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Moving ship detection based on context modeling and motion analysis

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1. Introduction

Port surveillance systems play an important role in managing ship traffic and controlling the waterway security. As a crucial task in port surveillance systems, video-based automatic ship detection becomes important because it offers high detection efficiency combined with low costs in installation and maintenance.

In the last decade, some papers proposed various approaches to perform ship detection in different circumstances. There are two main types of techniques that are mainly discussed in the research papers: background subtraction and appearance modeling. For background subtraction, the highly dynamic water regions and complex surroundings as background easily lead to failures. Moreover, such approaches are not functional in non-static camera-based systems. The appearance modeling methods largely rely on the local features, which leads to errors because ships have various appearances.

This paper targets an automatic ship detection system functioning on both static and moving cameras. We explore the context information and facilitate ship detection by analyzing the motion similarity and saliency. We evaluate our system and show that it outperforms two recent approaches.

2. Overview of Our System

Our ship detection system consists of two sequential stages. At the first stage, object-centric region labeling is used to classify segments, obtained by image segmentation, into water, vegetation, and unknown regions. Then, modified SRM (Statistical Region Merging) is employed to group labeled segments into regions based on motion similarity. By exploring semantic, spatial, and scale constraints of these regions, context is modeled and candidate ships are located. At the second stage, candidate ships are examined by analyzing salient motion to detect moving ships.

3. Context Modeling

In our system, the surveillance video implies an implicit gist of all frames: the port scene. Therefore, we focus on generating an object-centric context model through four steps. 1. Feature extraction. We first divide the image into several segments with uniform color and texture using graph-based segmentation. In segment level, global features (vertical positions of segments) and local features (pixel-based color/texture features) are extracted. 2. Segment classification. Multiple-SVM is trained off-line to label each segment based on the extracted features. 3. Region re-union. Motion similarity analysis is performed to re-union the segments with same labels and similar motion. Here, we apply a modified SRM (Statistical Region Merging) to merge the segments. In this step, different objects are separated to solve the clutter/occlusion problems. 4. Context modeling. Object-centric analysis is conducted to explore the spatial/scale relationships and co-existences among ships and other objects. Ships should travel inside the water region, which defines spatial and co-existence context. Candidate ships are unknown regions which are surrounded by water or have common borders with it. Limited by the size of other co-occurring objects, the size of candidate ships should fall in a certain interval which defines scale context. After applying the modeled context, the candidate ships $C_{cand}$ are located.

4. Ship Detection based on Motion Saliency Analysis

We need to examine the motion saliency of the candidate regions $C_{cand}$. We assume that ships have salient motion compared to their surroundings. We determine motion saliency at the region level to avoid expensive pixel-wise saliency checking. It is a three-step approach.

Step 1: ROI (Region Of Interest) extraction. We extract the ROI including the outer part of a candidate ship $C_{ship}$
and the local background \(C_{bg}\) around it. We consider only the outer part of a ship because the inner parts of big vessels are normally painted in same color which tends to bring errors in motion estimation. We use morphological operations to obtain a set of ROI, each of them containing a candidate ship.

**Step 2: Region-level motion calculation.** Relative motion of \(C_{chip}\) and \(C_{bg}\) is calculated, taking into account the global motion of the water. We define the relative motion of \(C_{chip}\) as \(rv_{chip} = v_{chip} - v_{water}\) and \(rv_{bg} = v_{bg} - v_{water}\). In the equation, \(v_{chip}\), \(v_{water}\) and \(v_{bg}\) are the region-level motion of the corresponding regions.

**Step 3: Motion saliency for ship verification.** We define two criteria to verify if the candidate ships are real ships: \(|rv_{chip} - rv_{bg}| > T_1\) and \(|rv_{chip} - rv_{bg}| > T_2\). In the first criterion, we filter out non-ship objects whose motion contrast with surroundings is not significant (e.g. floating buoy). In the second criterion, we remove non-ship objects (e.g. flicking water patch) with small distracting motion in a static water region (no motion). Both \(T_1\) and \(T_2\) are set empirically. The moving ships are detected as the candidate ship regions if the two criteria are satisfied.

5. Experimental Results

To evaluate the performance of our ship detection system, the algorithm is tested on real-life video sequences recorded in the harbor of Rotterdam, the Netherlands. The videos have an SD resolution of 720 × 576 pixels and are recorded between 9:00 AM and 7:00 PM during sunny and cloudy weather.

We evaluate the performance of region labeling using the coverability rate on a generic dataset and our dataset [1]. In the generic dataset, we achieve an average of 95% for six-class labeling (sky, vegetation, road, water, construction, zebra-crossing and “unknown”). In our dataset, we achieve an average of 96% for three-class labeling (water, vegetation and “unknown”) [1].

For ship detection, we categorize the test sequences into three scenarios: single/multiple ship without occlusion; ships present in occluded/cluttered scenes; ships during sunrise/sunset moment (highly flickering water). We compare our ship detection approach with the “Existing” approach [2] and “Cabin detector” [3]. Fig [1] shows our result (a) and the “Cabin detector”(b). In all three scenarios, our ship detection approach outperforms the other two algorithms with an optimal balance of precision (96.1%) and recall (85.5%) [1]. To evaluate the clutter/occlusion handling, we select 203 cases for occlusions and 175 cases for clutters. Our method solves 184 cases for occlusions, while “Existing” approach and “Cabin detector” solve 21 and 180 respectively. As for clutters, our methods solves 168 cases, compared to only 5 and 14 successes for “Existing” approach and “Cabin detector”.

6. Conclusion and Discussion

We present an automatic ship detection system for port surveillance. Context information is explored to improve the efficiency and reliability of the ship detection. The object-centric region labeling for context modeling is performed at region level, which increases the accuracy while decreasing the computation complexity to enable real-time operation. Motion analysis is the key to our ship detection system, which is well explored at three-levels: pixel, segment and region. The three-level motion analysis ensures the system not only a higher accuracy of ship detection but also improved robustness in handling clutters/occlusions in the surveillance video. The key features of our ship detection system are: (1) no prior knowledge of ship appearances is required to successfully detect various types of moving ships (container ships, speed boats, tanker ships, fishing boats and sailing boats); (2) entire ship can be detected not just a part of the ship (bow, cabin, stern); (3) pixel-true boundary of the ships is produced enabling indication of centroid and bottom line; (4) clutters/occlusions between different ships and vegetation can be handled; (5) all the algorithmic subsystems are designed to operate on both static and moving camera-based system. Tested in real-life videos, the system shows significant improvements in both robustness and accuracy, compared to two recent ship detection algorithms.

References

