasoning Method Based on Spatiotemporal Trajectory Similarity Assessment

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ABSTRACT Decision making are critical for disaster prevention and emergency response. To fully improve the effectiveness of emergency decisions by taking spatiotemporal information into consideration, this paper proposes a new method STGA-CBR for spatiotemporal case matching by using an integrated approach comprising a newly proposed spatiotemporal trajectory similarity measurement algorithm (Position-Frequency algorithm), a genetic algorithm (GA), and a case-based reasoning (CBR) technique. It consists of three main phases: (1) similar spatiotemporal trajectory retrieval; (2) weight determination; and (3) attribute similarity calculation. The proposed approach was employed in typhoon disaster, which contains a variety of spatiotemporal information. The results of matching were validated by comparing STGA-CBR with ST-CBR, GA-CBR and traditional simple CBR. The experimental results proved that the proposed STGA-CBR effectively screens out similar spatiotemporal trajectories and demonstrates higher matching performance than there other methods, indicating the high efficiency of the proposed similar case retrieval approach. The case pair selected are then used for prediction of the post-disaster social and economic loss and the average accuracy of prediction results are calculated, among which the integrated model rank the highest, thus rendering our approach superior in comparison to other traditional methods.

INDEX TERMS CBR, data analysis, decision making, risk analysis, similarity assessment.

I. INTRODUCTION

In recent years, various disasters and emergencies have occurred frequently in the world. It not only seriously threatens people's lives and property, but also jeopardizes economic development and social stability. It also tests the emergency management capabilities of decision makers at different levels [1].

The problem of rapid response to emergencies has received increasing attention. After an emergency occurs, it is a direct and effective method to quickly retrieve similar historical cases by using certain intelligent methods, and then assist decision makers to quickly formulate emergency response plans to cope with the current emergencies by referring to historical experience. Case-Based Reasoning (CBR) is able to extract relevant knowledge from past experience in a continuous and incremental manner and is often used as an effective method for emergency decision-making. Compared with the similarity matching based on subjective experience, historical knowledge and computer technology can not only accelerate the calculation process, but also improve the reliability, which is of great significance in saving precious time in the emergency and minimizing the damage caused by disasters [2].

While existing CBR method often neglect spatiotemporal characteristics, our study improve the effectiveness and accuracy of CBR by integrating spatiotemporal information into the case based reasoning method and proposed STGA-CBR to estimate the disaster damage for emergency response.

II. LITERATURE REVIEW

CBR has been widely used in decision making in different scenarios and in different fields. Yu et al. employ case-based reasoning method (combines case representation and retrieval) to illustrate a risk assessment framework for protecting power grid, being the pivotal part of emergency preparedness for critical infrastructure protection [3]. Chou et al.

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propose the modeling of CBR estimation that compares and retrieves the most similar instance across the case library, therefore helps improve the cost-efficiency control during the infrastructure asset management in developing countries [4].

In particular, many scholars have conducted in-depth research on CBR for natural disaster emergency response. Zhang Mingyuan et al. proposed a risk assessment method based on case-based reasoning, which evaluates urban risk and vulnerability from attributes such as earthquake frequency, population density, and building resilience, thereby realizing rapid and comprehensive assessment of natural disaster risks in urban area, assisting disaster prevention and mitigation work [5]. Based on a large number of historical forest fire data and fire-fighting cases collected from fire areas, etc., Zhang Chong et al. combined case-based reasoning and rule-based reasoning to extract similar cases, propose an optimal tactical plan, and automatically generate a forest fire fighting plan [6]. Using a series of shapes and texture features of the rainstorm radar image, Chen Jing constructed a CBR rainstorm case retrieval system based on rough set, effectively monitoring and warning the falling area, intensity and burst time of short-term heavy rain, and minimizing the loss to industrial and agricultural production caused by rainstorm [7]. Chang et al. constructed a two-stage CBR system for housing reconstruction after the earthquake, which significantly improved both the average case retrieved ratio and average case satisfactory degree, so as to reduce life and property losses as could as possible after a large-scale earthquake [8].

