INTERNATIONAL JOURNAL OF
NUMERICAL ANALYSIS AND MODELING
Volume 9, Number 2, Pages 338–350

CONFLICT ANALYSIS OF MULTI-SOURCE SST DISTRIBUTION

LINGYU XU,FEI ZHONG,PING-EN ZHANG AND GUIJUN HAN

Abstract. This article focuses on evaluating the quality of sea surface temperature(SST) observed by satellite remote sensing. Under the premises that the scarcity of field measurement data and the abundant but overlapped multiple satellites detect information, in this article the consistency of multiple source information is used to verify the accuracy and reliability of satellite remote sensing data. Due to the limitation of Grubbs test when analyzing multi-source satellites SST, an improved algorithm is proposed, which is found to be more effectively than the traditional variance method when quantifying the differences and conflicts of SST. And the method is applied to the data extracted from 11 SST products in East China Sea, so a large amount of points set with high consistent can be confirmed, the outlying data can be discovered and eliminated, the waters (not include the outlying data) with confliction can be dig out and the conflicting level also can be quantized. It provides reference for the subsequent researchers to evaluate the quality of marine information.

Key words. false-alarm, SST, interact-evaluation, remote sensing measurement, data fusion.

1. Introduction

In engineering measurement, because of the particularity of environmental targets and the measured indexes, some indexes cannot be measured directly and are difficult to be obtained, and it requires an indirectly way to obtain the measurement. Therefore, the measurement accuracy to some degree is limited to measurement method under this situation. At present, multiple-source measurement has a board application and becomes an effective method to improve the measurement accuracy. As for multiple-source measurement, various reasons (including the reason of measuring equipment itself, the changes of measurement environment and different precision among measuring equipment) will cause obviously differences in measurement results even for the same target at the same time. Thus, it has strong applied value to reduce the uncertainty and conflict of measure data in many fields.

As the development of satellite remote sensing technique, it can do repeated measurement in the same temporal and spatial in most of global areas, the series satellites which could provide high-quality and large-scale SST data, mainly including HY-1, FY-2(china), NOAA, SeaWiFS, EOS/MODIS (US) and MTSAT(Japan)[1]. SST, being one of the most important geophysical parameters in the ocean, plays an important role in global climate change. The technique to obtain SST has the problems of coverage overlapping, information redundancy and so on. Therefore, how to discover the conflict relationship and inconsistency has become an important subject as to investigate the marine information. Hosoda[2]used standard deviation to conduct cross-validation on GLI SST and AMSR SST, and drew a conclusion that the general value is about $\leq 1°C$. Iwasaki [3] made mutual contrast validation on the following four kinds of data: (CAOS) SST, (MWOI) SST, (MGD) SST and (RTG) SST, and he also analyzed the difference and defect of each data. Barton [4] conducted inter-comparison on the data (NOAA-16/AVHRR SST,

Received by the editors October 9, 2009 and, in revised form, January 5, 2010.
2000 *Mathematics Subject Classification.* 35R35, 49J40, 60G40.
This research was supported by The National Natural Science Foundation of China (No.40976108).

ENVISAT/AATSR SST, Terra and Aqua/MODISSST) for the year 2003, then obtained the conclusion that the temperature error is $\leq 0.61°C$ near the waters of Australia.

Due to the different measuring accuracy of satellites remote sensing, under the same condition, the result measured by different satellite remote sensing for the same object, will have certain difference that causes much uncertainty and even conflicts among the data obtained by multi-channel satellites. The technology adopted by satellite remote sensing to obtain Sea Surface Temperature has the characteristics such as wide coverage (almost cover all of the global waters) and long-term repetitive measurement that will compensate the shortage of field measurement to a certain extent. However, these characteristics also result the overlaps of coverage and the redundancy of information. Therefore, the research on how to find out the conflict and inconsistencies of multi-channel satellite data, especially on quantizing the conflict level, separating the kinds of the conflicts and providing basis for subsequent researchers to solve important problems in this area, has become an important subject for the research on marine data. This paper includes the following five parts. The first part is the background of multi-satellite remote sensing. The second part introduces the common methods to judge conflicts of measurement data from satellite remote sensing. The third part details the strengths and the weaknesses of Grubbs formula. In the fourth part, it introduces an improved Grubbs algorithm and its advantages by comparing to the original algorithm. The fifth part is experimental section. This paper compares the effects that obtained between the common method and the improved one in processing conflict data through experiments, and then uses the Argo buoy data to validate the correctness, feasibility and practicability of the processing results.

2. Traditional method of remote sensing SST

There are two methods for judging the differences of measurement data from satellite remote sensing: the field measurement data comparison [5][6] and the variance discriminance [7]. The variance discriminance is the most common one. However, both methods have shortages.

