2015 IEEE Symposium Series on Computational Intelligence

Study on Index Model of Tropical Cyclone Intensity Change Based on Projection Pursuit and Evolution Strategy

Huantong GENG Jiaqing SUN
School of Computer and Software
Nanjing University of Information Science and Technology
Nanjing, China
htgeng@nuist.edu.cn

Wei ZHANG Chao HUANG
College of Atmospheric Science
Nanjing University of Information Science and Technology
Nanjing, China

***Abstract*—This paper deals with the forecasting of tropical cyclone (TC) landed intensity change problem in which multi-level and multi-attribute decision are considered. A novel index model of tropical cyclone intensity change based on projection pursuit (PP) and evolution strategy (ES) is proposed to forecast the TC intensity change. We propose to use projection pursuit to project the high-dimensional TC intensity observation samples with 18 different attributes into one-dimensional projection index value. According to the projection index value distribution of learning samples, including TC intensifying and weakening, we can determine the cut off index value which distinguishes two different index value of intensifying and weakening samples. The final best projection unit vector can reflect degree of each attribute influence on TC intensity change. In order to solve the high-dimensional globally optimal problem in PP, evolution strategy with stochastic ranking is used to optimize the projection vector. The role of stochastic ranking is to balance the dominance of objective and penalty functions. Based on the index model, experimental results indicate that the accuracy of 693 TC intensity change samples reaches 89.2% when we take the index value 1.40 as the cut off value between TC intensifying and TC weakening, and the seven core attributes can also reflect the main meteorological characters of TC intensity change accurately.**

I. INTRODUCTION

The tropical cyclone (TC) is one of the most devastating natural disasters in the world. Accurate prediction of TC track and intensity thus plays a central role in reducing potential damages inflicted by TCs. Although the forecasting of TC track has been greatly improved over the decades, TC intensity forecast remains a big challenge to meteorological scientific community[1]. Difficulties in forecasting TC intensity are largely focused on our limited understanding of complicated processes and various factors pertaining to TC intensifying and weakening. With the rapid development of global coastal economy, the disaster loss caused by TC is more and more serious. Although TC track forecasting has high accuracy, the disaster loss is difficult to mitigate because of its intensity change uncertain. Thus accurate TC intensity change forecasting is essential for preventive measures to reduce TC disaster loss.

In recent years, the method for forecasting TC intensity change can be mainly divided into three categories. The first category is the method of subjective experience. The subjective experience is mainly based on Dvorak extrapolation technique by Velden[2], having good use the accumulated experience of human judgment but being too subjective to predict TC intensity change accurately. The second category is the method of linear regression. Linear regression is mainly based on the statistical forecasting, such as the extrapolation method of numerical techniques used by Bender[3]and the method of statistics and statistics-dynamical based on multiple linear regression technique used by Knaff[4], which can forecast TC intensity change objectively, but which need a large amount of computation and complex linear mode. The last category is the method of nonlinear regression. Nonlinear regression is mainly based on data mining (DM) and the evolutionary algorithms (EAs) which are a random search algorithm based on natural selection and genetic mechanism. For example, A decision tree, constructed by classical C4.5 algorithm, is applied to classify intensifying and weakening TCs[5], which have high precision and objectiveness but also exist complex rule set and structures.

Although the above methods have their advantages in forecasting TC intensity change, these methods are relatively complex and highly specialized. This study aims to find a simple way to design a forecasting index of predicting TC intensity change. The main idea of our study are summarized as follows: By learning on historical TC intensity observation samples, we may identify the relationship between the two classes (intensifying and weakening) samples and distribution of TC intensity change index, then find out the cut off index value of TC intensity change to predict the future TC intensity change. For this purpose, the paper introduces the projection pursuit (PP) and evolution strategy (ES) to construct the index model of TC intensity change according to the fact, which the different-class TC intensity sample owns the corresponding different index value distribution diagram. We expect that the new index model is to classify TC intensity change with high accuracy,

This work is jointly supported by the National Natural Science Foundation of China (Grant No. 41201045 and 41430427), the Natural Science Foundation of Jiangsu Province(Grants No BK20151458) and Jiangsu QingLan Project (2012).