However, in the process of using CBR to solve the disaster emergency problem, the static attribute information of the disaster case at a certain time point or time period is often used, and the case characteristics under the dynamic space-time scale are ignored, which cannot effectively describe the case and reflect the process of the case and the trend of change. Besides, the spatiotemporal characteristics and evolution process of the case can not be shown, which is not conducive to the relevant emergency personnel to fully grasp the historical case and analyze the existing case as well.

Meanwhile, weight determination in CBR needs to be fully considered. Genetic algorithms(GA) is a search algorithm proposed by Holland in 1975 based on natural selection and genetic theory[9] and is widely used to determine the optimal weight. According to the principle of survival of the fittest, GA chooses according to the performance of individual fitness function (objective function). As early as 1999, Hegazy based on GA, to achieve the search of approximate optimal solutions by minimizing the cost function to serve resource allocation and leveling [10]. Jia Zhaohong et al. used genetic algorithms to obtain feature weights on case-base for weight discovery and similar case retrieval [11]. In particular, combining GA with Analytical Hierarchy Process(AHP) and using the genetic algorithm to optimize the index weight of the AHP has received a lot of attention. Yuanting et al. combine AHP and GA to evaluate the development and decision-making order of scenic areas in 2014, which would provide scientific decision-making basis for geological tourism resources development [12]. For the accurate evaluation on risk level of break-dam in mine tailings pond, a GA-AHP model was established by Yuanting [13].

Aiming at problems introduced above, this paper focuses on typhoon, a typical natural disaster with long duration, wide range of influence and rich information of space-time trajectory, as the research object, and proposes a STGA-CBR method based on time-space trajectory similarity measure and genetic algorithm. The method utilizes the space-time trajectory data and disaster attribute data of the typhoon case. Based on the typhoon case with similar time-space attributes retrieved by Position-Frequency algorithm, a spatiotemporal trajectory similarity measurement algorithm, the final similar case matching result are obtained by using the AHP-GA and the case attribute similarity calculation method.

The experimental results prove that compared with the traditional CBR method that only considers the attribute information such as the property loss and typhoon intensity, the case matching result obtained by combining the space-time information is more accurate, and can serve the relevant prediction of the post-disaster social and economic loss, thereby assisting the relevant departments response timely, dispose reasonably, and react effectively during the disaster emergency.

III. STGA-CBR

Aiming at the lack of consideration of spatio-temporal information in the existing CBR model, this paper focus on improving the effectiveness of emergency decisions by employing STGA-CBR, an integrated approach comprising PF algorithm, AHP-GA and CBR, comprehensively. The process of STGA-CBR method is as follows.

A. PF ALGORITHM

Position-Frequency algorithm is a new method proposed in this paper for spatiotemporal trajectory similarity measurement. PF algorithm measures the degree of similarity between the trajectories from the two aspects of space-time distance and trajectory shape, and can judge the similarity degree of the moving path according to the space-time position and frequency characteristics of the space-time trajectory. The experimental results prove that the algorithm has accurate calculation results, and at the same time improves the resistance to noise, sampling rate variation and offset, and can effectively match similar trajectory pairs. PF algorithm selects the IMHD-ST distance, where IMHD stands for interpolated Modified Hausdorff Distance, and the sinuosity between the curves to describe the similarity between the space-time position and the trajectory shape of the typhoon track respectively.

The IMHD-ST algorithm is an improved Hausdoff distance algorithm based on interpolation proposed by Shao et al., which is mostly used for 3D spatiotemporal trajectory matching [9]. IMHD-ST regards the spatiotemporal trajectory of a moving object as a continuous set of points rather than discrete points, as shown in Fig.1. Therefore, IMHD-ST uses

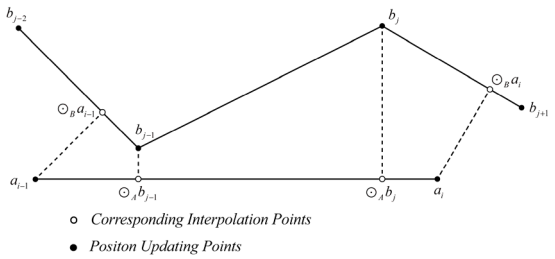

FIGURE 1. IMHD interpolation points algorithm.

