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Ship detection for visual maritime surveillance from non-stationary platforms☆

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ABSTRACT

This paper presents a new ship target detection algorithm to achieve efficient visual maritime surveillance from non-stationary surface platforms, e.g., buoys and ships, equipped with CCD cameras. In the proposed detector, the three main steps including horizon detection, background modeling and background subtraction, are all based on Discrete Cosine Transform (DCT). By exploiting the characteristics of DCT blocks, we simply extract the horizon line providing an important cue for sea-surface modeling. The DCT-based feature vectors are calculated as the sample input to a Gaussian mixture model which is effective in representing dynamic ocean textures, such as waves, wakes and foams. Having modeled sea regions, we perform the ship detection using background subtraction followed by foreground segmentation. Experimental results with various maritime images demonstrate that the proposed ship detection algorithm outperforms the traditional techniques in terms of both detection accuracy and real-time performance, especially for complex sea-surface background with large waves.

1. Introduction

Sea-surface platforms are commonly deployed for a wide variety of tasks and operations, such as open ocean exploration, supervisory control of Autonomous Underwater Vehicles (AUVs) and Remotely Operated Vehicles (ROVs), oil and gas drilling, ecological monitoring and sampling, and homeland security surveillance (Y. Zhang et al., 2016; Li et al., 2014). For non-stationary platforms, e.g., buoys and ships, it is of great importance to develop an automated maritime surveillance system, especially in wide open waters. Such a visual monitoring tool in the military applications enables significant capabilities for safeguarding maritime rights and interests, strengthening supervision and management of sensitive areas, resolving maritime disputes, and detecting illegal activities. It adds a great deal of convenience to civil applications as well, e.g., port traffic management, maritime search and rescue.

The current maritime surveillance systems are mainly based on air-/space-borne Synthetic Aperture Radar (SAR), High Frequency Surface Wave Radar (HFSWR), regular ship-based radars, and air-/space-borne optical sensors (Tello et al., 2005; Sciotti et al., 2002; Zhu et al., 2010; Künzner et al). The SAR equipment can cover an ultra-wide range and operate continuously under all-weather conditions at the expense of limited image resolution. For optical sensors, the infrared camera provides longer view distance relative to typical cameras, especially at night or in low visibility (Withagen et al., 1999; Broek et al., 2000). However, the low-resolution imagery and high power consumption of infrared cameras limit access to the deployment of autonomous surveillance systems. In comparison, visible-light images captured by optical cameras generally contain rich color and texture information, which enable people to interpret and recognize the scene more readily. Additionally, the visible-light camera has the advantages of low-cost, easy installation and low power consumption. More importantly, such a camera can be employed for military security, since the passive imaging modality does not expose the location of the surveillance system. This has motivated the development and improvement of optical systems over the past decades, to meet the critical need of maritime scene monitoring at improved imaging resolution by integrating with other sensors (Fefilatyev et al., 2012).

Based on the platform structure, the visual maritime surveillance system can be divided into two categories: video surveillance with stationary/non-stationary cameras. The stationary surveillance systems are generally employed in harbor, port, and coast applications where the background remains basically unchanged. On the other hand, the non-stationary surveillance equipment usually works in open waters far away from the coastline using cameras mounted on moving

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ships or swaying buoys. In this case, the captured scene keeps changing due to the platform movement. This study is aimed at devising a solution for ship target detection from buoy-/ship-based visual surveillance, which can motivate more maritime applications for the realization of intelligent visual sensor networks with on-board video processing and real-time bi-directional communication.

Some earlier works on automatic detection techniques for ships or surface objects have been proposed based on video imagery information. These methods generally fall into three categories. The first class is based on the background modeling and subtraction (Wang et al., 2005; Moreira et al., 2014; Prasad et al., 2017). Hu et al. (2011) proposed a vessel detection method in which the ocean background is simply modeled by median values of n video frames. Some authors (Bloisi and Iocchi, 2009; Frost and Tapamo, 2013; Grupta et al., 2009; Wei et al., 2009; Szpak and Tapamo, 2011; Robert-Inácio et al., 2007; Pires et al., 2010) used Gaussian functions to model the water surface followed by background subtraction. The Gaussian mixture model (GMM) statistically exploits the fact that each pixel belongs to the sea surface or to the ship (Moreira et al., 2014). Zhang and Zheng (2011) and Borghgraef et al. (2010) modified the conventional GMM to break down the challenging problem of fast moving maritime targets. However, these methods, primarily designed for fixed cameras, do not generally offer good detection/surveillance performance for non-stationary platforms with a high degree of variability.