978-1-4799-7560-0/15 $31.00 © 2015 IEEE
DOI 10.1109/SSCI.2015.31

lower professional requirements and easy interpretation.

The remainder of this paper is organized as follows. The next section gives the specification of data samples and main methodology. Section 3 presents the index model of tropical cyclone intensity change based on projection pursuit and evolution strategy. Experiment and results are discussed in section 4. Finally, section 5 provides the conclusion.

II. DATA AND METHODOLOGY

A. *Specification of data samples*

A lot previous research has mainly focused on three categories of factors governing intensity change: ocean characteristics (e.g., sea surface temperature, latent heat flux, ocean heat content), inner-core processes (e.g., eyewall, inner-core asymmetry, sea spray), and environmental interactions (e.g., vertical wind shear, flow pattern, moisture)[6].

For constructing the new index model of TC intensity change and verifying its effectiveness later, the western North Pacific TC intensity change samples from 2000 to 2008 are obtained from reference[5], which contains 18 attributes and 1 class label. The values of class label are identified as "1" and "-1", here "1" represents the intensifying of TC intensity and "-1" represents the weakening of TC intensity. The dataset consists of 693 samples which include 446 intensifying samples and 247 weakening samples. All 18 attributes for describing TC intensity change are listed in Table 1.

TABLE 1 EACH ATTRIBUTE FOR CLASSIFICATION OF TC INTENSITY CHANGE

Category	Attribute	Description	Status
ocean characteristics	LHF	Area-averaged($5^{\circ}\times5^{\circ}$) surface latent heat flux	S
inner-core processes	Initial MWS	Initial maximum sustained wind speed	S
	12-hMWS	Change in MWS during the past 12h	S
	STS	Storm translational speed	T
	Rainrate	Area-averaged(0-100km)inner-core rain rate	S
environmental interactions	JulianDay	Absolute value of(Julian day-248)	S
	Lat	Latitude of storm center	S
	Lon	Longitude of storm center	S
	MPI	Maximum potential intensity minus current maximum wind speed	T
	RH(850-700)	Area-averaged (200-800km) RH at 850-700hPa	T
	RH(500-300)	Area-averaged (200-800km) RH at 500-300hPa	T
	U200	Area-averaged (200-800km) zonal wind at 200hPa	T
	T200	Area-averaged (200-800km) temperature at 200hPa	T
	Div200	Area-averaged (0-1000km) divergence at 200hPa	T
	Con200	Relative eddy flux convergence within 600km at 200hPa	T
	VWS	Area-averaged(200-800km)200-850-hPa wind shear	T
	HWS	Area-averaged(200-800km)200-850-hPa zonal wind shear	T
	RV850	Area-averaged (0-1000km) 850-hPa relative vorticity	T

* Status: Static(S) or Time dependent (T)

B. *Projection Pursuit*

The projection pursuit (PP) concept was formally introduced by Friedman and Tukey[7]. PP seeks low-dimensional linear projections of the data that expose their interesting aspects. Projection pursuit index (PP index) is employed to express a measure of "interestingness". The main characteristics of PP method are, high dimensional data can be turned into low dimensional, interference of variables which have no relationship with data structure and characteristics can be excluded. PP method projects the high dimensional through some combination into low dimensional subspace by computer technology, and find out the best projection which can reflect the original data structure and characteristics of multivariable through minimization or maximization of a projection index in order to achieve the purposes of high dimensional data analysis and research.

PP model is an exploratory data analysis method, which can directly drive samples and be good at applying in non-linear, non-state high-dimensional data. PP model has been successfully applied in many fields, such as remote sensing image interpretation, light (color) spectral data analysis, environment quality assessment, environment toxicology analysis[8,9]. However, the current PP method have to meet the quality of a large amount of calculation, which limiting the application of depth research and extensive classification method.

C. *E*volution Strategy with stochastic ranking

Rechenberg and Schwefel developed a new algorithm of evolutionary computation-evolution strategy (ES) in the 1960s[10]. It has two remarkable features of implicit parallelism and group global search, but also has strong robustness. Especially, the ES algorithm with constraint-handling has unique advantages to solve the problem for some complex nonlinear system[11]. At present, this algorithm has been widely used in the solving of various optimization problems. In this paper, we also use the *(μ, λ)*-ES algorithm with stochastic ranking because the optimized problem is a constraint single objective problem. The special evolution strategy is described in algorithm 1.

