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Abstract. We present a method based on deep learning for detecting and localizing abnormal/extreme events in sea surface temperature (SST) of the Red Sea images using training samples of normal events only. The method operates in two stages; the first one involves features extraction from each patch of the SST input image using the first two convolutional layers extracted from a pretrained convolutional neural network. In the second stage, two methods are used for training the model from the normal training data. The first method uses one-class support vector machine (1-SVM) classifier that allows a fast and robust abnormal detection in the presence of outliers in the training dataset. In the second method, a Gaussian model is defined on the Mahalanobis distances between all normal training data. Experimental tests are conducted on satellite-derived SST data of the Red Sea spanning for a period of 31 years (1985–2015). Our results suggest that the Gaussian model of Mahalanobis distances outperformed 1-SVM by providing better performance in terms of sensitivity and specificity. © 2019 SPIE and IS&T [DOI: 10.1117/1.JEI.28.2.021012]

Keywords: abnormal events detection; deep neural networks; extreme temperature; Red Sea.

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1 Introduction

Marine heatwaves (MHWs) are “prolonged discrete periods of anomalously high sea surface temperatures (SST) with a certain duration, intensity, spatial extent, and rate of evolution.”^{1,2} SST is considered anomalously high if it rises above a certain seasonally varying threshold (98th percentile) and lasts for at least 5 days. MHWs may have significant ecological and economic impacts and damaging consequences on the functioning of the marine ecosystems. These impacts include coral bleaching, damage to underwater forests, extensive mortality or displacement of marine species, cessation or reduction in fisheries operations, a decline in tourism, and even population displacement.^{2–6} There may be other factors as well besides MHWs that may affect the ecosystem. For instance, coral bleaching may take place in response to different stressors that include unusually cold water, extreme variations in exposure to light, or increased dilution of seawater with fresh water. However, scientists believe that the primary cause of massive-scale coral bleaching is the prolonged exposure to MHWs.⁷ The extent and damage of MHWs is dependent on their duration, intensity, and spatial extent. Owing to climate change, an overall increase is observed in the ocean’s temperature, and the occurrence of El Niño events⁸ often brings the overall SSTs close to the baseline threshold. Even the marine ecosystems in certain parts of the world that are believed to be resistant to warm SSTs (e.g., the Red Sea corals) are also experiencing an increase in the frequency of bleaching events caused by anomalous SSTs.⁹ The occurrences of SST extremes have been observed more frequently in the

past couple of decades, and this is expected to intensify in the future,^{1,2} so there is a pressing need to understand the temporal trends and patterns of these extreme events.

The detection and localization of extremes are challenging tasks, as the definition of an extreme is subjective and context-dependent. The detection of extremes can be also casted as a detection problem of unusual anomalous behaviors. An important design consideration for an anomaly detection and localization method in SST images is the limited availability of abnormal events. Any such method should, therefore, extract the robust features from the normal images only and should be able to detect abnormal events with minimum false alarms and a good rate of detection.

Deep learning led to a revolution in the field of artificial intelligence and the processing of large datasets (big data).¹⁰ It is based on a multilayered architecture that is designed to reproduce the model of human perception. Deep learning has enabled significant and rapid progress in the fields of facial recognition, speech recognition, computer vision, and automated signal processing.¹¹

We propose a method for detection and localization of SST abnormal/extreme events based on deep learning using training samples of normal events. Our approach/method is basically divided into two stages: the first one is features extraction for each patch of the input data using the first two convolutional layers extracted from a pretrained convolution neural network (CNN). In the second stage, two methods are proposed for the classification of the abnormal events. The first one is based on one-class support vector machine¹² (1-SVM) and the second one utilizes Gaussian distribution of Mahalanobis distances (GDMD)

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between the extracted features. The results of these two methods are further analyzed and compared.

The proposed approach based on machine learning is trained with a set of preclassified normal SST images not associated with extremes. We define the image as abnormal when the SST is above the 98th percentile threshold for at least 5 consecutive days.¹ This approach is not limited to SST and is general enough to be applied to other environmental variables such as salinity, water height, atmospheric humidity, and rain.

This is the first work to deal with anomalies detection and localization in environmental data of the Red Sea using deep-learning methods on top of existing statistical methods for extreme events detection. The deep-learning framework presented in this paper also offers the flexibility to easily incorporate additional environmental variables that may capture conditions suitable for developing these extremes. Different regions in the Red Sea show different patterns of temperature variation; our proposed method is more robust to capture these variation patterns.

