Identification and Classification of Objects in Marine Image Data Set for Coastal Surveillance

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ABSTRACT
Detection of objects of interest and finding out anomalies in the ports of sea is of a very high magnitude considering the low amount of current video analysis in maritime surveillance systems present.Nearly about 80% of all world trade is carried by sea transport. With the growing use of maritime transport, an increase of illegal activities from traffic of prohibited substances, to terrorist attacks using sea transport is constantly occurring. This work is motivated by the importance of this above said issue and that there are no major surveys on video detection for object recognition and analysis system in a marine environment for surveillance. In this paper we propose a novel method to recognize an object and detect it by its feature set and later can be utilized to differentiate anomalies encountered.

Keyword
Maritime Surveillance system, Object recognition

1. INTRODUCTION
Video surveillance systems in dynamic environments is one of the most active research topics in computer vision [1], receiving much attention in the last decade [2]. Maritime surveillance can be defined as the effective recognition of all maritime activities that impact the security, the economy or the environment [3]. About 80% of all world trade is carried by sea transport. With the growing use of maritime transport, an increase of pirate attacks, activities such as traffic of prohibited substances, illegal immigration and fishing, terrorist attacks at port areas and collisions between marine vehicles primarily at channels and near the ports and coasts is occurring. It is estimated that the losses due to piracy may reach US$ 16 billion per year [4]. The 26/11 attacks in Mumbai in 2008, shook up the entire nation of India, where the terrorists made entry into Mumbai from the waterways. The attack against civilian and military marine vehicles is one way to hurt the economy and security of a country [5, 6]. The terrorist attack against the U.S. warship Cole DDG 67 occurred at port Aden, Yemen, caused the death of 17 people [5]. The French tanker Limburgalso suffered terrorist attack at the Yemen coast. The manual operation of surveillance systems is not efficient due to fatigue, stress and the limited ability of human beings to perform certain tasks, the development of automated systems for maritime surveillance is essential to reduce the occurrence of unwanted events. The use of cameras in maritime surveillance systems has increased [8]. Cameras are essential to assist and supplement the radars and other sensors. They are cheap, flexible[6, 9, 11, 12] and can be installed on almost every platform type [2]. The magnetometer detects vehicles by the change in the magnetic field around the vehicle, but is limited to detect vehicles within walking distance [10]. Low and high frequency radars are expensive, hampered by clutter [10], have blind zones close to the transmitting antenna [6] and detect with low efficiency the vehicles built with non-conductive materials [4, 6, 7].

2. RELATED WORK SURVEY
Various systems and methodologies were proposed for object identification in images. Kalman Filter - The Kalman filter KF [13] is an optimal estimation method of the state of a stochastic, non-stationary, dynamic and linear process. Kalman [13] introduced the representation of linear dynamical systems by state equations. The process is governed by discrete and linear equations. KF is a recursive algorithm that consists of two phases: time update and measurement update.Successive Clustering:The clustering applied to successive frames is one of the simplest tracking methods [14]. An image segmentation algorithm is applied at each frame image to generate a probability map. Then, a clustering algorithm forms the connected components in the map. P (OT (t)) is usually considered the centroid position of the connected component that is nearest to the OT centroid position estimated by the KF.

Mean Shift: The mean-shift algorithm considers the data as points in FS associated with an empirical probability density function, where regions of dense data present in FS correspond to local maximum or modes of the data distribution. A local gradient ascent algorithm is applied to the empirical probability density function to determine the data region corresponding to the mode. Given n points pi, i=1, n in Rd, the empirical probability density function EPDF (p) that has a radially symmetric kernel centralized and has a bandwidth Template Matching:The template matching in the context of object tracking is defined as the location of a small pixel set called template within the ROI [15]. The OT model is the template to be found within the ROI. Templates are constructed with the pixels inside a simple geometric shape region. Histogram Matching: The histogram matching is a technique frequently used for tracking objects because the histogram is invariant to rotation and scale transformations applied to the object and it is robust to partial occlusions [16]. The appearance model is defined extracting a histogram with the OT pixels. P (OT (t)) is the frame position that provides the maximum similarity measure between the OT histogram HM and histograms extracted from candidate regions HCActive Contour:The active contour tracking method represents the vehicle contour by one or more curves. The curves move dynamically at every frame toward the position of the vehicle edges, which by hypothesis is the place where the discontinuity of the pixel values is higher. Trackers generally use the final contour position at the previous frame as the initial position at the current frame [22]. The main advantage of the active contour is that it is relatively insensitive to lighting variations. Occlusion Handling:Partial and total occlusions may occur. The occlusion can cause a tracking failure. Teutsch and Kruger [17] proposed a tracker that combines 3 different trackers to increase the robustness to partial occlusions. When the response of one or two trackers is unreliable, P (OT (t)) obtained by them receives a lower weight. T1 and T2 trackers are based on pixel regions and T3 is based on feature points extracted by the algorithm proposed by Shi and Tomasi [18]. T1 tracker performs segmentation by adaptive thresholding at each frame I (t) and defines P (OT (t)) by the nearest neighbor rule applied to the centroids of connected pixel regions present at I (t) and I (t-1). T2 performs the association between blobs extracted at me (t) and me (t-1). T3 performs the association between feature points extracted from the ROI and the OT feature points and defines P (OT (t)) as the average position of each associated feature point. Teutsch and Kruger [19] associate an independent KFfor each OT and only update their models when the OT is not occluded. A total occlusion occurs when none of the trackers determines P (OT (t)) with high confidence. In this case, the KF continues estimating P (OT (t)). If the OT is not detected at N consecutive frames with high confidence, the reference to the OT is erased.