Algorithm 1 The (μ,λ)-ES algorithm with stochastic ranking

1) *Initialize population*

Each individual i is taken as a pair of real-valued vectors (x_i,σ_i), $i\in\{1,2,\dots,\mu\}$. The initial population of μ individuals is generated following a uniform distribution. σ_i is a standard deviation vector of the i-th individual.

2) *Evaluate fitness and penalty*

Each individual (x_i,σ_i) fitness value $f(x_i)$ and the degree of violation $\emptyset(x_i)$ are evaluated based on the objective function $f(x_i)$ and the penalty function $\emptyset(x_i), \forall i \in \{1,2,\cdots,\mu\}$.

3) For each generation

a) Mutation Operator

Each parent (x_i,σ_i) generates λ/μ offspring on average according to the next two formulas, so that a total of λ offspring are produced. The value of λ/μ is usually set to 0.7 [12].

$$x'_h(j) = x_i(j) + \sigma_i(j) \cdot N(0,1) \tag{1}$$

$$\sigma'_h(j) = \sigma_i(j) \cdot exp\ (\tau' \cdot N(0,1) + \tau \cdot N_j(0,1)) \tag{2}$$

Where i=1,2,…, μ; j=1,2,…,p and h=1,2,…, λ. $x_i(j)$, $x'_h(j)$, $\sigma_i(j)$ and $\sigma'_h(j)$ denote the j-th component of the vectors x_i, x'_h, σ_i and σ'_h, respectively. $N(0,1)$ is a normally distributed one-dimensional random variable with mean 0 and standard deviation 1. $N_j(0,1)$ indicates that the random number is generated anew for each value of j. The learning factors τ' and τ are set equal to $(1/\sqrt[4]{4p})$ and $(1/\sqrt{2p})$, respectively[13].

b) Evaluate fitness and penalty

Each individual (x'_h,σ'_h) fitness value $f(x'_h)$ and the degree of violation $\emptyset(x'_h)$ are evaluated based on the objective function $f(x'_h)$ and the penalty function $\emptyset(x'_h)$, $\forall h \in \{1,2,\cdots,\lambda\}$.

c) Stochastic ranking

In this paper, the optimized problem has constraints, and we will use the stochastic ranking method to select μ best individuals[14]. The main idea of stochastic ranking method is described as follows: the individuals is sorted according to the individual fitness in the case of an individual without violating constraints, the individuals is sorted by the individual fitness or the violation degree of the constraint equations based on pre-determined probability in the case of an individual with violating constraints.

d) Selection operator

Offspring $(x'_h,\sigma'_h), \forall h \in \{1,2,\cdots,\lambda\}$ are sorted by stochastic ranking, and select the μ best offspring out of λ to be parents of the next generation.

e) Judge condition

Return to step a) until the stopping condition is met.

4) Output result

The best individual in the last generation is obtained as the optimization results.

III. INDEX MODEL OF TC INTENSITY CHANGE BASED ON PP AND ES

Because the actual TC intensity change is influenced by multiple factors, the TC intensity accurate forecast is a typical multi-level and multi-attribute decision making problem involved optimization technology, environment, climate, etc. To obtain a reasonable and effective index model of TC intensity change, PP method is used to reduce the dimensionality of TC intensity change data effectively, and ES algorithm is applied to obtain the optimal PP vector.

A. Normalized processs of dataset

Assume the set $\{x(i,j)|i = 1,2,\cdots,n; j = 1,2,\cdots,p\}$ represent the measured dataset of TC intensity change, and $x(i,j)$denotes the *j*-th evaluating value of the *i*-th observation data, *n* and *p* is the number of data samples and sample attributes, respectively. In order to eliminate the dimension of each classification index and unify the range of each index, the sample $x(i,j)$of the efficiency positive index will be normalized by formula (3).

$$y(i,j) = \frac{x(i,j) - x_{min}(j)}{x_{max}(j) - x_{min}(j)} \tag{3}$$

Whereas the sample $x(i,j)$ of the cost negative index will be normalized by formula (4).

$$y(i,j) = \frac{x_{\max(j)} - x(i,j)}{x_{\max(j)} - x_{\min(j)}} \tag{4}$$

Where $y(i,j)$ denotes the normalized value of the observation data $x(i,j)$; $x_{\min}(j)$ and $x_{\max}(j)$ are the minimum and maximum of the *j*-th evaluating indicator in dataset.

