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Detection of mesoscale thermal fronts from 4 km data using smoothing techniques: Gradient-based fronts classification and basin scale application

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ABSTRACT

In order to optimize frontal detection in sea surface temperature fields at 4 km resolution, a combined statistical and expert-based approach is applied to test different spatial smoothing of the data prior to the detection process. Fronts are usually detected at 1 km resolution using the histogram-based, single image edge detection (SIED) algorithm developed by Cayula and Cornillon in 1992, with a standard preliminary smoothing using a median filter and a 3 × 3 pixel kernel. Here, detections are performed in three study regions (off Morocco, the Mozambique Channel, and north-western Australia) and across the Indian Ocean basin using the combination of multiple windows (CMW) method developed by Nieto, Demarcq and McClatchie in 2012 which improves on the original Cayula and Cornillon algorithm. Detections at 4 km and 1 km of resolution are compared.

Fronts are divided in two intensity classes ("weak" and "strong") according to their thermal gradient. A preliminary smoothing is applied prior to the detection using different convolutions: three type of filters (median, average and Gaussian) combined with four kernel sizes (3 × 3, 5 × 5, 7 × 7, and 9 × 9 pixels) and three detection window sizes (16 × 16, 24 × 24 and 32 × 32 pixels) to test the effect of these smoothing combinations on reducing the background noise of the data and therefore on improving the frontal detection. The performance of the combinations on 4 km data are evaluated using two criteria: detection efficiency and front length. We find that the optimal combination of preliminary smoothing parameters in enhancing detection efficiency and preserving front length includes a median filter, a 16 × 16 pixel window size, and a 5 × 5 pixel kernel for strong fronts and a 7 × 7 pixel kernel for weak fronts. Results show an improvement in detection performance (from largest to smallest window size) of 71% for strong fronts and 120% for weak fronts. Despite the small window used (16 × 16 pixels), the length of the fronts has been preserved relative to that found with 1 km data.

This optimal preliminary smoothing and the CMW detection algorithm on 4 km sea surface temperature data are then used to describe the spatial distribution of the monthly frequencies of occurrence for both strong and weak fronts across the Indian Ocean basin. In general strong fronts are observed in coastal areas whereas weak fronts, with some seasonal exceptions, are mainly located in the open ocean.

This study shows that adequate noise reduction done by a preliminary smoothing of the data considerably improves the frontal detection efficiency as well as the global quality of the results. Consequently, the use of 4 km data enables frontal detections similar to 1 km (using a standard median 3 × 3 convolution) in terms of detectability, length and location. This method, using 4 km data is easily applicable to large regions or at the global scale with far less constraints of data manipulation and processing time relative to 1 km data.

1. Introduction

Fronts are constitutive elements of almost all spatial structures observed at the ocean surface worldwide. These boundaries are equally as important in characterizing the epipelagic environment as continuous surface descriptors, such as temperature, salinity and ocean color. Fronts are primarily driven by physical displacements of surface waters; thus, sea surface temperature (SST) is by far the parameter by which fronts are most often detected. Synoptic satellite observations enable fronts to be identified at regional or even basin scale, according to data processing capabilities.

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There are two primary methods by which fronts are detected: the gradient-based approach and the histogram-based approach. The Canny operator (Canny, 1986) is the most commonly used gradient-based method. In general, this method applies an upper gradient threshold to identify a pixel as an edge and a lower threshold to discard it. If the pixel gradients are between both thresholds, only the pixels that are closest to the upper threshold are marked as an edge (i.e., skeletonization). The histogram-based approach detects the limit that divides two distinct pixel populations. The most commonly used method for this approach is the single edge detection algorithm (SIED) developed by Cayula and Cornillon (1992) that is based on a bimodal histogram of two water masses.

The SIED is developed in two main axes: the identification and correction of clouds and the edge detection itself. Prior to the detections, this method requires a standard preliminary smoothing of the images (generally using 1 km SST data), consisting of a 3 × 3 median filter in order to reduce the local noise. The detection process includes a division of the image into fixed windows of size 32 × 32 pixels, in which the algorithm searches for fronts. The algorithm examines the spatial properties of the SST field in each window to investigate the presence of a thermal limit between two water masses. Specifically, a SST histogram is computed from each window and tested for significant bimodality to determine if a frontal edge is present. Three internal parameters are defined by the SIED to formally identify a front: 1) the spatial cohesion threshold, $\theta = 0.90$, to test the bimodality, 2) the signal-to-noise ratio, $S = 4$, related to a maximum error probability and 3) the population threshold, $P_{wi} \geq 0.25$, that represents the minimum size ratio between water populations. The last stage of the analysis, termed the "following algorithm", joins contours that are slightly separated (Cayula & Cornillon, 1992).

Since 1992, many studies have developed upon the original Cayula and Cornillon method. In 1995, Cayula and Cornillon themselves applied their previous SIED algorithm to a sequence of SST images to develop the multi-image edge detector (MIED) method that simultaneously detects weaker fronts and improves the elimination of false detections.

