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A comparison of satellite-derived sea surface temperature fronts using two edge detection algorithms

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ABSTRACT

Satellite-derived sea surface temperature (SST) fronts provide a valuable resource for the study of oceanic fronts. Two edge detection algorithms designed specifically to detect fronts in satellite-derived SST fields are compared: the histogram-based algorithm of Cayula and Cornillon (1992, 1995) and the entropy-based algorithm of Shimada et al. (2005). The algorithms were applied to 4 months (July and August for both 1995 and 1996) of SST fields and the results are compared with SST data taken by the *M.V. Oleander*, a container ship that makes weekly transits between New York and Bermuda. There is no significant difference in front pixels found with the Cayula-Cornillon algorithm and those found in the in situ (Oleander) data. Furthermore, for strong fronts, with gradients greater than 0.2 K/km, the distribution of fronts found with the Shimada et al. algorithm is quite similar to that of fronts found with the Cayula-Cornillon algorithm. However, there are significant differences in the number of weak fronts found. This is seen clearly in waters south of the Gulf Stream where the gradient magnitude of fronts found is less than 0.1 K/km. In this region, the probability that the Shimada et al. algorithm detects a front rarely falls below 4% while neither the Cayula-Cornillon algorithm applied to the satellite-derived SST fields nor the gradient-based algorithm applied to the *Oleander* temperature time series find fronts more than 1% of the time. These results raise the question of exactly what qualifies as an SST front, a classic problem in edge detection.

1. Introduction

Oceanic fronts can be defined as relatively narrow zones in which the gradient of a given property is large compared to its background gradient in the region. Although not explicitly defined as gradients in the horizontal, or near horizontal, these are generally the gradients that one thinks of in the context of fronts. Fronts often correspond to boundaries between different water masses or to large shears in currents although other processes may give rise to fronts as well, e.g., a boundary between different vertical mixing regimes on the continental shelf. Of interest in this paper are enhanced horizontal gradients of temperature, specifically, sea surface temperature (SST) fronts.

With the broad availability of satellite-derived SST fields, there has been significant effort devoted to the development of front-detection algorithms – automated methods for detecting fronts in these fields – and to the use of the resulting front data sets in scientific investigations. Front-detection algorithms fall into several categories, three of which are relevant here: gradient algorithms (Moore et al., 1997), histogram algorithms (Cayula and Cornillon, 1992, 1995; CCA, referring to the Cayula-Cornillon Algorithm, hereafter), and entropy algorithms (Vazquez et al., 1999; Shimada et al., 2005; SEA, referring to the Shimada Entropy Algorithm, hereafter). These algorithms have been applied to thermal fronts in marginal seas (Hickox et al., 2000; Wang et al., 2001; Belkin and Cornillon, 2003) as well as open ocean regions (Ullman et al., 2007; Belkin et al., 2009). Several studies have also presented new views of oceanic fronts in coastal and regional seas, such as Ullman and Cornillon (1999) who applied the CCA to the northeastern coast of the US, and Shimada et al. (2005) and Chang et al. (2006, 2010) who applied SEA to the Japanese coast and northern South China Sea. Interestingly, the West Luzon Front detected by CCA in Belkin and Cornillon (2003) and by SEA in Chang et al. (2010) was not detected by Wang et al. (2001) in their application of a gradient based algorithm to SST fields of the northern South China Sea. This suggests that the gradient based approach may not be appropriate for the detection of SST fronts in regions of weak SST gradients (Chang et al., 2010).

When applying automated algorithms of front detection to satellite images, it is important to verify these methods. Ullman and Cornillon (2000) used SST fronts detected in along-track ship data to evaluate CCA detected fronts in satellite-derived fields. Fronts were identified in the in situ data based on along-track SST gradients. In this paper, we compare CCA and SEA detected fronts

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in satellite-derived SST fields with one another and with fronts detected from continuous temperature measurements conducted from a merchant ship in transit between New York and Bermuda, the same basic data set used by Ullman and Cornillon (2000). We do not include comparison with a gradient based algorithm applied to the satellite-derived SST fields because this was dealt with in detail in Ullman and Cornillon (2000). The result of that analysis was that the gradient based algorithm found false fronts at roughly twice the rate that CCA did.

2. Data and methods

Full resolution (1.2 km) July and August SST fields from both 1995 and 1996 were used for this study. These fields were derived from the level 2b (L2b)[1] Advanced Very High Resolution Radiometer (AVHRR) data in the University of Miami/University of Rhode Island (URI) archive with version 5.0 of the National Oceanic and Atmospheric Administration (NOAA)/National Aeronautics and Space Administration (NASA) Pathfinder algorithm (Smith et al., 1996). Data in the archive cover the waters off the northeastern coast of the United States and the southeastern coast of Canada, east to approximately 40°W. Following retrieval to L2b, the 2–4 passes available per day were manually navigated to within 1 pixel, ~1.1 km at nadir. The fields were then remapped to an equirectangular projection (L3) with 1.2 km pixel spacing at the image center, 38°N 70°W. Remapping from L2b was performed using the nearest neighbor L2b pixel to the target L3 pixel. The study area used for this project (Fig. 1), 78–63°W and 31–43°N, was extracted from these fields. Cloud removal was performed using the URI multi-image cloud detection algorithm described in Ullman and Cornillon (1999). Detection of fronts in declouded SST images was performed using both the CCA and SEA methods. Brief descriptions of these are given below. More detailed descriptions are available in the original references (Cayula and Cornillon, 1992, 1995 for CCA; Vazquez et al., 1999 and Shimada et al., 2005 for SEA).

