Application of a sea surface temperature front composite algorithm in the Bohai, Yellow, and East China Seas*

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Received Dec. 10, 2014; accepted in principle Jan. 18, 2015; accepted for publication Mar. 26, 2015

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Abstract The oceanic front is a narrow zone in which water properties change abruptly within a short distance. The sea surface temperature (SST) front is an important type of oceanic front, which plays a significant role in many fields including fisheries, the military, and industry. Satellite-derived SST images have been used widely for front detection, although these data are susceptible to influence by many objective factors such as clouds, which can cause missing data and a reduction in front detection accuracy. However, front detection in a single SST image cannot fully reflect its temporal variability and therefore, the long-term mean frequency of occurrence of SST fronts and their gradients are often used to analyze the variations of fronts over time. In this paper, an SST front composite algorithm is proposed that exploits the frontal average gradient and frequency more effectively. Through experiments based on MODIS Terra and Aqua data, we verified that fronts could be distinguished better by using the proposed algorithm. Additionally through its use, we analyzed the monthly variations of fronts in the Bohai, Yellow, and East China Seas, based on Terra data from 2000 to 2013.

Keyword: oceanic fronts; Sobel algorithm; frontal frequency; frontal average gradient

1 INTRODUCTION

Oceanic fronts are narrow zones with enhanced gradients of physical, chemical, optical, and/or biological parameters that may be observed at the sea surface (Wall et al., 2008). They can usually be observed as boundaries between two or more water masses with different physical and chemical features. Because of the diverse physical processes within the frontal zones, various substances such as nutrients, chlorophyll, and plankton are often enriched within these regions. Hence, the effective and accurate detection of these fronts is important in fields such as oceanic fisheries and environmental protection.

The sea surface temperature (SST) front is a classic and typical type of oceanic front. Satellite-derived SST images obtained from the Advanced Very High Resolution Radiometer (AVHRR) or Moderate-resolution Imaging Spectroradiometer (MODIS) have

been used widely for SST front detection. However, these SST data are often influenced by the presence of clouds, which can cause missing data. Although long-term averaged SST data (e.g., eight-day or monthly data) might partially recover missing data, the fronts themselves could also be averaged, which could cause some fronts to be lost or their strength reduced. Time series data are usually used to overcome these limitations and to accurately detect and analyze the long-term variability of fronts. Routine processes to analyze the long-term variability of fronts often consist of two major steps. In the first step, a traditional front detection algorithm is applied to each SST map within the time series data. In the second step, the

* Supported by the National Natural Science Foundation of China (No. 41271409)

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Fig.1 Long-term (2000–2013) mean maps of (a) frontal gradient, (b) frontal frequency, and (c) their product in the Bohai, Yellow, and East China Seas in January, based on Terra data

The parameters are normalized by variance and thus, they are dimensionless.

long-term mean frontal average gradient and frequency are calculated to reveal the front's variations (Shimada et al., 2005; Chang et al., 2008, 2010; Pi and Hu, 2010; Yao et al., 2012).

The long-term mean frontal average gradient or frequency can partially reveal the stability or strength of a front; however, because of the influences of the data quality and front detection algorithm, those two parameters also have some deficiencies. Figure 1a–c shows maps of the monthly mean frontal average gradient, frontal frequency, and product of these two parameters, respectively, for the Bohai, Yellow, and East China Seas in January. These results were calculated based on the MODIS Terra daily 4-km-resolution nocturnal data from 2000 through 2013. For comparison, the values of frontal average gradients, frontal frequencies, the product of these two parameters, and comprehensive gradients (Section 4) were normalized by variance in this paper. As shown in Fig.1 for the Bohai Sea (locations of main fronts are shown in Fig.2, mostly after Hickox et al. (2000)), the frontal average gradient of the Liaodong Bay front is comparatively large; however, this front is not detected frequently and the value of its frontal frequency is low. In the Yellow Sea, the frontal average gradient and frequency of the Shandong Peninsula front are both conspicuous. Average gradients of the Jiangsu front and Yangtze Bank Ring front are small but their frontal frequencies are high, as can be seen in the frontal frequency map. The Seohan Bay and Chejudo fronts can be seen in the frontal average gradient image, but