The rest of the paper is organized as follows: Sec. 2 discusses related earlier work and highlights their differences. Section 3 details the proposed SST anomaly detection and localization approach. Section 4 analysis and presents the experimental results. Section 5 concludes the work and discusses our future extensions and plans.

2 Related Work

An object is considered as abnormal if it does not respect the normal learned trajectories. Many works^{13–19} have focused on the analysis of the trajectories for the detection of abnormal events. These algorithms can be, however, sensitive to occlusions and generally require precise tracking techniques to locate the objects and differentiate them.

Several previous works have considered the extraction and analysis of low-level local features that train the models either for pixel-level background or normal events. For example, Ermis et al.²⁰ used temporal filtering, whereas Zhang et al.²¹ constructed the normal model with Markov random field. Adam et al.²² proposed the usage of an exponential distribution for the modeling of the histograms of optical flow (HOF) in local regions. Benezeth et al.²³ used a learning co-occurrence matrix to build the model of the normal events. Kratz and Nishino²⁴ constructed a Gaussian model with spatiotemporal gradient features and a hidden Markov model. Mittal et al.²⁵ used the spatiotemporal compositions of the features to build background and behavior models and then compared the new events to the model to decide whether it is abnormal or not. Zahares and Wildes²⁶ described the events using spatiotemporal-oriented energy filters to construct the activity model for each pixel. Wang and Snoussi²⁷ used HOF as motion descriptors and 1-SVM is then trained to detect the abnormal events, suggesting that the solution based on optical flow is efficient for detecting an abnormal object. Liu and Shah²⁸ used three-dimensional spatiotemporal pyramid matching, and Boiman and Irani²⁹ presented a method based on dense sampling to extract the spatiotemporal features. All these methods still, however, suffer from their high computational cost, which remains their main drawback.

Recently, Zhou et al.³⁰ proposed to use a CNN for features extraction based on learning examples for both normal and

abnormal events. But the number of abnormal events and their diversity make it impossible to provide relevant learning examples. So many unseen and under-represented abnormal events may indeed not be detected during the test phase. Erfani et al.³¹ proposed a hybrid anomaly detection model to extract features from high-dimensional dataset using deep belief networks that are resistant to irrelevant variations in the input data. These extracted features are then used for training the 1-SVM that provided comparable anomaly detection results with deep autoencoders, demonstrating good scalability and performance. Li et al.³² proposed a transferred deep CNN-based anomaly detection architecture for a hyperspectral imagery dataset using pixel pairs of labeled samples representing same and different classes for training and a testing phase based on differences between the neighboring pixels and a voting mechanism to detect anomalies. This approach requires tuning several parameters, such as the window size and learning rate, and the recurrent neural networks-based deep-learning framework proposed by Lyu et al.³³ is used for change detection in land cover in hyperspectral multitemporal images, and applied the learned changed rule to new target images without requiring an extra learning step.

3 Proposed Abnormal Sea Surface Temperature Detection Approach

A method for detecting and localizing abnormal extreme SST events in the Red Sea, based only on training dataset of normal images of SST is proposed in this section. We first resort to transfer learning in order to obtain a better descriptor for each region in the input data by extracting robust and discriminative features using the first two convolutional layers of a pretrained CNN. Two methods are then used to extract the model from the training data. The first method involves 1-SVM classifier to investigate the presence of outliers in the training dataset. In the second method, a Gaussian model is fitted on the Mahalanobis distances on the resulting features.

3.1 Features Extraction

The features of SST images are extracted using a pretrained CNN provided by Oxford's Visual Geometry Group, which is also known as VGG19.³⁴ To extract the representative features of SST images, VGGNet has been fine-tuned using 300 normal SST images of the Red Sea. These images are separated from the testing set and are used exclusively for this purpose.

Convolutional layers are considered as an important stage in CNNs because they allow the generation of feature maps. However, there is also another important concept called pooling layers³⁴ that enables the reduction of the spatial size of the feature maps progressively between the convolutional layers, which significantly reduces the number of parameters in network. Therefore, if the complete CNN (from end to end) for each input frame is used, then the resultant features after the fully connected layers will be feature vectors instead of feature maps. Representing each frame by a feature vector allows deciding if the frame is normal or not. This representation does not, however, provide a mechanism to localize the anomalies inside the frame. Our feature map is extracted from the first two convolutional

layers and one pooling layer between them, to achieve the objective of detecting and localizing anomalies in each input data. The resulting feature map of the second intermediate convolution of fully connected VGG is a matrix of dimension 3136×128 , each row representing the vector feature of one small patch in the input data. The selected patch size is 3×3 , pixels scanning completely the image with a stride of two between the adjacent patches. We further applied the principal component analysis (PCA) reduction technique to reduce the dimension of feature matrix, and the new resultant feature matrix has a size of 200×128 , retaining 99% of the total variance.

