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A NOVEL COMPUTER VISION-BASED TECHNIQUE TO DETECT OIL SPILLS

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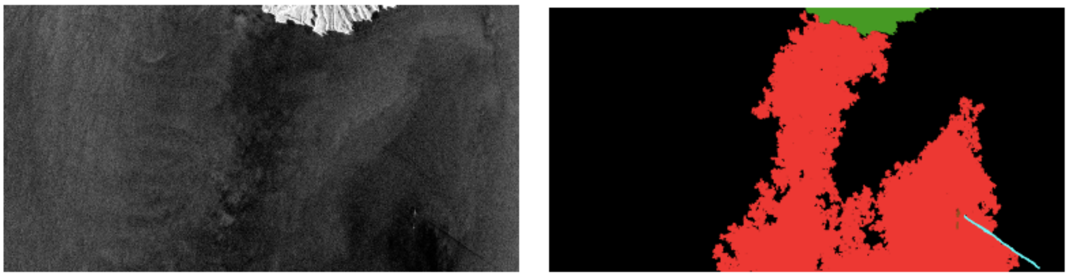
1. INTRODUCTION

Oil spills represent a big problem for the whole environment, especially marine ones. Despite their consequences, they are conditional upon the particular geographic, ecological, societal, and temporal contexts in which the disaster occurs [1]. According to Ribeiro et al. [2], generally, oil spills contaminate coral reefs, fishes, reptiles, and mammals, and, because of this, the environmental impacts on marine fauna due to this type of disaster are often immeasurable.

In this context, the rapid detection of this event is essential to prevent more extensive damage. The oil spill detection in images can be made specially in two ways, manual/visual detection and automated detection [3]. Thus, many approaches to detect oil spills automatically try to apply efficient methods capable of extracting good features from images to handle the referred problems that may arise. For example, methods based on computer vision (CV), machine learning (ML), and deep learning (DL) can be used to address this issue.

This work proposes a novel computer vision approach based on feature extraction by using the q-Exponential distribution-related functions combined with machine learning (ML) methods to automatically detect oil spills. The q-Exponential is the probabilistic model used in this work because it has an important characteristic in modeling rare events (power-law behavior) [4]. As the oil spills are normally small spots of the images (Figure 1), they can be seen as 'rare events' in images. In Figure 1, the oil spill is represented in the mask (1-b) by the cyan color, the look-alikes are in red, ship in brown, and sea surface in black. Additionally, there are two specific challenges in detecting oil spills: the look-alikes and the dark images. The first ones are natural ocean phenomena very similar to oil spills (e.g., wind shadows) [5]. And, the oil spill images are often especially dark due to the remote sensing radars mounted at a distance from the interesting object, which also difficult its analysis [6]. Thus, we apply the methodology on a Synthetic Aperture Radar (SAR) images database provided by Krestenits et al. [7]. Also, we compared the results of the proposed approach with one traditional CV technique (Local Binary Pattern-LBP [8]).



1-a 1-b

Figure 1: SAR image (1-a) and the corresponding ground truth mask (1-b).

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2. METHODOLOGY

In this work, we propose an image feature extraction method based on the q-Exponential distribution as a part of a CV methodology to assist in the automated detection of oil spills in oceans and seas. In our proposed CV methodology, we use the q-Exponential distribution for feature extraction. In this process, data augmentation (DA) as a pre-processing step and dimensionality reduction as a post-processing stage are optional, depending on the classification method applied. First, the image is load in a chosen size $(q \times p)$. Then, it is converted to a grayscale representation. Then, the zero-valued pixels of the image are replaced by value one once the feature extraction process uses the q-Exponential log-likelihood maximization for parameter estimation, and a model restriction is related to the positivity of values. Then, the choice of using DA or not is considered. The feature extraction then starts on the resized grayscale with no null pixels in the image. In this step, we take $n \times n$ image patches (i.e., n^2 pixels), maximize the q-Exponential log-likelihood function, using some numeric maximization method and compute the q-Exponential function $\emptyset_i$ (e.g., PDF, CDF, entropy). The process is repeated for the entire image considering a stride size (Δ). Hence, the output is the feature vector with the sizes depending on the image dimensions, the patches size, and the stride. The feature vector often presents a high dimension. For example, for $p = q = 64$, $\Delta = 1$ and $n = 4$, the output feature vector has dimension 3721. Hence, dimensionality reduction is applied through PCA (Principal Component Analysis) to obtain the first k principal components. Then, the reduced feature vector is ready to feed the ML classifier.

3. RESULTS

In this work, we applied two approaches to detect oil spills in SAR images automatically: a new feature extraction approach based on the q-Exponential distribution; and the classical LBP, originally proposed by Ojala et al. [9], combined with four LBP variants proposed by Liu et al. [10]. Besides, we applied in both approaches, five classification machine learning methods: multilayer perceptron (MLP); random forest (RF); support vector machine (SVM); logistic regression (LR); and extreme gradient boost (XGBoost). We trained the models with three train dataset sizes (400, 1002, 1572). All the models analyzed here considered the same test set. Figure 2 shows that our proposed approach outperformed the LBP classical CV technique. For example, considering 1572 images, SVM, XGBoost, and MLP were better than all the ML methods trained with the features extracted using the LBPs. Also, still considering 1572 images, SVM and XGBoost achieved a balanced accuracy of about 75% using the approach based on the q-Exponential against a balanced accuracy of about 66% obtained by the XGBoost using LBP.

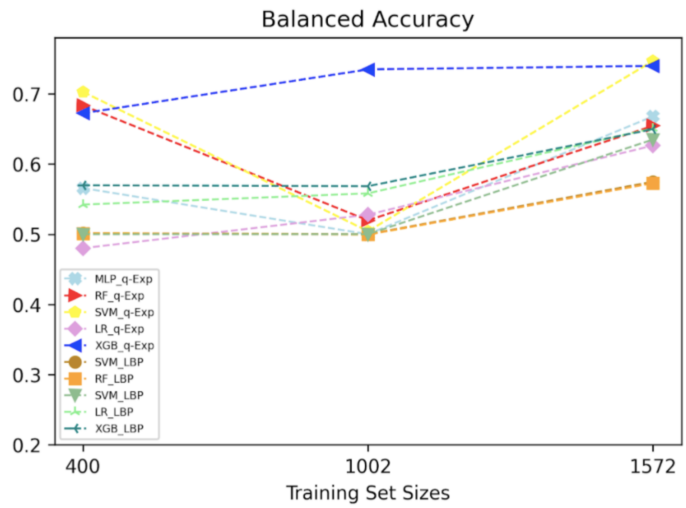

Figure 2: Average balanced accuracy of 10 rounds for the test set, considering the three dataset sizes, and the two applied approaches: one based on the q-Exponential distribution and the second based on the LBP.

4. CONCLUSION

This work proposed a new feature extractor based on the q-Exponential distribution to detect oil spills automatically. We used an available dataset to validate our models. The results were promising once they proved that it is possible to identify oil spills with satisfactory balanced accuracy. Besides, we compared our results with the ones obtained using LBPs as feature extractors, and the best result was provided by the proposed approach based on the q-Exponential model with the SVM and XGB. We intend to compare the results with other classical CV techniques and test other oil spill datasets in future works.

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