Fig.2 Experimental area showing main SST fronts

1. Liaodong Bay, Bohai Bay, and Laizhou Bay front (LBLF); 2. Bohai Strait front (BSF); 3. Shandong Peninsula front (SPF); 4. Jiangsu front (JF); 5. Seohan Bay front (SF); 6. Kyunggi Bay front (KBF); 7. Chejudo front (CF); 8. Yangtze Bank Ring front (YBRF); 9. Zhejiang-Fujian front (ZFF); 10. Kuroshio front (KF); 11. Taiwan Strait front (TSF).

they are too indistinct to be observed in the frequency image. In the East China Sea, the Zhejiang-Fujian front can be clearly observed in the frontal average gradient image but its frequency is low. In addition, this front is discontinuous in the frequency image. The Kuroshio front can be observed in both the frontal average gradient and frequency maps, but in the former, its shape is more distinct and complete.

According to the above analysis, the monthly mean frequencies of some SST fronts are comparatively high yet their frontal average gradients are low (e.g., Jiangsu and Yangtze Bank Ring fronts). In contrast, the frontal frequencies of some fronts are not large—some fronts in the frequency map are even discontinuous; however, the average gradients of these fronts are sufficient for them to be seen in the average gradient map (Zhejiang-Fujian front). This might result from the front detection and gradient calculation algorithms. In the experiments, we used the single-image edge detection (SIED) algorithm proposed by Cayula and Cornillon (1992, 1995) to detect the fronts and utilized the Sobel algorithm to calculate the gradient magnitude at every pixel. In every SIED window (size 32×32 pixels), fronts can be detected only when clear pixels constitute $>90\%$ of the total. For the gradient calculation, the window size was 3×3 pixels and therefore, the influence of missing data was weak. Consequently, in some areas of the time series images where data quality is good, fronts with relatively low gradients can be fully detected and thus, their frontal frequencies are high. These fronts can be observed clearly in the frontal frequency image yet may be missing in the frontal average gradient map. Conversely, some fronts with relatively high gradients might not be detected or be only partially detected due to missing data, resulting in low frontal frequencies.

The above analysis shows that single frontal average gradient or frequency is inadequate to reveal the variations of all fronts. Miller (2009) proposed a front composite algorithm based on frontal average gradient, frequency, and neighborhood information to analyze short-term changes of fronts. Miller (2004) also employed this idea to reflect the biological and physical characteristics of frontal zones using multispectral data. In the present paper, we only consider two parameters (frontal average gradient and frequency) and therefore, according to Miller's concept, we calculated the product of the frontal average gradient and frequency (the product is described as Miller's gradient in this paper). It can be seen in Fig.1c that the Miller's gradient image can partly synthesize the average gradient and frequency information, but the fronts are too indistinct to be observed. A new composite algorithm was proposed to attain an improved front composite map, which could detect fronts with small frontal average gradients and enhance the visualization of fronts with low frontal frequencies.

In the following, Section 2 introduces the experimental data and study area. Section 3 describes the frontal average gradient and frequency calculation processes. The new composite algorithm is presented in Section 4. The monthly mean variations of the SST fronts in the Bohai, Yellow, and East China Seas, based on this algorithm, are shown in Section 5, and our conclusions are given in Section 6.