B. Construct projection pursuit index function Q(a)

The essence of PP model is how to find the optimal project direction of reflecting the data features fully. Suppose $a = \{a(1), a(2), \cdots, a(p)\}$ is a *p*-dimensional unit vector, normalized data $y(i,j)$ is projected on unit vector a into one-dimensional projection value *z(i)* by the following formula (5).

$$z(i) = \sum_{j=1}^{p} a(j) y(i,j), i = 1,2,...,n \tag{5}$$

Then according to $\{z(i)|i=1,2,...,n\}$, one-dimensional scatter plot conducts scheme selection. *z(i)* is a unit length vector based on projection value, a good spread feature is expected as follows: Each inner projection point cluster is crowded together as far as possible, while between the different projection point clusters is disperse as far as possible. In order to obtain the good spread feature effectively, the projection pursuit index (PP index) function *Q(a)* is constructed in the following :

$$Q(a) = S_z \bullet D_z \tag{6}$$

In the formula, S_z is defined as the standard deviation of *z(i)*, which measures the spread feature between the different clusters. D_z is defined as the local density of *z(i)*, which measures the crowded feature in the cluster. S_z and D_z are calculated by formula (7) and (8), respectively:

$$S_z = \left[\sum_{i=1}^{n} (z(i) - \bar{z})^2/(n-1)\right]^{\frac{1}{2}} \tag{7}$$

$$D_z = \sum_{i=1}^{n}\sum_{j=1}^{n} (R - r_{ij}) \cdot u(R - r_{ij}) \tag{8}$$

In the above formula, $\bar{z}$ is the mean value of $\{z(i)|i=1,2,...,n\}$; *R* is the radius of the local density window. The setting of *R* requires that the average number of points contained within the window is not too little avoiding too much moving average deviation, and doesn't increase too quickly with the increasing of size *n*. According the experimental conclusion, the parameter R is usually set to $0.1S_z$. r_{ij} reflects the distance between the samples and is defined as $r_{ij}=|z(i)-z(j)|$. The unit step function $u(t)$ is defined as follows: if $t\geq 0$ then $u(t)=1$ otherwise $u(t)=0$.

C. Maximize Q(a) by (μ, λ)-ES with stochastic ranking

According to the above definition of the PP index function $Q(a)$, its value will be determined by the projection unit vector

a. Different projection unit vector a reflects different data structure characteristics, optimal projection vector can reveal the most interesting structure of high-dimensional data examples or observations. The degree of interestingness of the projection is measured by the formula (6), called the PP index. The p-dimensional optimal unit vector a can be found by maximizing the projection index function $Q(a)$. Therefore, the PP model can be formulated as the optimization problem in the next equation (9).

$$\begin{cases} Maximize\ Q(a) = S_z \cdot D_z \\ s.t.\ \sum_{j=1}^{p} a^2(j) = 1 \\ \quad a(j) \geq 0 \end{cases} \tag{9}$$

In equation (9), PP tackles the p-dimensional constrained optimization problem by converting it into a single-objective constrained optimization problem, i.e. it is a complex nonlinear optimization problem to searching the optimal p-dimensional unit vector $a=\{a(1),a(2),a(3),\cdots,a(p)\}$. Here we use the *(μ, λ)*-ES algorithm with stochastic ranking in the section 2.3 to optimize the equation (9). The optimizing process of maximizing PP index *Q(a)* is described in algorithm 2.

Algorithm 2 Maximize PP index Q(a) by (μ, λ)-ES algorithm with stochastic ranking

1) *Initialize population and running parameters*

Each individual i is defined as a pair of real-valued vectors (a_i, σ_i), $i\in\{1,2,\ldots,\mu\}$, here a_i and σ_i are two p-dimensional vector $a_i=\{a_i(1),a_i(2),\cdots,a_i(p)\},\forall j\in\{1,2,\cdots,p\}$, s.t. $0\leq a_i(j)\leq 1$; $\sigma_i=\{\sigma_i(1),\sigma_i(2),\cdots,\sigma_i(p)\},\forall j\in\{1,2,\cdots,p\}$, s.t. $0\leq\sigma_i(j)\leq 1/\sqrt{p}$. Initial population of μ individuals is generated randomly according to the range of $a_i(j)$ and $\sigma_i(j)$. Assume k is a counter of current generation; Maxgen is defined as the maximum number of iterations.