Both [5] and [6] use comparison method to find out the abnormality of satellite data, and believe the best way to inspect the accuracy of satellite remote sensing SST is that using field measurement during the observing time of satellite. By taking the data obtained from field measurement as real values and comparing those values with satellite remote sensing data, it can determine whether there are abnormal data in satellite remote sensing data. But due to the extensity of the ocean itself, the amount of the measured data obtained from field devices are limited. Thus, it needs a lot of manpower, material resources and financial power. Besides, what we got from satellite remote sensing is the Sea skin temperature, while the data from field measurement is the sea surface temperature. They are different [8].In [3][7], they used variance to analyze the abnormality of meteorological data. By computing the variance value of a group data from field measurement, it can determine whether there is inconsistency in those data. However, the variance method cannot describe the conflict comprehensively. For example, we cannot distinguish how many numbers affect the variance of a group principally. And this is the weakness of variance method.

In order to compare the consistency and conflict of the multi-source satellite data earnestly and effectively, this paper puts forward a new method based on the Grubbs method. Grubbs method cannot describe the conflicts effectively because of its defects such as missing-alarm and false-alarm. So it cannot reflect all the conflicts in all areas factually. The experiment shows that the new algorithm provides a well solution for the Grubbs method's defect, and it does better in quantization and description of the relationship of multi-source data. In addition, the new algorithm can distinguish consistence and conflicts of the data on either space or time. These works provide subsequent researchers with reference and accordance to evaluate or study the quality of marine information.

3. Grubbs test used in remote sensing SST

3.1. Probability distribution of SST.

According to the error theory, it is known that the measured value will obey the distribution of normal distribution after the system error is eliminated. According to expert experience, SST remote sensing data follow the normal distribution [9].

The probability density function is defined as

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\Big(-\frac{(x-\mu)^2}{2\sigma^2}\Big). \tag{1}$$

μ is Observations, σ is Standard Deviation.

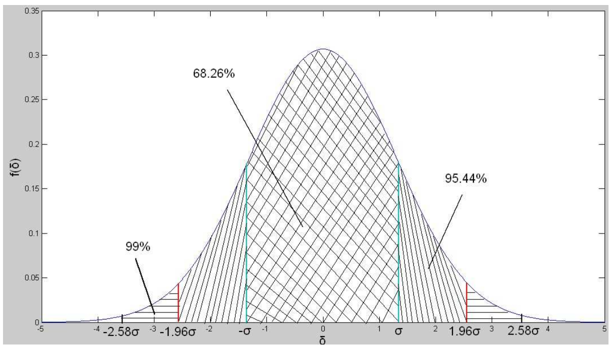


Fig.1. The distribution of the normal distribution

The probability of measured values fall into an interval is shown in table 1:

Table 1 The characteristics of the normal distribution

interval	probability
$\mu \pm \sigma$	0.6827
$\mu \pm 1.96\sigma$	0.95
$\mu \pm 2.58\sigma$	0.99
$\mu \pm 3\sigma$	0.9973

As shown in Fig.1 and Table 1when $t = 2.58$ The probability of measured values is 0.99 in interval $[\mu - t\sigma, \mu + t\sigma]$.

$$P(x) = \int_{x-2.58\mu}^{x+2.58\mu} \frac{1}{\sigma\sqrt{2\pi}} exp\Big(-\frac{(x-\mu)^2}{2\sigma^2}\Big)dx = 0.99, x \in (-\infty, +\infty). \tag{2}$$

Therefore, the probability of measured values out of the interval $[\mu - t\sigma, \mu + t\sigma]$ is 0.01, this is small probability event. According to expert experiencewhen the measurement is out of the confidence interval $[\mu - t\sigma, \mu + t\sigma]$ which is caused by measurement error, usually it is considered as abnormal value.

Grubbs test obtained parameter t by setting confidence probability, and the confidence interval of the measured value can be determined. The parameters μ and σ can be obtained according to the given data sets, therefore the value of confidence interval $[\mu - t\sigma, \mu + t\sigma]$ can be obtained according to the parameter t. The data is considered as abnormal, which is beyond the confidence interval.

3.2. Grubbs test.

There are 4 reason of the multi-satellite SST data conflict[9]: Firstly, defects and incorrect measurement. Secondly, the environment of the sensor monitoring is complexity, such as various interferences. Thirdly, the precision of multi-channel SST data processing methods are different. Finally, the increase of the number of information sources, which may also lead to the conflict even if they are the same.

The usually ways to judge abnormal data are include 3σ rule, Grubbs algorithm etc.