2 DATA

We selected the Bohai, Yellow, and East China Seas as the experimental area for this study (specifically: $21^{\circ}41' - 41^{\circ}41'N$, $116^{\circ}51' - 132^{\circ}28'E$). The experimental area, one of the largest marginal Seas of the Pacific Ocean, has a complicated underlying topographic structure and complex current system, and many typical oceanic fronts have been observed here. Figure 2 displays a 4-km-resolution annual mean Terra SST image obtained in 2007. According to Hickox et al. (2000), there are 11 main fronts within this area (corresponding to the order number in the image; only approximate frontal locations are shown). In the Bohai Sea: 1, Liaodong Bay, Bohai Bay, and Laizhou Bay front (LBLF) and 2, Bohai Strait front (BSF). In the Yellow Sea: 3, Shandong Peninsula front (SPF); 4, Jiangsu front (JF); 5, Seohan Bay front (SF); 6, Kyunggi Bay front (KBF); 7, Chejudo front (CF); and 8, Yangtze Bank Ring front (YBRF). In the East China Sea: 9, Zhejiang-Fujian front (ZFF); 10, Kuroshio front (KF); and 11, Taiwan Strait front (TSF).

For the experimental data, 4-km-resolution daily MODIS Terra nocturnal data from 2000–2013 and 4-km-resolution daily Aqua nocturnal data from 2002–2013 were selected. The dataset included 4 704 Terra and 3 891 Aqua images in total, which are available from the Jet Propulsion Laboratory.

Missing data are common in daily images. The temperatures in areas within and around missing data might have considerable differences, such that the boundary between the area of missing data and its surroundings could be detected as a front. In addition, missing data could have a serious effect on the histogram statistics of analysis windows (an important step in the SIED algorithm), degrading the accuracy of front detection. Therefore, before frontal detection can be performed, suitable pixels must be selected. A quality level ranging from 0 (best) to 4 (worst) was assigned to every pixel for which the sensor collected data and there was a corresponding SST value. In this study, pixels with a quality level of 0 were flagged as

good data and used in the histogram analysis of the SIED.

3 FRONTAL AVERAGE GRADIENT AND FREQUENCY

3.1 Single-image edge detection

Current methods to detect frontal structures mainly include the histogram-based separation of two water masses (Cayula and Cornillon, 1992, 1995; Diehl et al., 2002; Belkin et al., 2009; Yao et al., 2012), detection of horizontal gradients (Oram et al., 2008; Belkin and O'Reilly, 2009; Zeng et al., 2014; Zhang et al., 2014), and entropy-based approaches (Vázquez et al., 1999; Shimada et al., 2005; Chang et al., 2008, 2010). Furthermore, some new algorithms have been developed such as the gravitation algorithm (Ping et al., 2013, 2014) and morphology algorithm (Pi and Hu, 2010).

The histogram-based SIED (Cayula and Cornillon, 1992) has been used by various research groups and it is considered the best front detection tool. Because of its worldwide validation and robustness, we employed the SIED algorithm in this study. The median filter is a very efficient technique of digital filtering that removes isolated noise while preserving edges in data (Belkin and O'Reilly, 2009) and thus, it was used here to filter the data prior to using the SIED algorithm.

The SIED algorithm operates on three levels: image, window, and local. At the image level, the main objective is to detect and remove clouds. At the window level, the entire image is divided into overlapping 32×32 pixel windows. Then, the histogram distribution of each window is calculated. Only when the statistical histogram is bimodal and the data in the window can be separated reasonably can the frontal pixels be ascertained. At the local level, an edge-tracking algorithm is applied for front pixels to link them to complete fronts.

3.2 Front frequency

Front frequency can reflect the stability of a front, i.e., the more stable it is, the higher its frequency. For each pixel in the time series images, we calculated both the total number of images for which the given pixel had a front and the total number of images in which the given pixel was cloud-free. The ratio of these two parameters is the frontal frequency:

$$P_f(i, j) = \frac{|\{s, (i, j) \in \mathbf{C}(s)\}|}{|\{s, T(i, j, s) \neq t_{\text{cloud}}\}|},$$

$$\text{for } (i, j) \in \mathbf{I}, s \in \{1, \dots, \mathbf{S}\}, \quad (1)$$

where $P_f(i, j)$ is the frontal frequency of pixel (i, j) , $|\{\dots\}|$ indicates the number of elements in a set, $\mathbf{C}(s)$ is the set of SIED front contour pixels, $\mathbf{I}$ is the set of valid image coordinates, $T(i, j, s)$ is the SST of a pixel located at (i, j) in the time series images, and $\mathbf{S}$ represents those images.