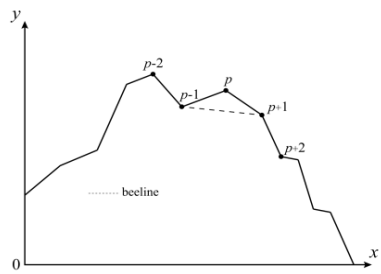

FIGURE 2. Trajectory feature.

an interpolation algorithm to define the distance between the trajectories as the weighted sum of the continuous point set and its shortest distance between the corresponding interpolation points on the other trajectory, so that interference caused by different scale units and track point sampling rates can be avoided.

The distance calculation based on IMHD-ST between the two tracks is shown in Eq. 1 and Eq. 2. The distance between each pair of points is assigned a corresponding weight based on the average length of its adjacent sub-tracks to eliminate the difference in sub-track length and the effect of segmentation. l_A is the total length of the entire track, used to normalize the calculated result value so that the difference between the tracks is independent of the track length.

$$h_{spatial}(A,B) = \frac{1}{|l_A|}\sum_{a_i\in A}\left(\frac{d(a_{i-1}-a_i)+d(a_i-a_{i+1})}{2} \times \min_{b_i\in B}(a_i-b_j)\right) \quad (1)$$

$$H_{spatial}(A,B) = \max(h_{spatial}(A,B), h_{spatial}(B,A)) \quad (2)$$

The measure of sinuosity for point p is computed as a ratio of the distance ±k points along the trajectory to the length of the beeline connector centered at the point (i.e. beeline at p for k = 1 in Fig.2). Where k is the lag parameter. The final sinuosity at p is computed as the average of the computed sinuosity values with different k, as shown in Eq. 3. If profile points are collinear about the given point p the sinuosity measure equals 0 and for a winding profile (i.e. a space-filling curve) it comes to 1.

$$\begin{cases} Sinuosity_{p,k} = \dfrac{\sum_{i=p-k}^{i=p+k-1}(d_{i,i+1})}{d_{p-k,p+k}} \\ Sinuosity_p = \dfrac{\sum_{j=1}^{j=k} Sinuosity_{p,j}}{|k|} \end{cases} \quad (3)$$

PF algorithm can extract typhoon cases with similar spatiotemporal tracks from the case base, and provide a basis for further case matching based on attributes.

B. AHP-GA WEIGHT DETERMINATION

Since the typhoon case attribute data is numerous, and the importance of each attribute is obviously different, the weight determination of each attribute becomes the premise and key of subsequent attribute similarity matching.

This paper combines AHP and GA, and uses the calculated value of AHP as the initial weight of GA first generation. When the value of the consistent index function (CIF) in AHP approaches zero, the consistency of the AHP's judgment matrix is higher, that is, the AHP result is more accurate. Therefore, the GA is used to minimize the CIF to obtain the final weight. This translates the consistency test problem in AHP into a nonlinear optimization problem for a specific target and decision, as shown in the following Eq. 4, where n is the total number of attributes and w_i is the weight of the i-th attribute.

$$\min CIF(n) = \sum_{i=1}^{n}\left|\sum_{k=1}^{n}(b_{ik}w_k) - nw_k\right|/n$$
$$s.t.\begin{cases} w_k > 0, \quad k = 1,2,\ldots,n \\ \sum_{k=1}^{n} w_k = 1 \\ b_{ik} = w_i/w_k \end{cases} \quad (4)$$

AHP-GA can not only improve the accuracy of AHP results, speed up GA convergence and improve computational efficiency, but also combine subjective experience with objective calculations to make the weight calculation results more reliable. In this paper, AHP is completed by 6 experts, and GA is realized by MatLab software. By setting the parameters such as crossover probability and mutation probability, the optimal weight is calculated.