The second category of ship detection methods is based on human visual attention model (Prasad et al., 2017). Itti et al. (1998) utilized a visual saliency map to analyze complex natural scenes. It segregates the regions of interest (high saliency) according to the local contrast which is consistently present at various length scales. However, it is not effective in dealing with wakes corresponding to the moving ships, since they introduce a high contrast over the surrounding pixels (Prasad et al., 2017). To achieve real-time detection, Hou and Zhang (2007) constructed the saliency map in spatial domain by extracting the corresponding spectral residual in spectral domain. Agrafiotis et al. (2014) designed a maritime tracking system by combining visual attention map with GMM. The tracking results are further refined using an adaptable online neural network tracker. Additional enhancement on visual attention model was realized by a two-scale detection scheme (Liu et al., 2013). At the larger scale, sea background is removed by a mean-shift smoothing algorithm. At the smaller scale, objects of interest are coarsely labelled using salient edge region extraction; post-processing for chrominance components provides more useful cues to select the output targets. Albrecht et al. (2011) modeled the visual maritime attention using multiple low-level image features in combination with a Bayes classifier. We conclude that these approaches based on visual attention model expect to reduce the noise of sea background at a larger scale as well as enhance the salient features of object regions. However, such methods usually do not perform well when large surface waves are involved in the scene. This is because the visual saliency map will probably become inaccurate if the salience of waves has the same or even higher order of magnitude compared to the original targets.

The other techniques apply edge and texture features to detect ship targets. For buoy-based visual surveillance, Fefilatyev et al. (2012) and Fefilatyev (2012) proposed a marine vehicle detection algorithm by exploiting the gradient information. After extracting the horizon by Hough transform, a global thresholding algorithm segments ship targets effectively from the background region above the estimated horizon. However, this method cannot work once the targets appear below the horizon. Although the edge and contour features (e.g., using Hough transform) are widely used in ship detection (Arshad et al., 2011; Yan et al., 2012; Xu et al., 2011), these methods generally do not achieve good performance for complex background. To make full use of various texture information in the sea-surface background, the detection accuracy can be significantly improved by incorporating fractal feature (Liang et al., 2012). Using both color and texture components, Kumar and Selvi (2011) and Selvi and Kumar (2011) introduced an object classification algorithm based on Local Binary Pattern (LBP) for ship detection. The Histogram of Gradients (HOG) (Wijnhoven et al., 2010) is a commonly used feature representation. Loomans et al. (2013) devised a combination of a multi-scale HOG detector and a hierarchical KLT feature point tracker to track ships in harbors. This tracking system also incorporates an active camera to improve the tracking results under challenging conditions. In the Pascal Visual Object Classes (VOC) challenge, the Deformable Part Model (DPM) based on HOG achieved the best detection performance for twenty classes, including boats (Everingham et al., 2015). In Sullivan and Shah (2008), an enhanced Maximum Average Correlation Height (MACH) filter was applied for vessel detection by matching appearance templates with testing sequences via Fast Fourier transform (FFT). The advantage of these appearance-based methods is that they do not rely on background modeling. In more recent works (Everingham et al., 2015; R. Zhang et al., 2016; Zou and Shi, 2016), the Convolutional Neural Network (CNN) features have achieved a substantial improvement in detection performance. While the above feature-based detection schemes benefit from the texture consistency within sea-surface background, their computational complexities pose a rather serious challenge to real-time video communication over visual sensor networks.

Aiming at visual maritime surveillance from non-stationary platforms, we propose an efficient ship target detection algorithm to achieve both high detection accuracy and real-time performance. Here, we first develop an effective learning strategy including simple horizon segmentation and complex sea-surface background modeling. In maritime scenario, ships usually appear around the position of the horizon line, occupying both sky and ocean regions. The horizon line can be used as a reference to limit the regions of interest and reduce the execution time of detection. After horizon detection, we can simply extract the sea-surface background regions below the horizon and only use these regions for background modeling. This lowers the probability of detection mistakes caused by the presence of background motion, e.g., waves, wakes, and foams. More importantly, such independent detectors for sky and sea regions increase the detection sensitivity to small objects around the horizon line. Therefore, an initial detector of horizon line is required before background modeling and object detection. In the proposed scheme, we can simply detect the horizon line by exploiting the characteristics of Discrete Cosine Transform (DCT) blocks. At the step of sea-surface background modeling, we present a novel DCT-based texture Gaussian mixture model to further separate ship targets from the complex sea-surface background below the horizon. Having detected the sea-surface background, we remove it and finally obtain ship targets according to the texture consistency. The main contribution of the proposed algorithm is to provide more accurate detection results within complex sea-surface background, which is of vital importance for ship-/buoy-based surveillance applications in the presence of large waves. Experiments with real images are presented to assess the effectiveness of the proposed ship detection approach, in comparison to traditional techniques.

In the remainder, we describe the implementation details of the proposed ship detection algorithm in Section 2, and compare its performance with previous techniques in Section 3. We present a summary and conclusions from this investigation in Section 4.

2. The proposed ship detection algorithm

The maritime images acquired from a non-stationary platform typically contain the foreground of ship targets and the background of sea surface as well as sky. The main challenge for background subtraction and detection of foreground objects is the difficulty in modeling the dynamics of water, including waves, wakes and foams (Prasad et al., 2017). In order to improve the detection accuracy of maritime surveillance systems in open sea, we present a novel ship