For some fronts, because of the influences of data quality and the SIED algorithm, their frequencies might be small but their average gradients large. To enhance the function of frontal frequency, we introduce a new concept, i.e., non-frontal frequency:

$$P_{\text{nf}}(i, j) = \frac{|\{s, (i, j) \in \bar{\mathbf{C}}(s)\}|}{|\{s, T(i, j, s) \neq t_{\text{cloud}}\}|},$$

$$\text{for } (i, j) \in \mathbf{I}, s \in \{1, \dots, \mathbf{S}\}, \quad (2)$$

where $P_{\text{nf}}(i, j)$ is the non-frontal frequency of pixel (i, j) and $\bar{\mathbf{C}}(s)$ is the set of the SIED non-front contour pixels. From this definition, we know that $P_{\text{nf}}(i, j) = 1 - P_f(i, j)$.

3.3 Average gradient

We used the Sobel operator to calculate the gradient magnitudes in the images. For every pixel, its 3×3 neighboring pixels were chosen to form a window. In each window, the horizontal and vertical gradients of the central pixel were calculated, and then the gradient magnitude was obtained from those gradients.

$$G_x(i, j) = -1 \times T(i-1, j-1) + (-2) \times T(i-1, j) + (-1) \times T(i-1, j+1) + T(i+1, j-1) + 2 \times T(i+1, j) + T(i+1, j+1),$$

$$G_y(i, j) = -1 \times T(i-1, j-1) + (-2) \times T(i, j-1) + (-1) \times T(i+1, j-1) + T(i-1, j+1) + 2 \times T(i, j+1) + T(i+1, j+1),$$

$$GM(i, j) = \sqrt{G_x^2(i, j) + G_y^2(i, j)}. \quad (3)$$

Here, $G_x(i, j)$ and $G_y(i, j)$ indicate the horizontal and vertical gradients of pixel (i, j) in one image, $GM(i, j)$ is the corresponding gradient magnitude, and T represents one of the SST time series images.

Average gradient can reflect the long-term mean strength of a front. Compared with the gradient magnitude obtained from one single image, the average gradient can partially eliminate the influences of noise and missing data. For each pixel in the time series images, its frontal average gradient can be defined as:

$$G_f(i, j) = \frac{\sum_{s=1}^S GM(i, j, \mathbf{C}(s))}{|\{s, T(i, j, s) \in \mathbf{C}(s)\}|}, \text{ for } (i, j) \in \mathbf{I}, \quad (4)$$

where $G_f(i, j)$ stands for the frontal average gradient

Table 1 Distribution of front frequency for entire year

Frontal frequency range	Proportion (%)											
	January	February	March	April	May	June	July	August	September	October	November	December
[0,0.1]	91.32	89.59	89.68	91.53	93.83	97.03	98.46	98.67	97.91	96.47	94.18	93.07
(0.1,0.2]	7.14	8.64	8.95	7.81	5.83	2.87	1.48	1.27	1.99	3.37	5.16	5.86
(0.2,0.3]	1.31	1.51	1.14	0.61	0.3	0.09	0.05	0.05	0.08	0.15	0.58	0.93
(0.3,1]	0.23	0.26	0.23	0.05	0.04	0.01	0.01	0.01	0.02	0.01	0.08	0.14

of pixel (i, j) , and $GM(i, j, \mathbf{C}(s))$ is the gradient magnitude of pixel (i, j) if it is determined as a front pixel in the time series images.