C. CALCULATING WEIGHTED ATTIBUTE SIMILARITIES

After completing the first two steps, it is necessary to combine the basic attributes of the case event with its weight, and further match cases with similar attributes from the typhoon case with similar spatiotemporal information to improve the matching accuracy. Different types of case attributes have different methods of calculating similarity. Generally, for determining the similarity of the numeric attribute, such as typhoon wind, this paper selects the commonly used nearest neighbor algorithm. The nearest neighbor method is easy to understand and is the most intuitive and versatile method. The calculation method is as shown in Eq. 5.

$$S(x_i, y_i) = 1 - \frac{|x_i - y_i|}{max_i - min_i} \quad (5)$$

where x_i is the i-th attribute of case X, y_i is the i-th attribute of case Y, and max_i and min_i are the maximum and minimum

value of the i-th attribute in all cases in the case base respectively.

Obviously, the closer the similarity is to 1, the more similar the same attribute of the two cases, and vice versa. For the similarity of fuzzy concept attributes, it is usually mapped to discrete deterministic numbers, and then calculated by the above formula. In the case of weather conditions, since the weather is usually changed from sunny to cloudy and then to rain, they will be mapped to 0-1-2, respectively, so that the degree of similarity can be expressed by the magnitude of the numerical difference.

The synthetic similarity of the case usually uses a weighted average operator to aggregate the similarity between all attributes of the case, as shown in Eq. 6.

$$S(X, Y) = \sum_{i=1}^{n} w_i \cdot S(x_i, y_i) \tag{6}$$

D. CALCULATING OUTPUTS AND ACCURACY

All typhoon cases in the case base are sorted according to similarity. After searching for typhoon cases that are most similar to the target case in terms of time and space and attribute, their socioeconomic data can be used to predict and estimate that of target case. This paper proposes three options based on the different number of selected cases and evaluates them through experiments. The first scheme directly adopts result of the most similar typhoon case; while the second and third schemes respectively select the two or three most similar typhoons, and estimate their weight according to the similarity degree. In the case of selecting three typhoons for prediction, the calculation formula is as in Eq. 7.

$$\begin{cases} x_i' = W_A^* A_i + W_B^* B_i + W_C^* C_i \\ W_j = \dfrac{S(X, j)}{S(X, A) + S(X, B) + S(X, C)}, \quad j \in \{A, B, C\} \end{cases} \tag{7}$$

where x_i' stands for the predicted value of the i-th attribute of socioeconomic data of case X. *A, B, C* are the three most similar typhoons of case X and A_i, B_i, C_i are the values of the i-th attribute of socioeconomic data of case *A, B, C* respectively.

Finally, the calculated predictions need to be compared with factual data for accuracy evaluation. The evaluation formula is as in Eq. 8. The lower the value is, the better the results.

$$Accuracy = \frac{1}{m} \cdot \sum_{i=1}^{m} \frac{|x_i - x_i'|}{x_i} \tag{8}$$

where m is the total number of socioeconomic data attributes, x_i, x_i' are the true and predicted values of the i-th attribute of socioeconomic data of case X.

IV. CASE STUDY

A. INPUTS

The paper uses the spatiotemporal trajectory data, attribute data and socioeconomic data of 22 typhoons in Fujian Province from 2004 to 2016 for experiments. Among them, trajectory data and attribute data are used for typhoon case similarity matching, and socioeconomic data is used to verify the accuracy of results considering that if two typhoon share the exact same trajectory and attributes, meaning they arrive at same places in the same sequential order with same wind level, pressure and all other attributes, they would cause similar or even same socioeconomic damages.

Spatiotemporal trajectory data are the best track data provided by the CMA Tropical Cyclone Data Center(tcdata.typhoon.org.cn)[15]. Best track records include typhoon intensity, latitude and longitude, minimum pressure near the TC center(PRES) and two-minute mean sustained wind(OWD) recorded every six hours. Part of trajectory data of Talim is shown in Table 1.

Attribute data includes the maximum wind level, maximum OWD, minimum pressure, landing wind level, landing OWD, landing pressure and duration of the typhoon. Considering that the study area is Fujian Province, the location where the typhoon lands is also very important, therefore the province where the landing place locates is also recorded as one of the attribute data. Besides, the population density of Fujian Province during the year of the typhoon may also affect the number of affected population and is thus taken into account in this paper as well. Especially, landing province needs to be mapped during case matching. According to method mentioned above, Fujian Province maps to 0, and Jiangsu, Guangdong and other neighboring provinces of Fujian Province map to 1.