The 3σ rule is the most common and simple criterion. It requires large number of measurements. For a certain series, if the measurement only contains random error, according to the normal distribution, about 0.3 percent values will be out of range $\pm 3\sigma$. It means, only one residual error will turn up in the 370 measurements. In a series of measurements, when find the measured value of residual error is more than 3σ, namely $|v_i| > 3\sigma$, then can think it contains the gross error and should be removed. However, the number of measurement is usually small, so 3σ rule only as an approximate criterion.

Grubbs test is a prevailing method to detect the outlying data in dataset, and had been collected by the Chinese criterion (G1B4883-85) and US criterion test method (ASTM E178-68) [10].

3.2.1. Grubbs test.

Assuming to conduct equally precise and independent multi-measurement on a certain variable[11][12][13], then we have $x_1, x_2, \cdots, x_n$.

Where,x_i obeys normal distribution, the average is

$$\overline{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{3}$$

and the residual variance is

$$v_i = x_i - \overline{x} \tag{4}$$

According to Bessel formula, we have the standard deviation,

$$\sigma \approx \sqrt{\frac{\sum\limits_{i=1}^{n} v_i^2}{(n-1)}} \tag{5}$$

In order to test whether there exists any gross error within $x_i (i = 1, 2, \cdots, n)$, arranging x_i into statistics $x_{(i)}$. we get $x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(n)}$ in the order.

Two equations are obtained: $g_{(n)} = \frac{x_{(n)} - \overline{x}}{\sigma}$ and $g_{(1)} = \frac{\overline{x} - x_{(1)}}{\sigma}$.

where, $x_{(n)}$ is the largest observation and $x_{(1)}$ is the smallest observation. Setting the value of significance level α (normally is 0.05 or 0.01), and we can query the critical value $g_0(n, a)$. Then two equations are obtained as following:

$$P\Big(\frac{\overline{x} - x_{(1)}}{\sigma} \geq g_0(n, a)\Big) = a \tag{6}$$

and

$$P\Big(\frac{x_{(n)} - \overline{x}}{\sigma} \geq g_0(n, a)\Big) = a \tag{7}$$

If $x_{(1)}$ and $x_{(2)}$ are questionable observations, we have

$$g_{(1)} = \frac{\overline{x} - x_{(1)}}{\sigma} \tag{8}$$

and

$$g_{(n)} = \frac{x_{(n)} - \overline{x}}{\sigma} \tag{9}$$

If $g_{(i)} \geq g_0(n, a)$ the ith measurement is supposed to be a possible outlier[10]. The largest value exceeding the threshold is regarded to be an outlier and the measurement is removed from the dataset. Then the Grubbs test is performed again to see if there is any more outlier.

Table 2 Grubbs table $g_0(n, a)$

Measurement times(n)	Confidence(P_n)		Measurement times(n)	Confidence(P_n)	
	0.99	0.95		0.99	0.95
3	1.16	1.15	11	2.48	2.23
4	1.49	1.46	12	2.56	2.28
5	1.76	1.67	13	2.61	2.33
6	1.94	1.82	14	2.66	2.37
7	2.10	1.94	15	2.70	2.41
8	2.22	2.03	16	2.74	2.44
9	2.32	2.11	18	2.82	2.50
10	2.41	2.18	20	2.88	2.56

It had been proved that the Grubbs Test achieves the best performance if there is only one abnormal value in a given data set [6]. According to the Grubbs Test, the value of $g(i)$, which is the ith measured value, is inversely proportional to the standard deviation directly. As for the SST data in this paper, it will cause missing-alarm and false-alarm. For example, the Grubbs Test gives the false alarm on the first data set to be abnormal while in fact, the data set is complete normal.

3.2.2. Example.

The following two sets of SST data were the measurement of multi-source satellite at the same time on the same latitude and longitude:

$Set1 : 24.300, 24.800, 24.900, 24.800, 24.600, 24.800, 24.700, 24.900, 24.700$

$Set2 : 22.300, 23.000, 22.900, 23.700, 21.800, 22.600, 22.300, 22.000$

Two groups data arrange respectively according to the numerical size:

$Set1 : 24.300, 24.600, 24.700, 24.700, 24.800, 24.800, 24.800, 24.900, 24.900$

$Set2 : 21.800, 22.000, 22.300, 22.300, 22.600, 22.900, 23.000, 23.700$

This article take $a = 0.05$ as significant level,Calculated the mean and standard deviation of the two sets respectively.

The average of first set $ave_1 = 24.722$, the standard deviation $\sigma_1 = 0.1856$.

Look-up the grubbs critical point table $g_1(0.05, 9) = 2.11$.

The average of second set $ave_2 = 22.575$, the standard deviation $\sigma_2 = 0.6135$.

Look-up the grubbs critical point table $g_1(0.05, 8) = 2.03$.

