A SIMPLE AND EFFICIENT APPROACH FOR COARSE SEGMENTATION OF MOROCCAN COASTAL UPWELLING

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ABSTRACT

In this work, we aim to develop a simple and fast algorithm using conventional methods in images segmentation for the automatic detection and extraction of upwelling areas, in the coastal region of Morocco, from the sea surface temperature (SST) satellite images. Our approach is based on the evaluation and comparison between two unsupervised classification methods, Otsu and Fuzzy C-means, and explores the applicability of these methods to our classification problem. The latter consists in coarse detection of the main thermal front that separates coastal cold upwelling waters from the remaining ocean waters. The algorithm has been applied and validated by an oceanographer over a database of 66 SST images corresponding to southern Moroccan coastal upwelling of the years 2004, 2005, 2007 and 2009. The results indicate that the proposed algorithm revealed is promising and reliable on different upwelling scenarios and for a wide variety of oceanographic conditions.

Index Terms— Upwelling, sea surface temperature, unsupervised classification, segmentation.

1. INTRODUCTION

The detection and monitoring of coastal upwelling using sea surface temperature images is necessary for many applications, not only to study the oceanic circulation but also in fisheries management and exploitation [1]. In particular, the AVHRR thermal infrared images are frequently used to track and study the main thermal upwelling front between the cold waters near the coast and warmer offshore waters [2].

When the northeasterly wind persists along the Moroccan coastline, upwelling takes place at the surface, which is characterized by the presence of colder and nutrient-rich waters over the whole shelf. The coastal region of Morocco is considered one of the four regions in the world that are affected by this phenomenon, making them rich in fishery resources [3]. In fact, the evolution of the pelagic ecosystem of this region is influenced by the high dynamics and variability in space and time of this phenomenon largely dependent on the winds regime changes. Usually, the detection of upwelling areas has been made using color scale map for each image, which is very time consuming when the number of images increases. To overcome these problems, it is necessary to develop automatic tools for the upwelling detection from satellite images.

In upwelling detection, many techniques and methods have been proposed, in order to detect the upwelling areas delimited by the main thermal front separating the cold water near the coast and the remaining water. Some methods such as in [4] and [5] provide a good upwelling segmentations, but they requires a complex pre-processing step. In [6] a neural network is used to label the original SST images and statistical information is gathered form each cluter in order to determine the presence of upwelling. More recently, the fuzzy C-means segmentation [2] was used to identifies the thermal upwelling front and sub-upwelling fronts on the coast of Portugal. The method starts by using the Iterative Anomalous Pattern (IAP) algorithm [7] that automatically determines the numbers of clusters in each image.

In this paper, we are not interested in a precise segmentation of the upwelling and sub-upwelling fronts as in [2], but rather in a coarse segmentation of the main upwelling front separating the cold water near the coast and warmer offshore waters, which concentrates particles and forms privileged areas of high biological activity as pointed out by Bakun [8]. We are also interested in developing a fast algorithm in order to efficiently process large amount of SST images. To achieve our goal, we follow the same philosophy as in [2] but we do not use the IAP algorithm. The encouraging results we obtain lead us to consider an even more efficient method, the classical Otsu method [9] , which we show that it yields similar performances.

The paper is organized as follows, in section 2 we present the database we use and the geographic area of study. Section 3 describes the methodology we propose. Results analysis of the proposed algorithm are showed and discussed in section 4. Conclusions and future work are presented in section 5.

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2. STUDY AREA AND DATA

The database used in this work is composed of 66 AVHRR thermal infrared images, covering the southern part of the Moroccan Atlantic coast during 4 years (2004, 2005, 2007 and 2009). The 20 first daily images were selected randomly between the years 2004, 2005 and 2009. The weekly second set is composed of 46 images covering the year 2007. The rational for using the time weekly synthetic products is that only the maximum pixels values in 8 daily images is retained based on the maximum value composite procedure [10]. This approach allows both, eliminating a maximum number of pixels contaminated by clouds and reducing the large number of images daily processed.

All data used in this study were received and processed at the Royal Centre for Remote Sensing (CRTS) of Morocco, including geometric, radiometric and atmospheric corrections, and generation of land and cloud masks.

Each SST image is represented by 714x750 pixels, spans from 20.51- 27.52°N, with a spatial resolution of 1.1 km and each pixel being a temperature in degree Celsius. A 26 color scale levels was applied to each image in order to help the oceanographers for visual inspection and easily identify the main thermal upwelling front, which is characterized by strong color variations, separating the two water masses (upwelling and no upwelling).

The two selected images in Fig. 1 represent different scenarios of the upwelling in our benchmark : well-defined upwelling with a continuity along the coast (Fig. 1(a)), and an upwelling where the presence of cloud and missing data in some regions on the image affects the structures and continuity of the upwelling along the coast. (Fig. 1(b)).