The socioeconomic data are obtained from the typhoon yearbook statistics, including the affected population caused by the typhoon in Fujian Province, the affected area and the direct economic losses.

B. RESULTS AND ANALYSIS

Considering that even if the typhoon properties are exactly the same, the typhoon disasters occurring in different regions are different, so the spatiotemporal similarity is the primary screening criteria for case matching. Firstly, the first 10 typhoon cases with the greatest spatiotemporal similarity to the target case are retrieved from the case base by using the PF algorithm. Then the most similar three typhoons are selected from those 10 cases by comparing their attribute similarity.

1) WEIGHT DETERMINATION

Pairwise weight comparison is often used for determining numerical priorities of attributes as people are inconsistent in eliciting weights and providing a cardinal scale to evaluate objects according to some subjective preference criteria while they are better at comparing pair of objects. The attribute data of the typhoon case can be classified as peak intensity (including maximum wind level, maximum OWD, minimum pressure), landing intensity (including landing wind level, landing OWD, landing pressure), duration, landing province, and population density of Fujian Province in the corresponding

TABLE 1. Example of typhoon trajectory data.

Time (YYYYMMDDHH)	Intensity	Latitude (0.1°N)	Longitude (0.1°E)	Minimum pressure (hPa)	OWD (m/s)
2005082518	TD, 10.8-17.1m/s	125	1446	1004	15
2005082600	TD, 10.8-17.1m/s	126	1440	1004	15
2005082606	TD, 10.8-17.1m/s	127	1435	1002	15
2005082612	TD, 10.8-17.1m/s	128	1430	1002	15
2005082618	TD, 10.8-17.1m/s	132	1426	1000	15
2005082700	TS,17.2-24.4 m/s	141	1423	996	18
2005082706	TS,17.2-24.4 m/s	156	1417	996	18
2005082712	TS,17.2-24.4 m/s	166	1412	992	20

TABLE 2. Comparison matrix of typhoon attributes.

	Maximun Intensity	Landing Intensity	Landing Hours	Landing Area	Population Density
Maximun Intensity	1	1	2	2	2
Landing Intensity		1	2	2	1.8
Landing Hours			1	1.1	0.9
Landing Area				1	0.9
Population Density					1

TABLE 3. Weights of typhoon attributes.

Attribute	Initial Weight	Weight
Maximun Intensity	0.286	0.278
Landing Intensity	0.280	0.282
Lasting Hours	0.143	0.140
Landing Area	0.138	0.145
Population Density	0.153	0.155

year of the typhoon. Their comparison matrix [16], [17] is obtained as shown in Table 2 below.

Then after calculating the eigenvalue and eigenvector of this systematic matrix by MatLab and further normalization, the weights of each criteria are shown as below in Table 3, and the CIF function expression can be obtained as in Eq. 9.

$$CIF = 3w_1 + 2.8w_2 - w_3 - 1.2w_4 - 0.74w_5 \quad (9)$$

Using the above weights as initial values, the CIF is minimized by GA, and the final weights are obtained in the 137-th generation as shown in Table 3. During GA calculation, the crossover fraction is 0.8 and the population size is 50.

2) TYPHOON CASE MATCHING

Taking Typhoon *Linfa* as an example, using the STGA-CBR algorithm in this paper to match the case. The most similar ten typhoons obtained by PF algorithm are shown in Fig.3 as below.

The most similar three typhoons obtained by STGA-CBR are Typhoon *Meranti*, *Saola* and *Kalmaegi*, sorted according to their calculated similarity. Their attributes are shown as in Table 4.

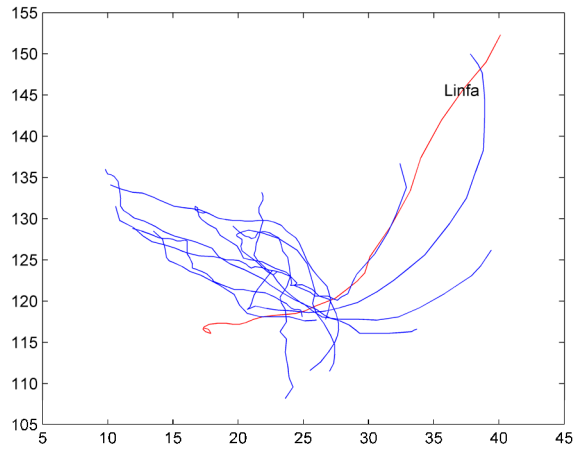

FIGURE 3. Spatiotemporal trajectory of similar typhoons.