2) *for k=1 to Maxgen do*

a) Mutation

By the mutation operator in section 2.3, a total of λ offspring are generated.

b) Evaluate fitness and penalty

For each individual (a_i,σ_i), fitness value $Q(a_i)$ and penalty function $\emptyset(a_i)=\left|\sum_{j=1}^{p}a_i{}^2(j)-1\right|$ are evaluated. Here, suppose $\emptyset(a_i)$ is not greater than ε, we think the individual doesn't violate constraint, where ε is a very small positive real number.

c) Stochastic ranking

```
fswap=true; s=1
while (s<λ and fswap ) do{
    fswap=false
    for t=1 to λ-1 do{
        sample u ∈U(0,1) // U(0,1) is a uniform random
        number generator
        if (∅(a_t) = ∅(a_{t+1}) = 0) or (u<P_f) then
        if (Q(a_t) > Q(a_{t+1})) then {swap(a_t, a_{t+1});
        fswap=true}
    }
    s=s+1
}
```

d) Selection

Select the first μ offspring out of λ parents to be next population according to the sequence sorted by stochastic ranking.

3) *Output the optimal individual*

The first individual is obtained from the last population of μ individuals, and outputted as the optimal projection vector $a^*=\{a^*(1),a^*(2),\cdots,a^*(p)\}$.

D. Determine TC intensity change index

In the above section, we have searched the optimal projection unit vector a^* by algorithm 2. Next, for each normalized TC observation data, a^* is plugged into formula (5), and we get $z^*(i)$ which is the one-dimensional projection value of the i-th TC intensity sample. When the two different $z^*(i)$ and $z^*(j)$ are closely, both two TC intensity sample belong to the same class. Conversely, when the two TC intensity samples belong to the same class, their projection values are also closely. Therefore, we expect that the different classes of TC intensity change have different projection value distributions, i.e., they are distinguishable and are located in different projection interval.

Through the distribution of one-dimensional projection point of each TC intensity sample, the optimal projection cut off value between TC intensifying and TC weakening can be obtained as the TC intensity change index. Finally, using the found TC intensity change index, we can forecast the TC intensifying or weakening change for a new TC intensity change observation sample.

IV. EXPERIMENT AND RESULTS

A. Experimental setup

To verify its suitability in TC intensity classification tasks, the experimental evaluation conducted over index model of TC intensity change based on PP and ES is presented in the section. The main steps are organized as follows: Firstly, 100 TC intensifying samples and 100 weakening samples are selected randomly from 693 TC observation samples of two different classes in section 2.1. All 18 attributes for describing TC intensity change are already described in Table 1. Secondly, we apply our proposed index model of TC intensity change based on PP and ES to learn the best projection vector and the TC intensity change index from the chosen 200 samples. Finally, using the obtained best projection vector and TC intensity change index, all TC observation samples are tested. The effectiveness of our model will be validated by calculating the forecasting accuracy.

Some parameters in all algorithms are set as follows. Set stochastic evolution strategy initial population size μ=30, offspring size λ=200, maximum number of iterations *Maxgen*=1000, stochastic probability P_f = 0.45, minimum degree of violating constraints ε=0.0001.

B. Result and dicussions

. All algorithms in the paper are realized in Matlab R2010b. The algorithms are executed for 1000 iterations and the best projection vector a^* is obtained as follows:

$$a^* = \begin{pmatrix} 0.16282, 3.4455e-08, 0.15975, 0.099653, 0.067429, 0.049806, \\ 6.4373e-08, 0.025307, 0.72445, 0.27559, 0.35971, 5.2635e-08, \\ 3.5153-07, 0.084369, 0.088224, 0.3613, 0.22933, 0.046555 \end{pmatrix}$$

Each component weight in the best projection vector a^* reflects the significance degree of the corresponding attribute for influencing TC intensity change. Seven most important attributes are chosen when their projection weights are greater than 0.15 and are shown in Table 2.