Ullman and Cornillon (2000) evaluated different gradient-based and histogram-based edge detection algorithms using Advanced Very High Resolution Radiometer SST data and compared their results with SST fronts obtained from in situ data. They tested false front detections and failures to detect fronts and concluded that the false front error rates were less important for the SIED than for gradient-based method. They suggested that SIED frontal detection algorithm can be useful in providing accurate statistics of front occurrence at scales >10 km, but that gradient-based methods were more accurate at scales <10 km. Ullman and Cornillon (2001) then applied the MIED algorithm to 12 years of SST images, revealing the presence of persistent fronts off the northeast US coast.

Diehl, Budd, Ullman, and Cayula (2002) investigated an approach using "geographic window sizes" (window size is determined by the correlation of the data surrounding the window's central point) to avoid the limitation of the unique window size used by the SIED algorithm. They found that front detection is improved where fronts are smaller or more dense, mostly in coastal regions, but at a cost of a complex data re-composition.

In terms of expanding the SIED to other data types, Miller (2004, 2009a) was among the first to apply the SIED to Sea-viewing Wide Field-of-view Sensor data to detect chlorophyll-*a* (Chla) fronts and boundaries of suspended matter. He combined these with SST fronts to describe the physical and biological interactions involved in coastal areas under tidal influence.

Using Chla data, Wall et al. (2008) applied a gradient-based and a histogram-based algorithm on the coastal waters off Florida, combining 32 × 32 and 16 × 16 pixel detection windows and modifying some SIED parameters. They found that the gradient-based algorithm was better at identifying near-shore Chla fronts than weaker offshore fronts.

More recently, Nieto, Demarcq, and McClatchie (2012) proposed an improved implementation of the Cayula and Cornillon (1992) algorithm termed the combination of multiple windows (CMW), initially applied to 1 km SST data. This method, used in the present study, applies grids of frontal detection in the x and y directions that overlap by half their size in order to overcome the edge effect of the original SIED algorithm, whose detection efficiency decreases towards the edges of the windows. This method provides huge improvements from the standard Cayula and Cornillon SIED approach in terms of both edge detection (140%) and front length (30%).

Prior to the detection of fronts, a pre-processing of the data based on smoothing filters is needed in order to remove the noise introduced by the sensor and the uncorrected atmospheric effects. The smoothing procedure helps to preserve valid information from the original noise (the high frequency signal in the spatial domain) by improving the quality of the subsequent frontal detection. At the same time, the selection of an adequate window size is critical for the performance of the detection. All methods based on SIED have been almost exclusively applied to 1 km data (and mostly SST data) that facilitates the tuning of the algorithm and supplies the most detailed and accurate results. They generally use similar preliminary smoothing methods (a median filter with a 3 × 3 kernel) and the 32 × 32 pixel window. Table 1 summarizes the data resolution, preliminary smoothing and internal parameters used by several authors in the application of the SIED method. The only study known to us that uses a different smoothing method is that by Belkin and O'Reilly (2009). This study applied a median filter that considers a small window (3 × 3 pixels) within a larger one (5 × 5 pixels) before the detection process applied to both SST and Chla data.

The objective of our study is to define an adequate pre-processing procedure to detect fronts using 4 km data without losing relevant information (e.g., general patterns, detection of weak fronts, coherence of detections, and length). The considerable advantage of such upscaling is the ability to process data at the basin or global scale, minimizing processing time and avoiding data handling constraints.

Thus, we extensively test frontal detections made with different combinations of preliminary smoothing parameters, including median, average, and Gaussian filters at four different kernel sizes (i.e., 3 × 3, 5 × 5, 7 × 7, and 9 × 9 pixels) and using different detection window sizes (16 × 16, 24 × 24, and 32 × 32 pixels). We aim to propose a new conditional smoothing method that maximizes edge detection quality from 4 km data.

We then perform a classification of the fronts at the basin scale, based on the intensity of their thermal gradient. The resulting patterns are described in particular for coastal and offshore regions, highlighting some oceanographic processes.

It is important to note that while we do not validate our frontal detections with in-situ measurements, we test the performance of the contextual smoothing method using 4 km data and consider all fronts that are detected to be real.

2. Methods

2.1. Satellite data

Daily 1 km and 4 km SST fields are obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) of the Aqua platform, for the period between 2002 and 2011 (http://oceancolor.gsfc.nasa.gov/). Another data set of 2 km resolution is sampled from 1 km data in order to analyze the variability of the frontal gradients according to different spatial resolutions (i.e., 1, 2 and 4 km). The quality flags available for 4 km (i.e., 0, 1, 2) are tested to evaluate their effect on the detection of frontal structures. Flag 0 gathers initial detectability tests that are considered as a minimal requirement for pixels without cloud cover. Since flags 1 and 2 include a threshold that masks the highest SST gradients along with cloud borders, only flag 0 is kept.