In the first set, we know$| 24.300 - 24.722 |= 0.422 >| 24.900 - 24.722 |= 0.178$, and$\frac{0.422}{0.1856} \approx 2.72 > g_1(0.05, 9) = 2.11$. According to the grubbs judgment, existing abnormal data in the first set, there are conflicts.

In the second set, we know$| 21.800 - 22.575 |= 0.775 <| 23.700 - 22.575 |= 1.125$ and$\frac{1.125}{0.6135} \approx 1.83 < g_1(0.05, 8) = 2.03$. According to the grubbs judgmentthere is no abnormal data in the second set.

The first SST set of multi-source satellite, belong to normal measurements, have no outlier. And Grubbs judgment make an error conclusion, this paper says this kind of mistake as False-alarm. In contrast, the second SST set contains at least two outliers; The Grubbs judgment makes an error conclusion also, this paper says the mistake as Missing-alarm.

4. Improved Grubbs measure method

4.1. The limitations of the traditional Grubbs measure algorithm.

There are several obvious flaws in Grubbs test during judging multiple abnormal data [14]. According to the Eq.(5) and Eq.(8), the value of $g(i)$ is more likely to be affected by a smaller standard deviation, say, $g(i)$ will decrease quickly with the increase of a small standard deviation. For example, missing-detection is inclined to occur if the value of standard deviation is too small. However, on the other hand, false-detection may be introduced when the standard deviation is too large. To balance both sides and avoid these problems, the standard deviation needs to be control in a limited range [15][16] and it is necessary to improve the Grubbs Test algorithm.

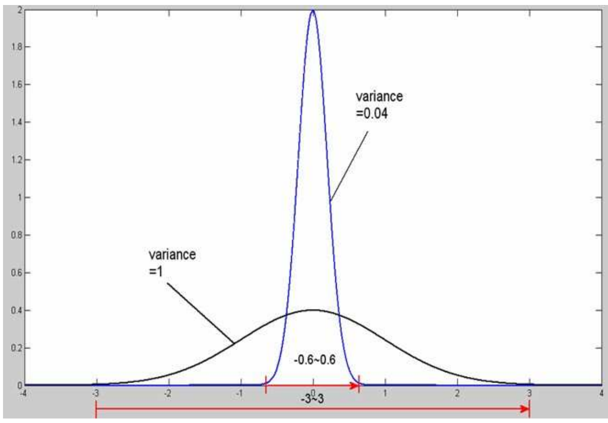


Fig.2. The situation of abnormal variance

4.2. Clustering algorithm.

The steps of weighted clustering algorithm

Suppose there are $N(N \geq 2)$ data samples $\{Z_s = Z_1, Z_2, \cdots, Z_N\}$.

$Z_1 \leq Z_2 \leq \cdots \leq Z_N$, According to the characteristics of ocean data, this paper set the threshold size $T = 0.2$ to cluster and analysis set of data samples.

1.Calculate the distance $d_{2t}(i > t > 2)$ between all data which belong to cluster T_1 except the center of T_1 and the center Z_i of the cluster T_2 respectively. When $d_{1t} > d_{2t}$, delete data Z_t from clusterT_1 and classified as cluster T_2.

2. Calculate the distance between the remain data samples Z_s and the center of the cluster T_2 separately, and classified all these data. Repeat step 2and 3, until all data sample have been processed, and get K clusters at last.

3. According to the number of elements in each cluster, each element should be given appropriate weight by the cluster which it belong to. The more number of elements contained in, the greater weight of data should be given in this cluster.

4. Calculate the approximate true value of this dataset by the result of clustering and corresponds weight. The formula can be describe as

$$\overline{Z} = \sum_{i=1}^{n} \frac{W_i}{W} Z_i, W = \sum_{i=1}^{n} W_i \tag{10}$$

4.3. Grubbs algorithm base on the approximate true value.

In Grubbs's formula, the error of measurement equals to the difference between measured value and the average. It is unadvisable to use the average of a dataset as the true value to evaluate measurement error because sometimes there is a big deviation between the average and the true value. There is a boundedness of Grubbs method that the judgement of exceptional data exists the phenomenon of missing or false detection during the variance of a dataset is oversize or undersize.

Considering this boundedness, Grubbs' algorithm is improved by weighted clustering. The steps of this improved method are as follows:

Step 1: Judge the outliers with Grubbs' formula and then delete them from the dataset.

Step 2: Get K clusters by clustering the dataset.

Step 3: If $K = 1$, it means all the data are centralized so there is not outlier (the probability of false detecting phenomena judged by Grubbs' method is eliminated). if $K > 3$,it means all data in dataset is scattered, so there are outliers in the dataset (the probability of missing detecting by Grubbs' method is eliminated), when $K = 2$ or $K = 3$,go to step 4.