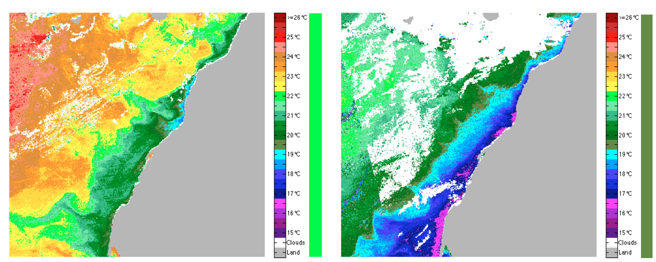
The second color bar on right sides in Fig. 1(a) and Fig. 1(b) corresponds to the annotation made by the oceanographer, indicating the color of the upwelling front separating cold waters near the coast from the warmer oceanic waters. For example, this front corresponds to a temperature of 22°C in Fig. 1(a).

3. SEGMENTATION METHODOLOGY

Clustering, also known as unsupervised classification, aims at classifying objects according to similarities among them, and organizing data into groups. The existing clustering methods can be grouped according to whether the data memberships are soft (fuzzy clustering) [11] [12] or crisp (hard clustering) [13] [14]. Hard clustering methods are based on classical set theory, where each object belongs to one cluster, and the data is divided into distinct clusters c. Fuzzy clustering methods allow each object to belong to several clusters, with different degrees of membership. The data set is thus partitioned into c fuzzy clusters.

In unsupervised classification [15], the number of clusters c is rarely known a priori and has to be chosen with great care in order to have the optimal number of classes, which represents different homogeneous clusters in images. Many criteria have been developed for automatic determination of the appropriate number of clusters [16] [17] which better fits the data. In general, the optimal number of clusters is calculated by using validity indices for several values of c and then evaluate the goodness of the obtained c-partition. The main limitations of these indices is that they can be very time consuming for large datasets. This is the case of the IAP algorithm [7] used in [2]. In this work, we are entirely focused on the identification of the main thermal upwelling front, which separates the cold upwelling waters near the coast from the warmer oceanic waters in offshores. We are not interested (at this moment) in the segmentation of sub-upwelling fronts as in [2].

Due to the nature of our study area, covering the southern part of Moroccan Atlantic coast, characterized by a strong and variable upwelling throughout the year, and our will to develop a fast segmentation algorithm, we thus set the number of clusters to 2 (c=2) and we proceed to check whether the method in [2] can yield satisfactory segmentation results to identifies the areas covered by upwelling waters on a SST image. This way we avoid the over computational burden of the IAP algorithm and the method in [2] collapses to fuzzy C-means (FCM) classification. Moreover, in order to potentially develop a faster algorithm, we compare FCM with the classical classification method proposed by Otsu [9]. The latter has indeed the advantage to be highly efficient when the number of classes is 2: $O(L)$ where L is the size of the support of data histogram, while FCM has a complexity of $O(N)$ [18], where N is number of data points. In the following two sub-sections we briefly recall the FCM and Otsu algorithms.



(a) (b)

Fig. 1: SST images obtained on (a) 07/29/2005, (b) 13/05/2005, showing the two upwelling scenarios, with oceanographers annotation in right sides.

3.1. Fuzzy C-means algorithm : Fuzzy clustering

Based on the temperature value of each pixel, the SST image is converted into a feature vector $X = \{x_1, x_2, ..., x_N\}$ of N pixels. Thereafter, fuzzy C-means algorithm (FCM) is applied to minimize an objective function. A commonly used object function is the within cluster error [19] [20]:

$$J(X;U,V) = \sum_{i=1}^{c}\sum_{k=1}^{N}(\mu_{ik})^m ||x_k - v_i||^2, \tag{1}$$

where X is the dataset and c is the number of clusters; N and v are respectively, the number of points in the dataset and clusters centroids. $U = [\mu_{ij}]$ represents the fuzzy partition matrix and $||x_k - v_i||$ is the Euclidean norm. The weighting exponent m controls the fuzziness of membership of each point and has been set to $m = 2$.
Statistically, (1) can be seen as a measure of the total variance of x_k from v_i. The minimization of the objective function (1) represents a nonlinear optimization problem that can be solved by using respectively the following cluster centroids and membership functions :

$$v_i = \frac{\sum_{j=1}^{N}(\mu_{ij})^m \, x_j}{\sum_{j=1}^{N}(\mu_{ij})^m}, \, 1 \leqslant i \leqslant c \tag{2}$$

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}(\frac{||x_k - v_i||}{||x_k - v_j||})^{\frac{2}{(m-1)}}}, \, 1 \leqslant i \leqslant c \, , 1 \leqslant k \leqslant N \tag{3}$$

The goal of FCM is to iteratively improve a sequence of sets of fuzzy clusters by a simple iteration through (2) and (3) until no further improvement in equation (1) is possible.