3.2 Classification

Two classification methods are proposed in this section to train our model of normal data: the first is 1-SVM, and the second uses the GDMD³⁵ between the features.

3.2.1 Abnormal sea surface temperature detection using 1-SVM

The SVM proposed by Vapnik³⁶ is considered as a statistical learning method for classification and regression of linear problems. The objective of 1-SVM is to define a region in the space X that contains most of the data. This could be achieved by seeking a hyperplane in the feature space and then trying to maximize its distance from the origin, although only a small set of the data is located between the hyperplane and the origin.¹⁵ It has been later adapted to nonlinear problems using kernel methods,^{15,27} with the kernel function defined as

$$k(X, X') = \Phi(X) \cdot \Phi(X'), \quad (1)$$

where $\Phi(X)$ is introduced to solve nonlinear classification problems and project the original input data X to a new feature space $\mathcal{H}$ where the classification problem exhibits a linear solution. In our case, we use the polynomial kernel:

$$k(X, X') = (X, X')^d, \quad (2)$$

where d is the polynomial degree.

A hyperplane separator function to classify the input data is then defined as

$$f(X) = W \cdot X + b, \quad (3)$$

where W is a matrix of weights and b is a bias parameter corresponding to the decision function:

$$y(X) = \text{sgn}[f(X)]. \quad (4)$$

The statistical learning theory states that the optimal classifier can be found by maximizing the margin.¹⁵ This can be expressed as a minimization problem:

$$\text{Min } \frac{1}{2} \|W\|^2, \quad (5)$$

subject to

$$y_i(W \cdot X_i + b) \geq 1, \quad i = \{1, \dots, n\}, \quad (6)$$

where n is the size of input training data and y_i is a data label (-1 or $+1$). In a 1-SVM framework, only data from one class

Fig. 1 Flowchart of the proposed ASST detection and localization method. The blue dashed rectangle represents feature extraction stage of our algorithm. The green dashed rectangle represents detection/localization stage.


```

===== Training =====
1- Input:  $N$                                 => Number of normal training data ( $N$ )
2- Features = [];                             => Initialize the features vector
3- For  $i=1$  to  $N$  do                           => loop on training data
4-   Features = [Features ;  $VGG(F_i)$ ]         => Features extraction
5- Redu_Features= PCA(Features)               => Dimension Reduction
6- Model=train_1-SVM(Redu_Features)           => Train 1-SVM classifier

===== Testing =====
7- For  $j=1$  to  $m$  do                             => loop on test data
8-   TestFeatures =  $VGG(F_j)$                    => Size:  $X$  vectors of  $Y$  dimensions
9-   [labels,score] = predict(Model,TestFeatures) => Size(score): $X*1$ 
10- For  $k=1$  to  $X$  do
11-   If score( $k$ ) < threshold
12-   Patch_k  $\leftarrow$  abnormal

```

Fig. 2 Algorithm for abnormal ASST detection and localization using 1-SVM.

are available, which fit our problem framework well as we only use the normal event images from the SST data.

We extract the feature map from the first two convolutional layers and one pooling layer for detecting and localizing anomalies in each SST frame. The resulting feature map is a matrix of dimension 3136×128 , with each row representing the vector feature of one small patch in the input frame (Fig. 1). We apply the PCA to reduce the dimensionality of this feature matrix before passing it to the training phase.

The algorithm is composed of two stages: the first involves the features extraction and the second deals with the classification. The proposed algorithm is presented below and summarized in Fig. 2.

Step 1—Initialization: The features are extracted from N training images (the resulting matrix Features_train is

of dimension $200 \times N \times 128$ after applying PCA). These features are then used to train a nonlinear 1-SVM.

Step 2—Abnormal events detection: For each new test frame, we extract features (the resulting matrix is Features_test, each row in Features_test represents one patch in the test frame) that will be passed to the trained SVM model to decide whether it is normal or abnormal.