Analogously, we introduce the non-frontal average gradient concept, as calculated by:

$$G_{\text{nf}}(i, j) = \frac{\sum_{s=1}^S GM(i, j, \bar{\mathbf{C}}(s))}{|\{s, T(i, j, s) \in \bar{\mathbf{C}}(s)\}|}, \text{ for } (i, j) \in \mathbf{I}, \quad (5)$$

where $G_{\text{nf}}(i, j)$ signifies the non-frontal average gradient of pixel (i, j) , and $GM(i, j, \bar{\mathbf{C}}(s))$ is the gradient magnitude of pixel (i, j) if it is determined as a non-front pixel in the time series images.

4 FRONT COMPOSITE ALGORITHM

Based on the aforementioned algorithms, we calculated the monthly mean frontal average gradients and frequencies of the Bohai, Yellow, and East China Seas from MODIS Terra nocturnal data from 2000–2013. Table 1 shows the distribution of frontal frequency for each month, divided into four ranges: 0–0.1, 0.1–0.2, 0.2–0.3, and 0.3–1. It can be seen that irrespective of month, the frequency is concentrated within the 0–0.1 range, i.e., this range accounts for >90% for each month. Hence, substantial frontal information might be missed if only frontal frequency were used.

To take greater advantage of the frontal average gradient and frequency, a new composite algorithm is proposed here. Based on the SIED algorithm, each pixel in the time series images was determined as a front or non-front pixel. Then, we calculated the frontal/non-frontal average gradient and frequency of this pixel. Based on these four parameters, we introduced a concept called the comprehensive gradient, which could be calculated as follows:

$$GC(i, j) = G_{\text{f}}(i, j) \times P_{\text{f}}(i, j) + G_{\text{nf}}(i, j) \times P_{\text{nf}}(i, j), \quad (6)$$

where $GC(i, j)$ represents the comprehensive gradient of pixel (i, j) .

Figure 3a–d shows maps of the long-term mean

frontal average gradient, frontal frequency, Miller's gradient, and comprehensive gradient, respectively, for the Bohai, Yellow, and East China Seas, using 4-km-resolution daily MODIS Terra data from January from 2000 to 2013. It can be seen that the LBLF in the Bohai Sea (indicated by the orange arrow in Fig.3d) is visible in the frontal average gradient image, hardly distinguishable in the frontal frequency image, but distinct in the comprehensive gradient map. In the Yellow Sea, although the frontal average gradient and frequency of the SPF (identified by the green arrow) are both large, the frontal strength in these two maps is not as great as in the comprehensive gradient map. The JF and YBRF can be observed better using the proposed algorithm, as indicated by the yellow arrows in Fig.3d. In the East China Sea, the ZFF is conspicuous in the frontal average gradient map but its frontal frequency is low; however, in the comprehensive gradient map, this front is more evident. The positions of the KF and TSF are both strengthened, as indicated by the red and white arrows, respectively. Compared with Miller's gradient, the fronts in the comprehensive gradient map are displayed better. For example, the ZFF appears a little discontinuous in Fig.3c but it is clearer and its shape more complete in Fig.3d. In particular, the LBLF and CF are unremarkable in Fig.3c but they can be observed clearly in the comprehensive gradient image.

Figure 4a–d shows the long-term mean maps of frontal average gradient, frontal frequency, Miller's gradient, and comprehensive gradient of the Bohai, Yellow, and East China Seas using 4-km-resolution daily MODIS Aqua data from January 2002–2013. Similar to the results obtained using the Terra data, the LBLF in the Bohai Sea is detected better in the comprehensive gradient map. In the Yellow Sea, although the SPF can be observed in both the frontal average gradient and frequency maps, the comprehensive gradient enhances its strength and makes it more distinct (Fig.4d). The approximate locations and shapes of the JF and YBRF can be seen

Fig.3 Long-term (2000–2013) mean maps

a. frontal gradient; b. frontal frequency; c. Miller's gradient; d. comprehensive gradient from Terra daily data in January (the parameters are normalized by variance and thus, they are dimensionless).

in the comprehensive gradient image. The frontal frequencies of the SF and CF are not very distinct, but their positions are more obvious using the proposed algorithm, especially the CF. In the East China Sea, the ZFF is identified better by the proposed algorithm, even though its frequency is unremarkable, and both the KF and TSF are strengthened somewhat. Similarly, comparison of Miller's gradient and the comprehensive

gradient shows the latter is better able to distinguish the shapes and continuities of the fronts. Additionally, the LBLF and CF, which are hardly discernible in the Miller's gradient map, are shown clearly in the comprehensive gradient map.