3.2. Otsu algorithm : Hard clustering

The Otsu's algorithm, that we call Otsu, is a thresholding method based on the automatic selection of the optimal threshold t^* from the gray-level histogram of an image that maximizes the between-class variance [9]. Otsu defines the between-class variance using discriminant analysis based on statistics of the one-dimensional histogram [21],

$$\sigma_B^2(t) = \omega_1(\mu_1 - \mu_T)^2 + \omega_2(\mu_2 - \mu_T)^2, \tag{4}$$

where μ_T is the mean intensity of the whole image. In Eq. (4) $\omega_1 = \sum_{i=1}^{t} p_i$ and $\omega_2 = \sum_{i=t+1}^{L} p_i$ represent respectively the zeroth-order cumulative moment of the 1^{st} and 2^{nd} classe, where L is the length of gray-level histogram. $\mu_1 = \sum_{i=1}^{t} \frac{ip_i}{\omega_1}$ and $\mu_2 = \sum_{i=t+1}^{L} \frac{ip_i}{\omega_2}$ are the first-order cumulative moment of the 1^{st} and 2^{nd} classe, respectively.

The optimal threshold t^* is chosen so that maximizing the between-class variance:

$$t^* = arg\,max\{\sigma_B^2(t)\} \tag{5}$$

3.3. Region growing process

We applied the two unsupervised clustering methods described above to our database. For each SST image, we (first) define the upwelling region as the cluster with the lowest mean value. A systematic result of this binary thresholding is the addition, to areas covered by upwelling, of non-upwelling pixels/regions due to the presence of isolated cold waters and cloud pixels not properly masked by the cloud mask method (Fig. 2(a) and Fig. 2(b)). There exists several techniques that address the problem of noisy structures. The most popular ones are morphological operators [22] [23] [5].
Unfortunately, these operators could not remove the big isolated structures present in our images. Thus, and based on the fact that all the segmented pixels pertaining to the upwelling must have connectivity with the coastline, we used the region growing process [24], using three seed points near the coastline which are known to correspond to upwelling sources. This method aims at grouping a set of pixels according to homogeneity and adjacency criteria. In our study, we have chosed 8-connected neighborhood for the adjacency criteria. While for homogeneity, since we apply the region growing process on a binary image, the stop condition is the value 0.
The result of region growing algorithm is presented in Fig. 2, showing its effectiveness to remove spatial isolated pixels, not belonging to coastal upwelling.

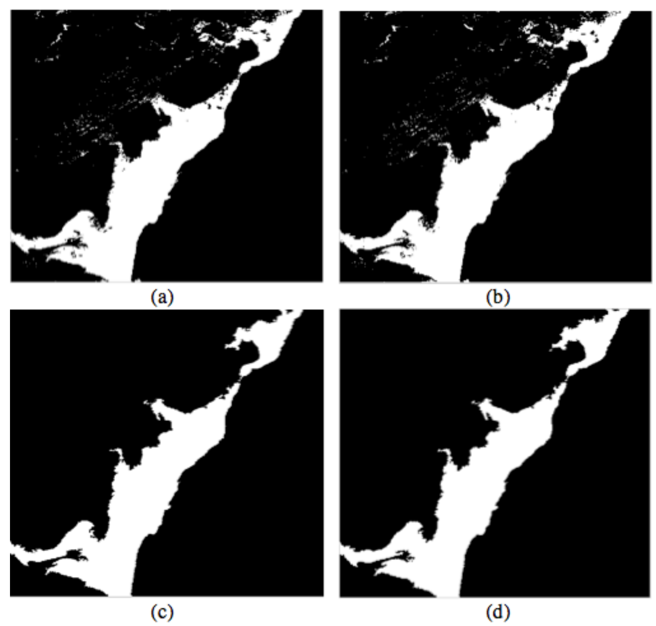
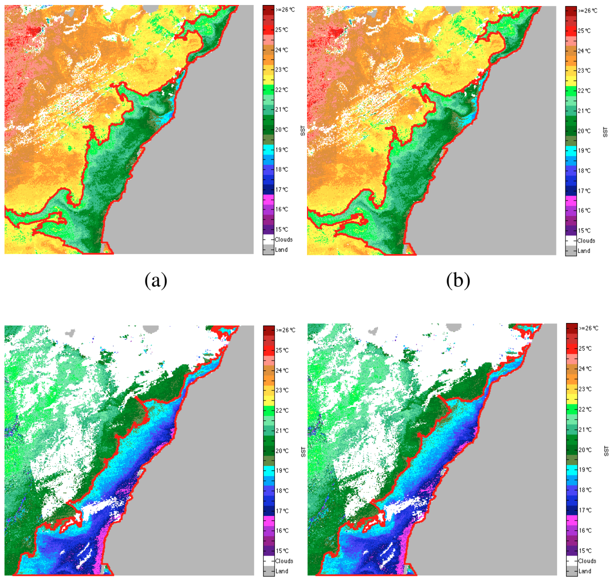