3.2.2 Abnormal sea surface temperature detection using Gaussian distribution of Mahalanobis distances

The second classification approach is also composed of two stages: training and detection. In the training stage, a GDMD between the extracted features F_i is used as a classifier to

```

===== Training =====
1- Input:  $N$                                 => All normal training data
2- Features = [];                             => Initialize the features vector
3- For  $i=1$  to  $N$  do                           => loop on training data
4-   Features = [Features ;  $VGG(F_i)$ ]         => Features extraction
5- Redu_Features( $F_i$ )= PCA(Features)           => Dimension Reduction
6- For  $j=1$  to  $m$  do                             => loop on extracted features
7-   Dist_mahal[j] = Find_distances( $F_i, F_{i+1}$ ) => Find the matrix of distances
8- Model_G=Gaussian(Dist_mahal)               => Use the Gaussian distribution

===== Testing =====
9- For  $j=1$  to  $m$  do                             => loop on test data
10- TestFeatures =  $VGG(F_j)$                    => Size:  $X$  vectors of  $Y$  dimensions
11- [dist] = mahal_dist(Model_G,TestFeatures) => Size(score): $X*1$ 
12- For  $k=1$  to  $X$  do
13-   If dist( $k$ ) < threshold
14-   Patch_k  $\leftarrow$  abnormal

```

Fig. 3 Algorithm of ASST detection and localization using GDMD.

20-07-1994

07-08-1995

26-07-2001

31-10-2002

18-10-2015

Fig. 4 Examples of outputs from our proposed deep-learning method. Left column: Input images of SST in the Red Sea. Middle column: Ground truth (anomalies detection and localization) based on the definition of extreme events proposed by Hobday et al.¹ Colored regions represent areas where the anomalies are detected. Right column: Centers of red rectangles represent the location of ASST provided by our method.

model the normal behavior of the training dataset. Mahalanobis distance provides a better fit as compared to Euclidean distance, as shown in Fig. 1.

The Mahalanobis distance between each row of the features matrix and the Gaussian distribution derived from normal images is then calculated, and if this distance is greater than a threshold (selected based on the experiments), then this patch is classified as abnormal SST (ASST); otherwise, it is considered as a normal patch. Once the patch or feature of ASST is detected, we can localize it on the input test data considering the fact that the convolution and pooling of a fully connected network are approximately invertible. The proposed algorithm of detection and localization of ASST is outlined in Fig. 3.

4 Experimental Results

4.1 Performance Evaluation of Abnormal Sea Surface Temperature Detection

The performance of the proposed deep-learning approach for ASST detection is evaluated on Red Sea SST images. The SST dataset is obtained from the Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) system.^{37,38} The OSTIA SST dataset is a combination of two products: satellite data provided by international agencies via the Group for High Resolution SST, and *in-situ* observations from the International Comprehensive Ocean-Atmosphere Data Set database. OSTIA system is developed and run by the UK Met office on a $1/20^\circ$ deg (~ 5 km) grid.

The dataset contains daily images of SST over the Red Sea, spanning over 31 years (1985–2015) with dimensions of 360×240 pixels. These images were resized using bilinear interpolation to match the input size expected for CNN.

We conducted two experiments for our deep-learning approach. The first experiment consists of daily SST images, spanning for a period of 20 years (1996–2015). We divided these images further into two sets: training and testing. The training dataset consists of 10 years data (1996–2005), for a total of 3650 images, and the testing dataset also consists of 10 years data (2006–2015), equivalent to 3650 images. We excluded 300 images from the testing data for fine-tuning the network.

The second experiment uses summer data (July–September) equivalent to 92×31 days for the entire period of 31 years (1985–2015). We further divided the summer dataset into two sets: (1) training dataset that consists of 20 years data ($92 \times 20 = 1840$ images), and (2) testing dataset that consists of 11 years data ($92 \times 11 = 1012$ images).

We used the summer dataset to conduct separate experiments because, as expected, the extremes in the Red Sea are mostly detected in summer.

The dataset is provided with manual ground-truth annotation for each image, indicating the location of each ASST region. To apply the ground-truth annotation in the satellite-derived daily SST, we first annotate the pixel points for anomalously warm (extreme) events in space and time, following the procedure of Hobdey et al.¹ To do so, we calculate the seasonally varying climatology and 98th percentile threshold using the 31 years (1985–2015) satellite-derived daily SST data. The climatology and threshold are defined relative to the day of the year. The average climatology and 98th percentile threshold are calculated within an 11-day window centered on the specific date of interest. They are

further smoothed using a 31-day moving window. When the observed SST exceeds percentile threshold for at least successive 5-day period (the difference is generally called temperature anomaly), then that pixel point in space and time is marked as an anomalous event. This process is repeated for each pixel time series for the duration from 1985 to 2015 over the Red Sea. Furthermore, a daily image of Red Sea is marked as anomalous for ground truth, if it contains at least 100 anomalously warm pixel points.