Analysis of the results from various data shows the proposed algorithm can exploit the advantages of the average gradient and frequency to distinguish the

Fig.4 Long-term (2002–2013) mean maps

a. frontal gradient; b. frontal frequency; c. Miller's gradient; d. comprehensive gradient from Aqua daily data in January (the parameters are normalized by variance and thus, they are dimensionless).

fronts better. Use of this algorithm can make fronts with small average gradients (e.g., the JF and YBRF) or low frontal frequencies (e.g., the ZFF) more obvious, and it can strengthen fronts whose average gradients and frequencies are both strong (e.g., the SPF). Hence, the proposed algorithm is demonstrated as more suitable than the previous one for representing the long-term variations of fronts.

5 FRONTS IN BOHAI, YELLOW, AND EAST CHINA SEAS

Using the proposed algorithm, we analyzed the monthly mean variations of fronts in the Bohai, Yellow, and East China Seas, based on 4-km-resolution daily MODIS Terra data from 2000–2013. The results are shown in Fig.5.

Fig.5 Long-term (2000–2013) mean maps of comprehensive gradient in the Bohai, Yellow and East China Seas

a. January; b. February; c. March; d. April; e. May; f. June; g. July; h. August; i. September; j. October; k. November; l. December (the comprehensive gradient is normalized by variance and thus, it is dimensionless).

To be continued

Fig.5 Continued

5.1 Bohai Sea

There are two main fronts in the Bohai Sea: the LBLF and BSF.

(1) Spring (March through May). Fronts are not obvious. In March, the presence of part of the LBLF at the tops of the Liaodong, Bohai, and Laizhou bays is somewhat remarkable and the front distribution is sparse. In April, no front is evident in this area. In May, the LBLF is a little stronger and the front in Laizhou Bay is linked to the SPF.

(2) Summer (June through August). In June, the LBLF is obvious and it presents a C-shaped curve linked to the BSF. In July, the BSF and part of the LBLF located at the top and eastern side of Liaodong Bay are obvious. In August, all these fronts are strengthened and interlinked, forming a ring shape.

(3) Autumn (September through November). In September, the LBLF appears a little sparse. The BSF is distinct and linked to the northern part of the SF. In October, only the fronts at the top and western side of Liaodong Bay and those in Bohai Bay are strong. In November, fronts are only observable in the western side of Liaodong Bay.

(4) Winter (December through February). The LBLF and BSF are both strong. In this Season, part of the LBLF located on the western side of Liaodong Bay is remarkable. The BSF is also obvious in this Season and it is most complete and apparent in February.

5.2 Yellow Sea

There are roughly six main fronts in the Yellow Sea, the SPF, JF, and YBRF and from north to south

on the western side of the Korean Peninsula, the SF, KBF, and CF.

(1) Spring. In March, only part of the SPF surrounding the upper Shandong Peninsula is evident. The YBRF in the middle of the Yellow Sea is distinct and its shape defined as a semi-enclosed loop with an opening to the northwest. The SF and CF are completely visible. Although part of the KBF can be seen, its strength is not strong. In April, all the fronts in the area are indistinct; however, they are strengthened in May. The SPF located near the northern and southern parts of Shandong Peninsula is distinct. In addition, the SF, KBF, and CF are relatively complete.