Evidently, many attributes of the matching results obtained by STGA-CBR are quite similar. In order to verify whether the matching result of STGA-CBR is accurate, and to evaluate the effectiveness of STGA-CBR more intuitively, the results obtained by STGA-CBR is compared with CBR without weight determination (ST-CBR, all attributes are equal), CBR without spatiotemporal algorithm (GA-CBR, the PF algorithm is omitted) and CBR without both weight determination and spatiotemporal algorithm (pure CBR). The most similar three typhoons obtained by ST-CBR are Typhoon *Saola*, *Meranti*, and *Kalmaegi*. The most similar three typhoons obtained by GA-CBR are Typhoon *Bilis*, *Fung-wong*, and *Meranti*. The most similar three typhoons obtained by traditional CBR are Typhoon *Bilis*, *Fung-wong*, and *Saola*.

TABLE 4. Attribute data of related typhoon.

Typhoon	**Linfa**	Meranti	Saola	Kalmaegi	Bilis	Fung-wong
Landing Province	**Fujian**	Fujian	Fujian	Fujian	Fujian	Fujian
Maximun Wind Level	**11**	12	13	12	11	14
Maximun OWD(m/s)	**30**	35	40	33	30	45
Minimun Pressure(hPa)	**980**	970	960	975	975	955
Landing Wind Level	**10**	12	10	10	10	12
Landing OWD(m/s)	**28**	35	25	25	25	33
Landing Pressure(hPa)	**980**	970	985	985	980	975
Lasting Hours(h)	**186**	174	222	234	222	186
Population Density per km^2	**296**	298	302	293	289	293

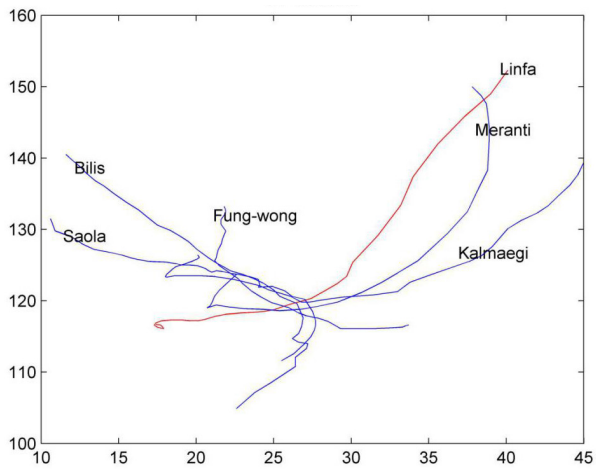

FIGURE 4. Spatia distribution of related typhoon.

Through the experimental results, we found that the results obtained by the traditional CBR are the worst. There are matching cases where some of the attributes are similar and others are quite far apart. In the case of typhoon *Linfa*, when adding the PF algorithm, the weight determination does not have much effect on the result, that is, the three most similar typhoons obtained by STGA-CBR and ST-CBR are exactly the same, only the internal ordering is different. By comparing STGA-CBR with GA-CBR and CBR, we found that when spatiotemporal information is considered, the similarity between Typhoon *Bilis* and *Fung-wong* and the target typhoon is reduced, while the similarities of typhoon *Meranti*, *Saola,* and *Kalmaegi* are increased. Their spatial distribution as shown in Fig.4 above.

The trajectories of Typhoon Meranti, Kalmaegi and the target case Linfa are similar in the starting and ending range and track direction, while the typhoon Bilis and Fung-wong are quite different. We noticed that the STGA-CBR algorithm can effectively screen out similar spatiotemporal trajectories and typhoon case pair, providing a calculation basis and spatial-temporal foundation for case matching. Compare all socioeconomic data of related typhoons in Table 5.