TABLE 2 SEVEN MOST IMPORTANT ATTRIBUTES AND THEIR PROJECTION WEIGHTS

Attribute	Projection weight
MPI	0.72445
VWS	0.36130
RH(500-300)	0.35971
RH(850-700)	0.27559
HWS	0.22933
LHF	0.16282
12-hMWS	0.15975

These core attributes in the Table 2 are very similar to those used to build the decision tree for classification of TC intensity change by Zhang[5], and they are also similar to those used to develop the rapid TC intensification index by Kaplan[15]. Therefore, these most important attributes play a vital role in TC intensity change, and they are highly consistent with the main characteristics of meteorological background. These attributes largely reflect the core process of TC, dynamical roles of atmosphere on ocean and large-scale environment control on TC intensity change. On the other hand, for training the index model of TC intensity change, we apply the found best projection vector a^* to calculate the projection values of 200 chosen TC intensity observation samples by equation (5). The projection value distribution graph of 200 chosen samples is illustrated in Fig. 1.

In Fig. 1, the possible optimal cut off value between the TC intensifying and TC weakening, i.e. the possible TC intensity change index value is between 1.3 and 1.5. In order to find its exact value, we use the simple exhaustive searching algorithm to seek from 1.3 to 1.5 by the step of 0.01, and when the optimal TC intensity change index value is equal to 1.40, the classification result for 200 chosen TC intensity observation samples owns the best accuracy.

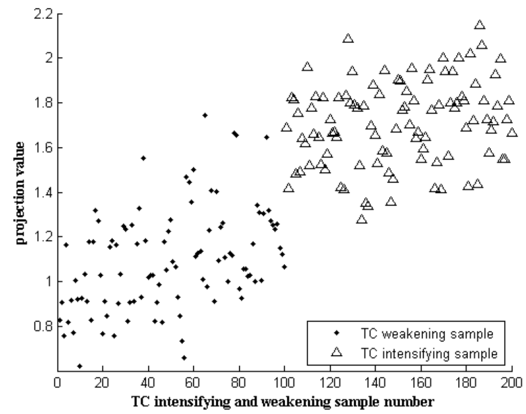

Fig.1.Projection value distribution of 100 TC intensifying and 100 weakening observation samples

On the other hand, all 693 TC intensity observation samples are also calculated like 200 chosen samples, we can obtain their projection values of all samples and corresponding distribution graph in Fig. 2. Finally, we still use index value 1.40 to classify all samples, i.e., if the projection value of a sample is greater than 1.40, the sample belongs to class of TC intensifying, otherwise belongs to class of TC weakening.

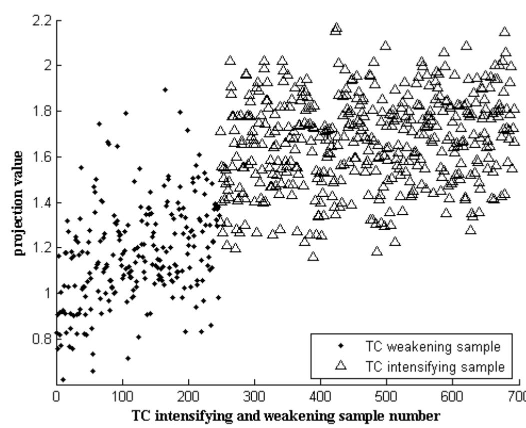

Fig.2. Projection value distribution of all 693 TC intensity change observation samples

In applying the obtained TC intensity change index value (1.40) to perform the TC classification task, our classification accuracy also reaches 89.2% which is very close to the accuracy 90.2% by C4.5 algorithm, and our method has better accuracy in the classification of the weakening samples. Compared to the results of C4.5 algorithm, the final experimental results are shown in Table 3.