Step 4: Obtain improved Grubbs' formula by using the approximate true value calculated by weighted cluster algorithm to replace the average of the dataset in Grubbs formula.

Step 5: If $|Z_i - \overline{Z}| > t\sigma$,it means x_i is an outlier, otherwise xi is normal. $\overline{Z}$ stands for the approximate true value of the dataset.

Step 6: Obtain cluster A and cluster B through clustering the dataset $S = \{x_1, x_2, \cdots, x_n\}$ by the clustering algorithm. As shown in Fig 3, C is the approximate true value of dataset S calculated by weighted clustering algorithm and D is the average value of dataset S.

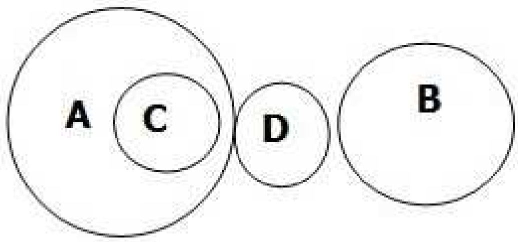


Fig.3. The distribution of SST data

The probability of outliers existence in cluster B is greater than that in cluster A because cluster A is larger than cluster B. The approximate true value of dataset S is close to the data elements in cluster A. As shown in the Fig 3, D as the average of S is between data in cluster A and cluster B. The appropriate true value calculated by cluster algorithm is contained in cluster A and is closer to data in cluster A which is the expected result. It is believed that C is closer to the true value than D.

The different between data from cluster A and the appropriate true value C are significantly less than the different between data from cluster B and C, so the appropriate true value C is much more effective in measuring the difference among the data from dataset S compare with the average value. In Grubbs formula, if one data x_i from dataset S satisfy $|x_i - D| > t\sigma$, the data can be considered as outlier, D and $\overline{x}$ is the average value, t is a constant of Grubbs coefficient. σ is the standard deviation of dataset S.

If the appropriate true value C of dataset S is calculated, the data of cluster A or B displayed in Fig3 satisfy$|x_A - C| < |x_B - C|$, the probability of $|x_B - C| > t\sigma$ is bigger than the probability of $|x_A - C| > t\sigma$, which is correspond to the probability of data abnormal in cluster B bigger than that of cluster A.

For data of cluster A, $|x_A - C| < |x_A - D|$.

For data of cluster B, $|x_B - C| > |x_B - D|$.

The improved formula trends to believe that data of cluster A are more reliable than that in cluster B and the probability of existence of outliers in cluster B is greater than that in cluster A.

5. Analysis of Experiments

In the experiments: First, using Grubbs judgment to process data; Second, according to the improved algorithm's steps revises the determine results, to compare and analysis the results; Finally, using the Argo buoy data to check the revised result by Grubbs methods.

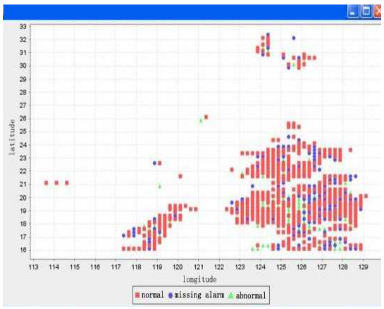
5.1. Application and Improvement of Grubbs Measure Algorithm.

In this paper, East China Sea waters are chosen as the trial area to conduct the analysis of conflict relationship, area coverage $(16.125°N \sim 33.125°N, 122.125°E \sim 139.875°E)$ spatial resolution 4.7km. All locations which have 7 satellite monitor values at least will be selected from Data samples detected in 2006 by 11 kinds of SST remote sensing satellites, and totally 625 data samples were gained.

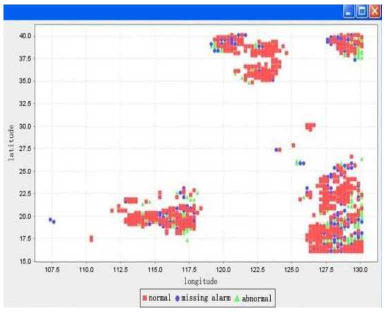
Table 4 The attribute values Observation satellite

Remote sensing device	Measurement error	Product type
Avhrr	0.4	Nighttime Ascending
Avhrr	0.4	Daytime Descending
Amsr-E	0.5	Amsr-E Ascending
Amsr-E	0.5	Amsr-E Descending
Tmi	0.5	Tmi Ascending
Tmi	0.5	Tmi Descending
Modis	0.3	Daytime MODIS-Terra Data
Modis	0.3	Nighttime MODIS-Terra Data
Modis	0.3	Nighttime MODIS-Terra Data
Modis	0.3	Daytime MODIS-Aqua Data
Modis	0.3	Nighttime MODIS-Aqua Data

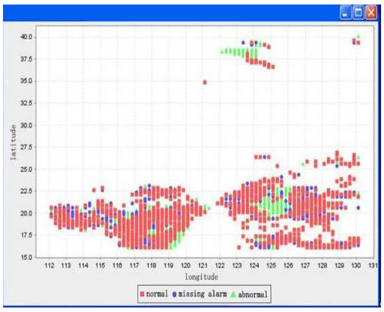
In order to confirm the validity of the improved methods, a comparison experiment between original method and improved methods was done, and the result as shows in Fig.4.