TABLE 5. Socioeconomic data of related typhoons.

Typhoon	Affected population (10,000 people)	Affected area (10,000 hectares)	Direct economic loss (100 million yuan)
Linfa	47.48	5	6.5
Meranti	30.6	1.65	5.2
Saola	91.8	4.7	14.8
Kalmaegi	27.51	1.57	5.01
Bilis	402.8	17.6	46.85
Fung-wong	138.69	6.02	14.22

The socioeconomic attributes of Typhoon *Meranti*, *Saola*, *Kalmaegi* are more similar to that of the target typhoon *Linfa*, while the three attributes of the typhoon *Bilis* obtained by ignoring the PF algorithm are much different. The deviation between the affected population and direct economic loss attributes of the typhoon *Fung-wong* and target typhoon *Linfa* is also large, and the result is apparently incorrect. In the case of typhoon *Linfa*, the experimental results prove that introduction of the PF algorithm into the traditional CBR method can effectively fill the gaps in which the space-time information is ignored, and STGA-CBR can fully and comprehensively consider the spatiotemporal characteristics and attribute information of the case at the same time. Compared with the traditional CBR, STGA-CBR can match the typhoon case pairs more accurately, thus serving the subsequent case reasoning.

V. DISCUSSION

For the results of STGA-CBR, the most similar one, two or three typhoons in the case matching results are used for prediction. The average accuracy of each predicted socioeconomic attribute calculated by experimenting with all typhoons in the casebase are shown in Table 6. The accuracy is best when two typhoons are selected for prediction.

The accuracy is the worst when three typhoons are selected for prediction. The choice of one or two typhoons has little effect on the accuracy in this paper. However, since that

TABLE 6. Comparison of different typhoon number results.

Number of Typhoon used for prediction	One	Two	Three
Accuracy of Population Attribute	0.95	0.99	2.53
Accuracy of Area Attribute	1.11	1.02	2.52
Accuracy of Loss Attribute	0.65	0.66	2.12
Average Accuracy	0.90	0.89	2.39

TABLE 7. Comparison of results obtained by different algorithms.

Algorithm	STGA-CBR	ST-CBR	GA-CBR	CBR
Accuracy of Population Attribute	0.99	1.05	1.42	1.37
Accuracy of Area Attribute	1.02	1.08	1.18	1.24
Accuracy of Loss Attribute	0.66	0.75	1.28	1.19
Average Accuracy	0.89	0.96	1.29	1.27

choosing only one typhoon would provide less information and is more easily affected by the quality of the typhoon casebase, it is better to select two typhoons.

In order to further verify the accuracy of STGA-CBR, when two typhoons are selected for prediction, the results obtained by STGA-CBR are compared with that by ST-CBR, GA-CBR and traditional CBR, and each typhoon in the case base is tested. The average accuracy results for each socioeconomic attribute are shown in Table 7.

The accuracy is greatly improved when spatiotemporal information is taken into consideration, which fully reflects the importance of spatiotemporal attributes in case matching and the effectiveness of the proposed algorithm STGA-CBR. However, the weight determination in this paper shows limited effect on the matching result, which may be due to the inappropriateness of the selected data attributes.

VI. CONCLUSION

Aiming at the problem that the traditional CBR ignores the spatiotemporal features of the case and thus are not reliable enough for emergency decision-making, this paper proposes a STGA-CBR method based on the similarity measure of space-time trajectory, and uses the typhoon trajectory data and disaster attribute data to conduct experiments. Based on spatiotemporal similarity measurement results achieved by PF algorithm, the final case matching result are obtained by using the AHP-GA and the case attribute similarity calculation method. The experimental results prove that compared with the traditional CBR method that only considers the attribute information such as property loss and typhoon intensity, the case matching result obtained by combining the space-time information is more accurate, and can serve the relevant prediction of the post-disaster social and economic loss, thereby assisting the relevant departments response timely, dispose reasonably, and react effectively during the disaster emergency. However, the weight determination in this paper shows limited effect on the matching result. In the following, the author will focus on decision-making in real-time case and experiments with a variety of weighting methods for relevant experiments based on the characteristics of spatiotemporal data.

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