2.1. Front detection using satellite-derived data

The Cayula-Cornillon algorithm (CCA) used in this study is the multi-image version of the original multi-image edge detection algorithm developed at URI. In the first step, the SST fields are median filtered with a 3 × 3 (3.6 × 3.6 km^2) kernel to reduce noise in the field. This provides for a sharper separation of peaks corresponding to different water masses in the histograms used in the next step. Reducing the noise in the image is also beneficial in the contour following step. In the second step, the single image edge detector (SIED) is applied to each image in the time series. The SIED performs a set of statistical tests on histograms of the temperature field in a moving $n \times n$ (32 × 32 in this study) pixel window to identify candidate front pixels. It then descends to the pixel level and follows contours identified by the candidate front pixels. Segments shorter than m (10 in this study) pixels are subsequently eliminated from consideration. A second pass is then made over the images in the archive. First a zero-one image, initialized to zero, is formed in which each pixel flagged as a front pixel in any image within n (60 in this study) hours of the given image, excluding the image of interest, is set to one. (It is important to note that the window used here does not exclude shorter time scale fronts; any front found in any of the adjacent images is included. Furthermore, this step is used to 'help' the algorithm find fronts in areas partially contaminated by clouds, it does not eliminate fronts.) The resulting image is then thinned, based on the local SST gradient, to lines one pixel wide. In the last step, the SIED algorithm is applied a second time to each image in the archive, but this time it uses the thinned persistent fronts associated with that image in the contour following step along with candidate pixels found in the analysis of histograms in the image. Fig. 2B shows fronts resulting from this procedure for the AVHRR-derived SST field shown in A.

The Shimada et al. algorithm is specifically designed for finer-scale front detection at full image resolution of 1.2 km (Shimada et al., 2005). As typically employed, the original SST fields are not filtered prior to application of this algorithm. However, for comparison with CCA, SEA has been applied to both the original data, as is normally done, and to the 3 × 3 median filtered version of the data. Edge detection begins with an estimate of the Jensen-Shannon divergence in SST in two 5 × 5 pixel subwindows in four directions (shown in Fig. 3 of Shimada et al. (2005)). A composite matrix is built from the four Jensen–Shannon divergences, and the maximum value is taken as the final divergence value to be assigned to each pixel. If this value exceeds 0.6 then the pixel is designated a front pixel. Finally, a thinning algorithm is applied to obtain pixel wide frontal segments. The results, again for the SST field in Fig. 2A, are shown in C for the unfiltered SST field and in E for the 3 × 3 median filtered field. However, in order to compare this with CCA derived fronts, frontal segments shorter than 10 pixels are removed from further comparisons. These fronts are shown in Fig. 2D and F. Following front-detection, the SST gradient was calculated at each front pixel resulting from each of the two algorithms using the Prewitt operator to obtain the latitudinal and longitudinal gradient components. The gradient magnitude, $|T_S|$ where T_S is SST, was determined from the Prewitt components.

2.2. Processing of ship measurements

Comprehensive validation of the Cayula-Cornillon algorithm for satellite-derived SST images using in situ data is described by Ullman and Cornillon (2000). In this study we compare SEA and CCA detected fronts with fronts detected in continuous ocean temperature measurements made from the container vessel *M.V. Oleander* (*Oleander* in the remainder), which regularly navigates between Port Elizabeth, NJ and Bermuda. The mean ship track is superimposed on Fig. 1 (black line). The *Oleander* temperature data were measured by a flow system at a depth of between 5 and 6 m sampled every 15 s, a corresponding spatial sampling of approximately 110 m at a ship speed of 15 knots. For comparison with the AVHRR data, the *Oleander* data were averaged to a 1.2 km spacing along the ship's track. SST fronts in the *Oleander* data were identified by their along-track gradient as described in Ullman and Cornillon (2000). Specifically, an along-track location was defined as a front if one of the two criteria was met. (1) The SST gradient magnitude exceeded 0.2 K/km or (2) SST gradient magnitude exceeded 0.1 K/km and the gradient magnitude at the along-track location was five times larger than the mean gradient magnitude averaged over a 70 km section centered on the point of interest – the definition of a front used by Fedorov (1986). For the comparisons undertaken in this study, only satellite-derived SST fronts intersecting a ship track within 6 h of the passage of the ship were selected for further analyses.

3. Results

3.1. SST front probability and mean gradient maps

Monthly composite maps of front probability were produced from the fronts detected in the individual satellite-derived images for June to August in both 1995 and 1996. Front probability at

[1] We use the NASA designation for data processing levels: http://science.nasa.gov/earthscience/earth-science-data/data-processing-levels-for-eosdis-data-products/.