Autonomous collision avoidance for unmanned surface ships using onboard monocular vision

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***Abstract*—This study presents the development of vision-based techniques for autonomous collision avoidance by an unmanned surface ship using an onboard monocular camera. In order to determine the initiation of an evasive maneuver, the range and bearing measurements of each target traffic ship with respect to the observer (e.g., own ship) need to be provided for trajectory estimation. A tracking estimator is used to estimate the target ship trajectory in the framework of bearings-only tracking based on the extended Kalman filter (EKF) algorithm with a Continuous White Noise Acceleration (CWNA) model. To enhance the observability of the tracking filter, the vertical pixel distance from the water horizon to each target ship is used as a range measurement. When the estimated separation distance between the target and own ships is less than a predefined minimum separation, the own ship alters its heading angle to avoid an imminent collision following the standard marine traffic rules. Field experiment results are presented and discussed to demonstrate the feasibility and validity of the proposed approach.**

***Keywords*—Monocular camera, trajectory estimation, feature-based detection algorithm, extended kalman filter, unmanned surface vehicle**

I. Introduction

Technological advancements of unmanned systems recently have greatly increased onboard capabilities in many aspects of vehicle navigation, guidance, and control. A variety of sensing modalities for autonomous situational awareness capabilities have become available, including lidar, radar, and camera [1], [2]. In order to avoid any imminent collision between surface ships, it is necessary to accurately estimate the ship's trajectory and establish an appropriate evasive action using a reliable obstacle detection and avoidance system. In particular, with advances in computer vision and computational technologies, vision-based automatic target detection and tracking have attracted significant attention to unmanned vehicle systems [3]–[6]. In marine applications, computer vision can be applied to automatic collision avoidance between unmanned surface vehicles (USVs), and it can play a critical role in providing autonomous navigation capability to USVs in the future marine traffic systems.

In general, a monocular vision system only provides the relative bearing between the observer and the target object but no explicit range information is available from a static image. The range information can be extracted from the relative lateral motion between the observer and the target in the framework of bearings-only tracking (BOT). However, the performance of BOT is highly dependent on the relative trajectory [7]–[10]. For example, in a head-on situation between two ships, the bearings-only tracking performance may significantly degrade due to the poor observability of the tracking filter [11]. The large state uncertainty due to the low observability results in poor estimation performance of the BOT filter [12]. The observability can be improved by changing the course of the observing ship; however large course-changing maneuvers are not always desirable or allowed. To deal with the lack of observability, the vertical pixel distance between the horizon and the target ship in the image is used to extract the relative range information.

In order to realize automatic collision avoidance using a monocular camera, a reliable detection technique is required. For automatic feature detection without a priori knowledge about the target ships, image filtering techniques are applied to minimize inherent noises (e.g., water reflection and ship wake) that arise in the ocean environment. The Features from Accelerated Segment Test (FAST) corner detection method is then used to detect real-time features and extract the relative bearing and range measurements of target traffic ships in camera images. These measurements are employed to estimate the trajectories of the detected target ships using a tracking filter based on the extended Kalman filter (EKF) algorithm with a Continuous White Noise Acceleration (CWNA) model.

The aim of this paper is to develop vision-based techniques for autonomous ship collision avoidance using an onboard monocular camera. For collision avoidance, surface ships should comply with maritime traffic rules according to the International Regulations for Preventing Collisions as Sea (COLREGs) defined by the International Maritime Organization (IMO) [13]. The rules provide a set of guidelines for safe navigation of traffic ships at sea. In this study, the own ship is commanded to change its course to avoid the detected target ship according to the IMO requirements. The separation distance between two approaching ships is estimated by the tracking filter. If the estimated distance is less than a predefined minimum separation, the own ship changes its heading. Once the risk is alleviated, the own ship is commanded to follow the original line of sight (LOS) direction to a predefined target waypoint.

The remainder of this paper is structured as follows: Section 2 describes the vision-based techniques for autonomous collision avoidance with the marine rules. Section 3 presents hardware platforms and experimental results with some discussion. Finally, conclusions are given in Section 4.

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II. AUTONOMOUS COLLISION AVOIDANCE

The collision avoidance procedure of the proposed approach is depicted in Fig. 1. The proposed approach mainly consists of three steps: automatic detection, trajectory estimation, and collision avoidance steps. The detection step includes image preprocessing and feature-based target detection using a monocular camera. The trajectory estimation step entails the extraction of relative measurements, including bearing and range information from the given images, followed by tracking for estimation of the trajectories of detected target ships. The collision avoidance step involves computing the relative distance between the own and target ships, and determining an evasive action according to marine traffic rules to reduce the collision risk. This process is described in the following subsections.