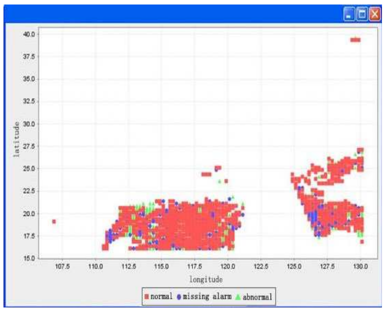
4(a)



4(b)



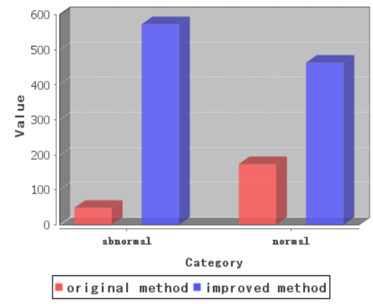
4(c)



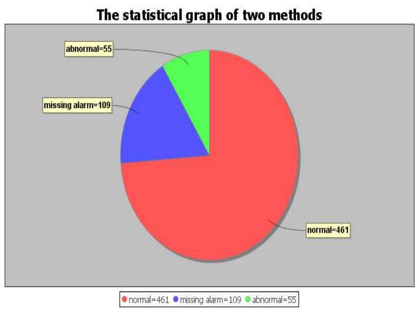
4(d)

Fig.4 The comparison of two methods

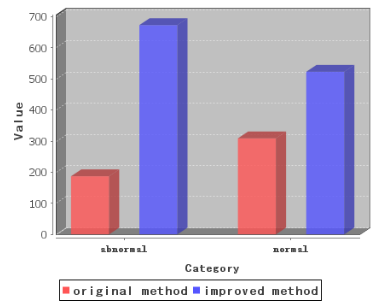
The (a), (b), (c) and (d) are the statistical results of Fig.4.



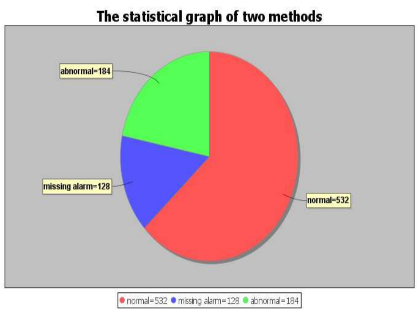
5(a1)



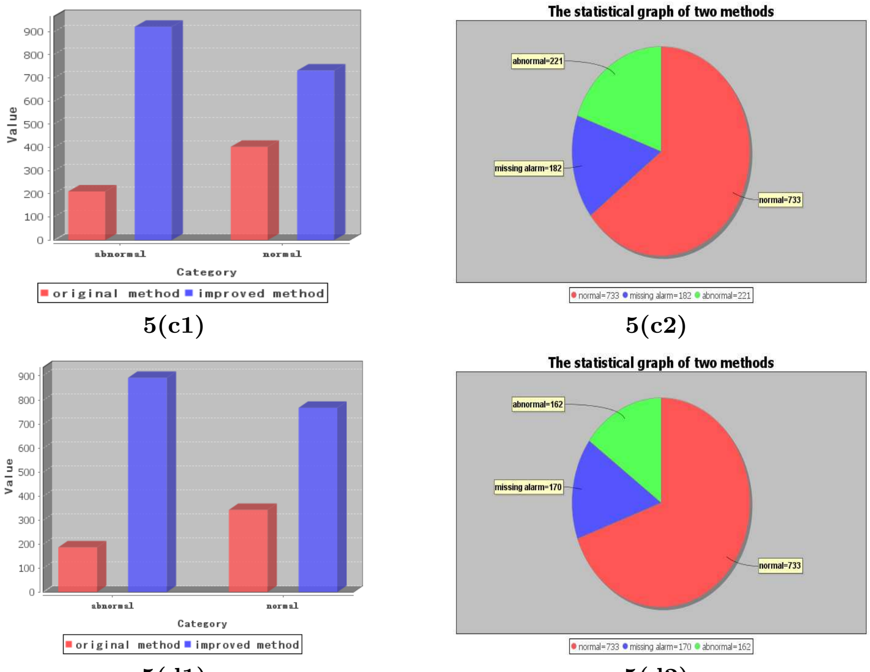
5(a2)



5(b1)



5(b2)



5(c1) 5(c2)

5(d1) 5(d2)

Fig.5 The statistical graph of two methods

As seen from Fig.4 and Fig.5, the number of normal points, missing points, and abnormal points were 461, 109 and 55. The red diamonds indicate the region is non-confliction area determined by two algorithms, known as non-confliction area and the number is 461. The blue circle area represents the area is non-confliction region determined by original method, but it has the conflict determined by new method. The region is called the missed area and the number is 109. The green triangle can be considered as the conflict points by two algorithms. The region known as the confliction area and the number is 60.