Figure 4 illustrates the output of the proposed method on a sample of the Red Sea SST images. The proposed method detects and localizes the ASST in these samples. One can observe the outputs of our detection in Fig. 4, where the first column represents some examples of daily input data, the second column shows the ground truth, and the last column shows the outputs of our method against these samples where the red rectangles represent the localization information as inferred by our method.

The performance of the proposed algorithm is evaluated based on two measures:

Table 1 Quantitative results of the ASST detection method in the Red Sea.

	1-SVM			GDMD		
	Train	Test	Sensitivity	Specificity	Sensitivity	Specificity
All data	3650	3350	0.72	0.76	0.83	0.81
Summer data	1840	1012	0.77	0.78	0.86	0.84

Table 2 Quantitative results: EER of the proposed method on the Red Sea SST dataset.

SST dataset	EER (%)
1985–1989	29
1990–1994	33
1995–1999	28
2000–2004	26
2005–2009	28
2010–2015	25

Table 3 EER comparison of our method with the state-of-the-art method.

Method	EER (%)
Bouindour et al. ³⁹	32
Proposed method	28.2

Fig. 5 Comparison of EER for ASST localization with the state-of-the-art method.

$$\text{sensitivity} = \frac{TP}{TP + FN}, \quad (7)$$

and

$$\text{specificity} = \frac{TN}{FP + TN}, \quad (8)$$

where

- TP is the number of SST images classified as abnormal when the ground truth has ASST event.
- TN is the number of SST images classified as normal when the ground truth has no ASST event.
- FP is the number of SST images classified as abnormal when the ground truth has no ASST event.
- FN is the number of SST images classified as normal when the ground truth has ASST event.

Table 1 presents the results of the sensitivity and specificity rates of 0.83 and 0.81 for all the data and 0.86 and 0.84 for the summer data, respectively.

4.2 Performance Evaluation of Abnormal Sea Surface Temperature Localization

We used the equal error rate (EER) to evaluate the localization performance of ASST, which is calculated as

$$\text{EER} = \frac{FP + FN}{NI}, \quad (9)$$

where NI is the number of SST images in a span of 5 years. Table 2 shows EER of the performed experimentation on the SST images that spans over 31 years (1985–2015); we divided them into five sets of images. Our algorithm of ASST localization achieves an average EER of 28.2.

We compare our method with the state-of-the-art method proposed by Bouindour et al.³⁹ They used a deep-learning approach based on Alexnet⁴⁰ for feature extraction from video sequences, and then used 1-SVM classifier for detecting anomalies. Our method is more performant in terms of average EER (Table 3) and for each of the five-year sets from 1985 to 2015 (Fig. 5).

4.3 Discussion

The proposed algorithm enables analysts to formulate and address problems involving querying anomalies detected in SST images within a certain spatiotemporal range. The

modular design supported by our methodology makes it suitable for use in the backend of interactive analytics systems as it does not require substantial computational resources because we are using a pretrained CNN with classifier based on 1-class SVM or GDMD.

This is the first time, to the best of our knowledge, that a deep-learning-based approach has been applied for anomalous events detection in the Red Sea. Owing to this limitation, there are limited results available for comparison from other deep-learning approaches, applied to similar datasets. We do, however, provide comparisons of our results with one state-of-the-art method proposed by Bouindour et al.³⁹ We also demonstrate the suitability of our classifier based on the GDMD as compared to 1-SVM. One significant advantage of the GDMD-based algorithm proposed in this paper is the flexibility to incorporate additional environmental variables to capture the extreme events that we plan to do in our future work.

5 Conclusions

This work proposes an approach based on deep learning for the detection and localization of ASST in the Red Sea. The proposed algorithm operates in two stages: features extraction from normal events using pretrained CNN and GDMD for detection and localization of anomalies in the SST images. We have performed two sets of experiments utilizing daily SST datasets of the Red Sea over a period of 31 years. The experimentation results suggest that the Gaussian model of Mahalanobis distances outperformed 1-SVM in terms of sensitivity and specificity for ASST detection in the Red Sea. We have further compared the results of the proposed method with one state-of-the-art method³⁹ to demonstrate the relevance of the proposed approach. Our results show a better performance in term of average EER for ASST localization in the Red Sea. In future work, we plan to extend our work by doing more comparisons of deep-learning-based method with other non-CNN methods to show the robustness of our approach and to incorporate additional environmental variables for extreme events detection.

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