(2) Summer. In June, the SPF, SF, KBF, and CF are relatively complete. The JF gradually strengthens with a shape that represents a curve with an opening to the southwest; however, the SPF largely disappears. In May, the JF, SF, KBF, and CF are all weaker but they remain observable and then, they all strengthen and have shapes that are more complete in August.

(3) Autumn. In September, part of the JF can be seen. The SF, KBF, and CF are all linked around the Korean Peninsula. The results in October and November are similar and the SF, CF, JF, and YBRF are conspicuous in these two months. The SPF lies mainly to the south of Shandong Peninsula.

(4) Winter. All fronts are strengthened. The SPF is complete and it surrounds Shandong Peninsula. The JF and YBRF gradually strengthen, reaching their strongest intensity in February. The SF and CF are clear along their lengths and the KBF turns from weak to strong.

5.3 East China Sea

In the East China Sea, the main fronts are the ZFF, TSF, and KF.

(1) Spring. The strength of fronts initially turns from strong to weak and then becomes strong again. In March, the ZFF, TSF, and KF are obvious; however, in April, although the locations of these three fronts are discernible, they are generally weak. In May, the ZFF starts south of the mouth of the Yangtze River and extends along the coast to the Taiwan Strait, where it links with the TSF. Compared with April, the KF is stronger in May.

(2) Summer. The fronts are unremarkable in this Season. In June and July, only the TSF is obvious and the ZFF and KF are so weak as to be undetected. In August, the ZFF and TSF become more obvious and the KF is observed only in the area to the northeast of Taiwan.

(3) Autumn. In September, it is possible to see the KF to the northeast of Taiwan, the ZFF south of the mouth of the Yangtze River, and the complete TSF. The fronts are weak in October and November, except the ZFF, which is distinct only in November.

(4) Winter. In February, the fronts are the most obvious of the entire year. The ZFF extends along the Chinese mainland to the Taiwan Strait where it is linked to the TSF. The KF becomes more obvious and in February, it presents its most complete shape.

6 CONCLUSION

Because a single frontal average gradient or frequency cannot completely reflect the temporal variability of fronts, a new SST composite algorithm, based on these two parameters, was proposed in this paper. With the use of the SIED algorithm, it was possible to determine whether a cloud-free pixel in the time series images was a front or non-front pixel. From this, it was possible to calculate four basic parameters for the given pixel: front average gradient, non-front average gradient, front frequency, and non-front frequency. According to Eq.6, the comprehensive gradient for that pixel could be obtained. Based on this, the comprehensive gradient map could be acquired. Through comparison between the long-term mean maps of the frontal average gradient, frontal frequency, Miller's gradient, and comprehensive gradient from MODIS Terra and Aqua data, the algorithm was validated as better suited than the original method for reflecting frontal changes.

Using the algorithm, we analyzed the monthly

mean variations of the fronts in the Bohai, Yellow, and East China Seas, based on daily 4-km nocturnal Terra data from 2000 to 2013, and found the following:

(1) Strengthening of the fronts in the Bohai Sea begins in August, although they might become weak in October and November. Beginning in March, fronts start to weaken. Hence, in autumn and winter, the fronts are obvious but they are indistinct in spring and summer;

(2) The SF exists almost throughout the entire year and it is found mainly at the top of Seohan Bay. The KBF and CF are weak in summer and strengthen in autumn and winter. Beginning in May, the JF can be observed and it reaches its maximum strength in July and August. The YBRF is obvious in winter and becomes most remarkable in February;

(3) The KF is weak in summer and gradually turns into a strong front from autumn to winter. The ZFF is weak in spring and summer but it becomes obvious beginning in the autumn, eventually becoming complete in winter. The weakest period of the TSF is spring and, in summer through winter, this front can be seen in the comprehensive gradient image.

7 ACKNOWLEDGEMENT

The authors would like to thank Wuhan University and the Institute of Geographic Sciences and Natural Resources Research for their support. The authors also express their appreciation to Prof. Peter Cornillon of the University of Rhode Island for his advice and technical support.

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