By the original method, the Fig.5(a) shows, the number of confliction area is equal to the number of green triangle; the non-confliction area is the sum of red diamonds and blue circle. But in the new method, the number of confliction area is the sum of blue circle and green triangle, and non-confliction area is the number of red diamonds. It can be seen the improved method can identify 164 confliction areas, however, the number of original method is only 55.

5.2. Argo float data prove the correctness of improved method.

This experiment obtains the argo float SST data from the argo float data center, as the argo float data is sparse, 50 argo float data were gained in this study where the time and space correspond with the satellite remote sensing. The area coverage is $(16.125°N \sim 33.125°N, 122.125°E \sim 139.875°E)$. Firstly, original method and improved method were respectively used to identify the conflict relationship of these 50 satellites remote data in responding place in this study; and then argo float data were used to validate the results of these two methods. As can be seen from Fig6, Fig7.

As to the data under test, 19 outlying data and 31 normal data were identified by original method; while 30 outlying data and 20 normal data were identified by improved method. Through analyzing, it is discovered that there are 14 right results and 37 wrong results in the original method compared to 42 right results and 8 wrong results in improved method. A conclusion was drawn that the improved

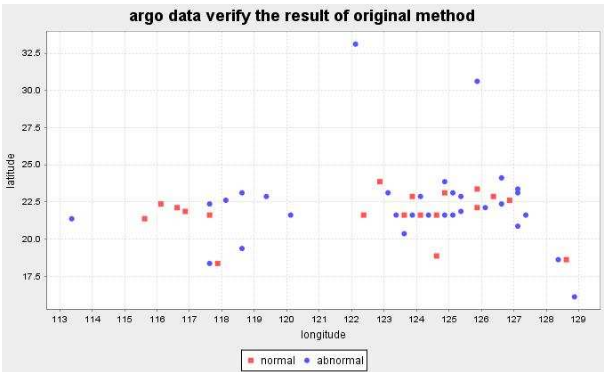


Fig.6. The results of argo verify the Grubbs algorithms

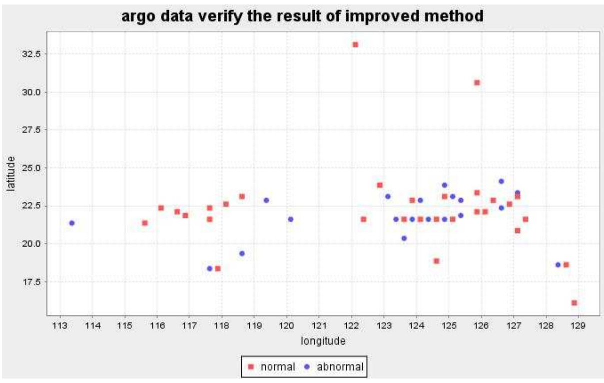


Fig.7. The results of argo float data verify the improved algorithm

method is superior to identify the conflict relationship of marine data. Therefore, we think that the improved method of Grubbs has practical application on massive data processing, and can effectively identify the relationship of marine data.

5.3. Application of improved method.

In the following, this paper will apply the improved method to analyze area confliction relationship of satellite field data in East China Sea waters, the area arrange is $(16.125°N \sim 33.125°N, 122.125°E \sim 139.875°E)$. The analyzing results can be seen from Fig.8.

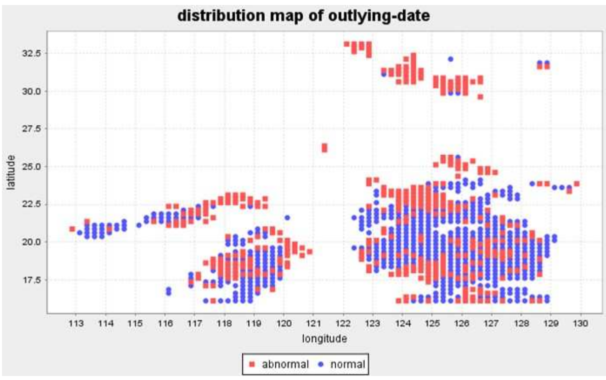


Fig.8. Conflict relationship of East China Sea waters in the year 2006

Through the analyses of Fig.8, it was discovered that the conflicting relationship of the satellites data is quite serious in the East China Sea waters, where the area coverage is about $(16.125°N \sim 33.125°N, 122.125°E \sim 139.875°E)$; the phenomenon is likely caused by the warm current or cold snap in this area. However, in the area where the coverage range is about $(16.125°N \sim 33.125°N, 122.125°E \sim 139.875°E)$, the SST data among satellites is reliable.