Fig. 2: (a),(b) Results of binary thresholding of the segmented SST image obtained on 07-29-2005 using respectively Otsu and FCM methods; (c),(d) region growing algorithm applied respectively to (a) and (b)

Fig. 3 shows the results of the segmented upwelling areas with our algorithm (2 unsupervised clustering methods), in which the main upwelling front was automatically contoured with the red color.

The mark attribute by the oceanographer for the first 2 images in Fig. 3-a and Fig. 3-b is 'Excellent'. For the images Fig. 3-c and Fig. 3-d, the mark 'Good' is attributed.

One can observe that both Otsu and FCM-based methods yield very similar segmentations on these examples.



(a) (b) (c) (d)

Fig. 3: (a),(b) upwelling zone automatically contoured respectively by Otsu and FCM of the SST image obtained on 2005-07-29; (c),(d) upwelling zone automatically contoured respectively by Otsu and FCM of the SST image obtained on 2005-05-13

4. RESULTS ANALYSIS ON THE WHOLE DATABASE

A thorough evaluation has been carried out by an oceanographer over the data set of 66 SST images. This evaluation was based on the scientific and technical knowledge of the coastal ocean of Morocco. Throughout this evaluation, we used 4 grades: "bad", "poor", "good" and "excellent". "bad" was assigned when the upwelling areas is not well delimited by the algorithm, and "excellent" was assigned when the areas is well delimited.

Regarding the results of this evaluation (Fig. 4), we can conclude that the results of the two methods are nearly similar concerning the "bad" and "poor" grades. For the grade "Good" the Otsu and the FCM classification obtained respectively 25% and 36%. For "excellent" grade a value of 64% was achieved using Otsu method and only 55% with FCM. Overall, 89% and 91% were reached by the two grades "good" and "excellent" together respectively for Otsu and FCM methods. We also mention that we have obtained very similar results using different variants of FCM [25].

After this evaluation of the two segmentation methods, over this representative database, we can conclude that the proposed algorithm have provided similar and satisfactory results. The Otsu-based method have however the advantage of being much more computationally efficient than FCM. More importantly, the segmentation quality obtained by these very simple methods suggest that they can be fairly used to obtain a first approximation of the upwelling area and serve as a basis for a further more precise segmentation and processing.

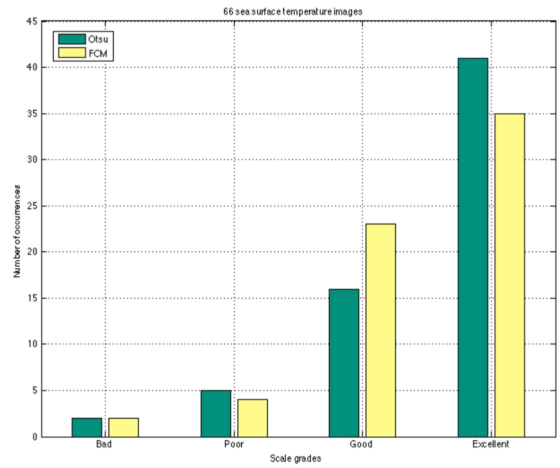


Fig. 4: Qualitative evaluation made by the oceanographer of segmentation results produced by Otsu and FCM methods applied on the 66 SST images.

5. CONCLUSIONS AND FUTURE WORK

In this paper we presented an automatic tool for coarse detection of upwelling areas using SST images. The algorithm starts by segmenting a given SST image by application of two unsupervised classification methods to provide a labelled image, followed by a region growing process that extracts the upwelling areas from the remaining waters. The algorithm have been evaluated and validated by an oceanographer over a data set of 66 AVHRR SST images during the years 2004, 2005, 2007 and 2009 covering the coastal ocean of Morocco. The data set included daily, as well as, weekly images. The method we proposed is very simple and very efficient, still the results were very satisfactory and promising.

Our future work will consist in using the coarse segmentation provided by this method as an initial step of a more involved algorithm for precise segmentation of upwelling and sub-upwelling fronts. Another goal is to process a much larger database of SST images in order to validate and improve the effectiveness of our method for detecting the main thermal upwelling front.

6. REFERENCES

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