TABLE 3 CONFUSION MATRIX OF OUR PP INDEX MODEL AND DECISION TREE

		Observed		
		Intensifying	Weakening	Accuracy
C4.5	Intensifying	415	37	
	Weakening	31	210	
	Accuracy	93.0%	85.0%	90.2%
PP	Intensifying	404	33	
	Weakening	42	214	
	Accuracy	90.6%	86.6%	89.2%

V. CONCLUSIONS

The forecasting of TC intensity change has long been a challenging problem because of its own inherent complexity. Classification and prediction for TC intensity has important theoretical and practical significance. Nevertheless, significant progress has been made during the last decade in the forecasting methods of TC intensity change. It is necessary to develop a simple and practical detector model for forecasting the TC intensity. This paper uses projection pursuit and evolution strategy to design index model of tropical cyclone intensity change. This method is not only a novel way to examine TC intensity change but also has great potential for solving the non-linear and high-dimension problems. The conclusions are summarized as follows:

1) Seven core attributes are determined by the optimal projection unit vector a*, including MPI, VWS, RH(500-300), RH(850-700), HWS, LHF and 12-hMWS. These attributes really play a vital role in TC intensity change, and they are highly consistent with the main meteorological features. These core attributes largely reflect the core process of TC, dynamical roles of atmosphere on ocean and large-scale environment control on TC intensity change.

2) The index model of tropical cyclone intensity change is a novel forecasting TC intensity method, which has its own multiple advantages including simplicity, practicability and high accuracy. The accuracy obtained by our method almost reaches 90%. ES with stochastic ranking has great contribution to obtaining the final best project unit vector of PP. Therefore, this study shows that a combination of projection pursuit and evolutionary algorithm will be great interest in our future study and the other field.

REFERENCES

[1] E. N. Rappaport, J. L. Franklin, L. A. Avila, et al. Advances and challenges at the National Hurricane Center. Weather and Forecasting. 2009. 24(2).395-419.

[2] T. L. Olander,C. S. Velden. The advanced Dvorak technique: Continued development of an objective scheme to estimate tropical cyclone intensity using geostationary infrared satellite imagery. Weather and Forecasting. 2007. 22(2).287-298.

[3] M. A. Bender, I. Ginis, R. Tuleya, et al. The operational GFDL coupled hurricane-ocean prediction system and a summary of its performance. Monthly Weather Review. 2007. 135(12).3965-3989.

[4] J. A. Knaff, C. R. Sampson, M. DeMaria, et al. Statistical tropical cyclone wind radii prediction using climatology and persistence. Weather and Forecasting. 2007. 22(4).781-791.

[5] W. Zhang, S. Gao, B. Chen, et al. The application of decision tree to intensity change classification of tropical cyclones in western North Pacific. Geophysical Research Letters. 2013. 40(9).1883-1887.

[6] Duan Yi-Hong,Yu Hui,Wu Rong-Sheng.Review of The Research in The Intensity Change of Tropical Cyclone.Acta Meteorologica Sinica.2006. 63(5).636-645.

[7] J. H. Friedman,J. W. Tukey. A projection pursuit algorithm for exploratory data analysis.IEEE Transon Computer,1974,23(9):881-890.

[8] B.-J. M. Webb-Robertson, K. H. Jarman, S. D. Harvey, et al. An improved optimization algorithm and a Bayes factor termination criterion for sequential projection pursuit.Chemometrics and intelligent laboratory systems. 2005. 77(1).149-160.

[9] V. Lovchinov,S. Tsakovski. Multivariate statistical approaches as applied to environmental physics studies. Central European Journal of Physics. 2006. 4(2).277-298.

[10] Yun-Qing Xia, Evolution Algorithm,Beijing: Metallurgical industry publishing house,2000.

[11] T. Back, Evolutionary Algorithms in Theory and Practice. New York: Oxford Univ.Press,1996.

[12] ZHOU YongQuan,ZHANG Ming,ZHAO Bin.Solving Numerical Inte gration Based on Evolution Strategy Method.
Chinese Journal of Computers. 2008. 31(2).196-206.

[13] B.T.Envolutionary programming and envolutionary stragety:similarities and differences. Granada:Proceeding of European Conferences on Alifes. 1995.

[14] T.P.Runarsson,X.Yao.Stochastic ranking for constrained evolutionary optimization. Evolutionary Computation, IEEE Transactions on. 2000. 4(3).284-294.

[15] J. Kaplan, M. DeMaria,J. A. Knaff. A revised tropical cyclone rapid intensification index for the Atlantic and eastern North Pacific basins. Weather and Forecasting. 2010. 25(1).220-241.