6. Conclusion

In SST remote sensing monitoring, it is cause conflict in multi-source data that the differences among different satellite equipments and measurement methods. Use conflict index can evaluate the quality of multi-source data effectively. Traditional Grubbs algorithm has several limitations. The new algorithm is based on Grubbs algorithm which improved accord to variance. It is more effective than traditional methods in describing SST conflict problems, confirming a set of highly consistent points, finding and eliminating outlying data and digging out abnormal areas. The new algorithm not only can be used in the evaluation of conflict in multiple-source SST data, but also can be extended to the information fusion of multiple-source measurement. At the same time, it would contribution to the next step research in conflict analysis of huge data.

Acknowledgments

This research was supported by The National Natural Science Foundation of China (No.40976108).

References

[1] Shi Suixiang, Study on Soft Fusion Strategy of Multi-Channel Incertitude Information in Digital Ocean, Shenyang:Northeastern University 2005.
[2] Hosoda H, Murakami H, Difference Characteristics of Sea Surface Temperature Observed by GLI and AMSR Aboard ADEOS-II, Journal of Oceanography, 2006.
[3] Iwasaki S, Kubota M, Tomita H, Inter-comparison and evaluation of global sea surface temperature products, International Journal of Remote Sensing, 2008.
[4] Barton I, Pearce A, Validation of GLI and other satellite-derived sea surface temperatures using data from the Rottnest Island ferry, Western Australia. Journal of Climate, 2006.
[5] Gao Guo-ping, Qian Cheng-chun, Bao Xian-wen, Shi Mao-chong, Difference between the PFSST and the in-situ data in East China Sea, Acta Oceanologica Sinica, 2001.
[6] Zhang Chun-gui , Zhang Xing , Zeng Yin-dong , Pan Wei-hua , Lin Jing, Retrieval and validation of sea surface temperature in the Taiwan Strait using MODIS data, Acta Oceanologica Sinica, 2008.
[7] Tao Shi-wei, Hao Min, Xue Ji-shan, Duo Yi-wen, Analyses of Observation Data Error in Numerical Forecasting Assimilation System, Meteorological Monthly, 2008.
[8] Barnett V,and Lewis T, Outliers in statistical data. John Wiley and Sons, New York.
[9] Fang Xiao-jun, Consistency Analysis and Study on Fusion Technique of Multi-Channel Monitoring SST Information, Shanghai University2008.
[10] Shen Yi-ying, Ran Qi-wen, Liu Yong-tan, Application of Improved Grubbs' Criterion to Estimation of Signal Detection Threshold, Journal of Harbin Institute od Technology,1999.
[11] Fei Ye-tai, Error theory and data processing, Beijing: China Machine PRESS,1987.
[12] Grubbs F.E., Procedures for detecting outlying observations in samples, Technometrics,1969.
[13] Grubbs F.E.,Beck G., Extension of sample sizes and percentage points for significance tests of outlying observations, Technometrics,1972.
[14] Lu Xiao-qing, Monitoring Ocean using satellite remote sensing technique in China, Marine Forecasts,2008.
[15] Liu Rong-wei, A Brief Discussion on IPv6 Mechanisms' Application on Domain Name System, Journal of Xinzhou Teachers University, 2005.
[16] Li Guang-xue, The Error Analysis in Numerical Calculation, Journal of Henan University, 1996.

[17] Tietjen,G.L.,and moore, R.H., Some Grubbs-type statistics for the detection of several outliers, Technometrics, 1972.

[18] Xiao Shuchen, Qin Yuxun, Han Jiqing, A Test Analysis Method Based on Grubbs in Experiments, Journal of Projectiles, Rockets, Missiles and Guidance, 2007.

[19] SHI Suixiang, XIA Dengwen, YU Ge, Method of fusing the data reversed from satellite remote-sensing with the assimilation data for sea surface temperature based on D-S theory, Acta Oceanologica Sinica, 2005.

[20] Lefevre E, Coiot O, Vannoorenberghe P and moore R.H., Belief function combination and conflict management, Information Fusion, 2002.

1.Department of Computer Science and Engineering, University of Shanghai University, Shanghai CN 200072 China.

E-mail: xly@shu.edu.cn

2.National Marine Data and Information Service, Tianjin CN 300171 China.