3. METHODOLOGY

The work proposed has followed the following steps:-

3.1 Detect SURF Features

The first step is to detect the features that surf features and analyse over it to do the background subtraction to remove the errors which may occur due to noise, clutter, waves, dynamic and unpredictable ocean appearance, sunlight reflections, bad environmental conditions, low luminosity and image contrast, presence of objects that float over the ocean, white foam, geometric shape and the presence of birds, clouds, fog and aircraft that arises immediately above the horizon. This step detects these cluttersand features and eliminates them using histograms together background elimination method. The histograms applied along with background elimination leads to a faster identification for elimination.

3.2 Feature set creation and Analysis

Features of different types of objects pertaining to the costal environment like ships, boats are taken and a data set for each of the object that can be a vital part of surveillance is done. Image segmentation is done on these image objects and the contour set of an object pertaining to the essential features like points depicting curves, lines are stored for the analysis. In this work weanalysed that if the best set of 100 feature points is adequate to identify amarine object. Fig-1 depicts a valid image and the features pertaining to the objects contour is analysed and points related to the feature set is captured and stored for identifying the objects in the input considered.

Fig 1: Points considered for feature set

Remove outliers while estimating geometric transform using RANSAC - The Random sample consensus (RANSAC) algorithm [21] is an algorithm for robust fitting of models in the presence of many data outliers. Considering the data from the feature set created in the previous step, which behaves as the inliers that are the data that fit the model in the image consider the objects are mapped to the features of the two images. This step estimates the geometric transformations in the input data set by mapping with the feature set using RANSAC removing outliers. By mapping it to all types of transformations example like scaling it to identify a smaller object of the same type, this gives a best match.

- RANSAC algorithm - the algorithm[20]:
  Selects N data items at random

Estimates parameter X Finds how many data items (of M) fit the model with parameter vector X within a user given tolerance. Call this K. If K is big enough, accept fit and exit with success.

Repeat 1...4L times e estimated forward geometric transformation to locate object: the geometric transformation is done using,transformPointsForward, the function for forward geometric transformationon to the mapped data set from the previous estimation and locating the objects of consideration in the image set. This is used to identify which objects relate to the data set considered and which objects is a part of the anomaly, and helps in tracking them in surveillance.

4. RESULTS& CONCLUSIONS

The Fig-2 depicts an input scene considered for object identification in costal surveillance. Fig- 3 gives the initial set of matches to identify the object and on that fig-4 gives the filtered matches which are sufficient to analyze the object from the feature set considered. In this work we used background elimination, histograms and did a RANSAC algorithm to eliminate the sea clutter and identify an object from the feature set created in the data base. This work gives about a 90% of identification based on the feature set and can recognize the objects not present as anomalies, resulting for a secured system for surveillance on the coast.

Fig 2: Input Scene for Identification

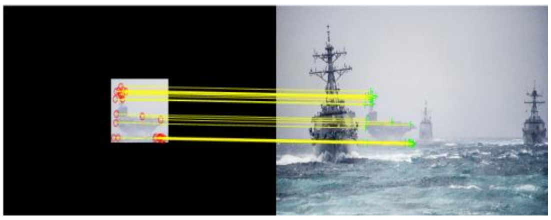

Fig 3: Initial matches from the feature set

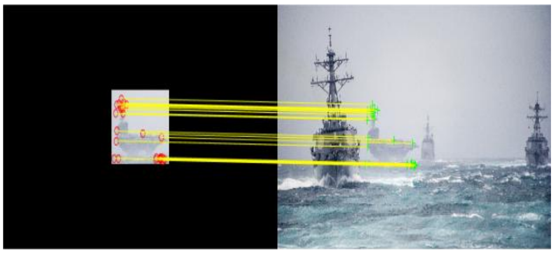

Fig 4: Filtered Matches in the object identification

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