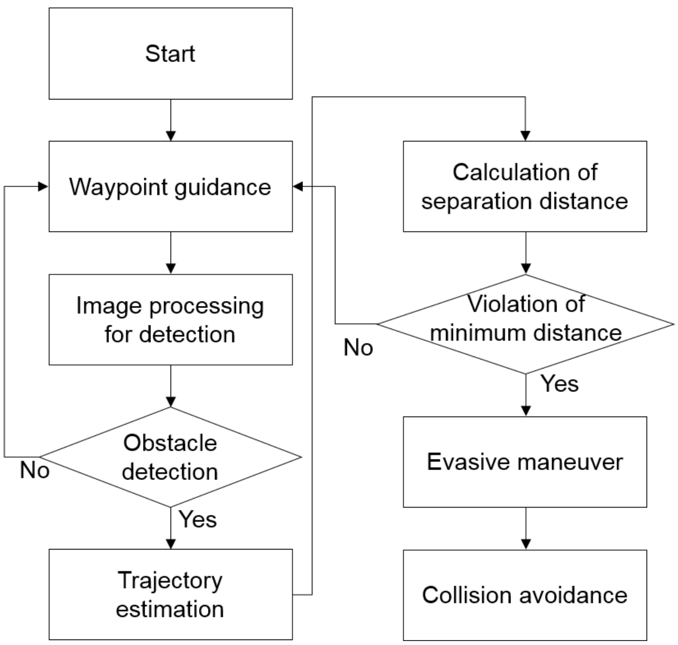


Fig. 1: A procedure of the vision-based collision avoidance for autonomous navigation.

A. Automatic detection of target ship

For effective automatic detection of approaching ships, image intensity equalization techniques and morphological and bilateral algorithms are applied to image filtering, which enables reducing image noise inherent in ocean environments such as reflection and glint of light, waves, and ship-induced wake on the water surface. Traffic ships in camera images always appear below the horizon. Hence, the region of interest (ROI) for searching for target traffic ships is confined below the horizon, which allows for computationally efficient detection of target ships. The horizon can be determined from the geometric configuration of the camera mounted on the own ship.

Once the horizon is determined, the accelerated segment test (FAST) corner detector algorithm is applied to find salient target features in the image [14]. FAST features are widely used in real-time applications mainly because of their computational efficiency. The extracted features are clustered based on the Euclidean distance, and the candidate feature clusters are selected when the number of features existing within each cluster exceeds a predefined threshold. The moving average filter is then applied across n consecutive images to reduce the effect of time varying disturbances and minimize false detection. The bounding box that encloses the feature points in each candidate cluster is determined and denoted as the detection region. Figure 2 shows the result of the automatic feature detection, which was applied to real image data of an approaching target ship in a real sea environment.

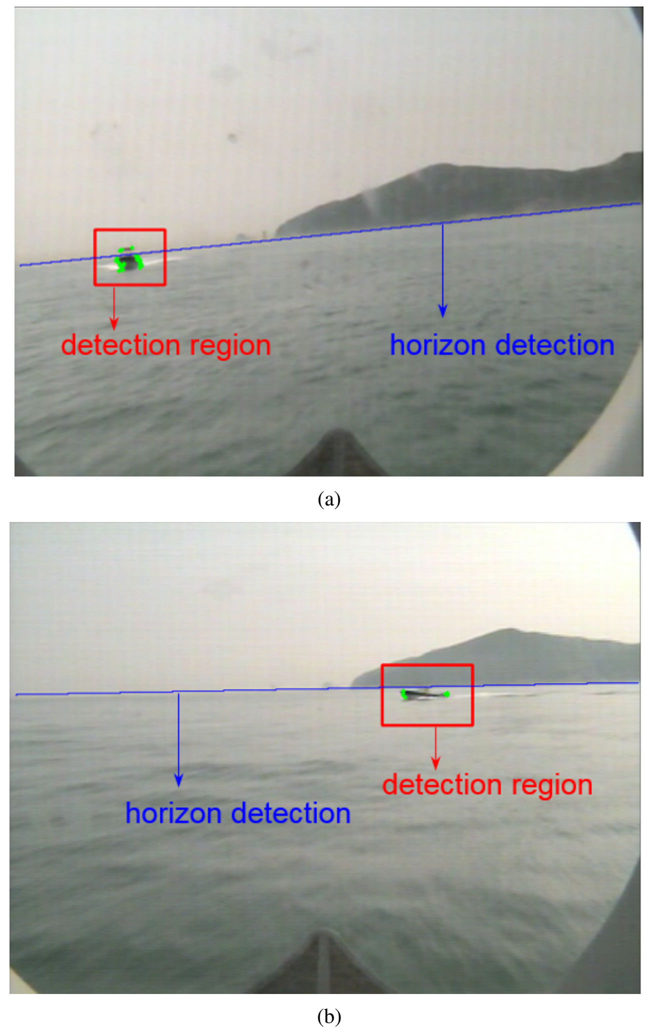
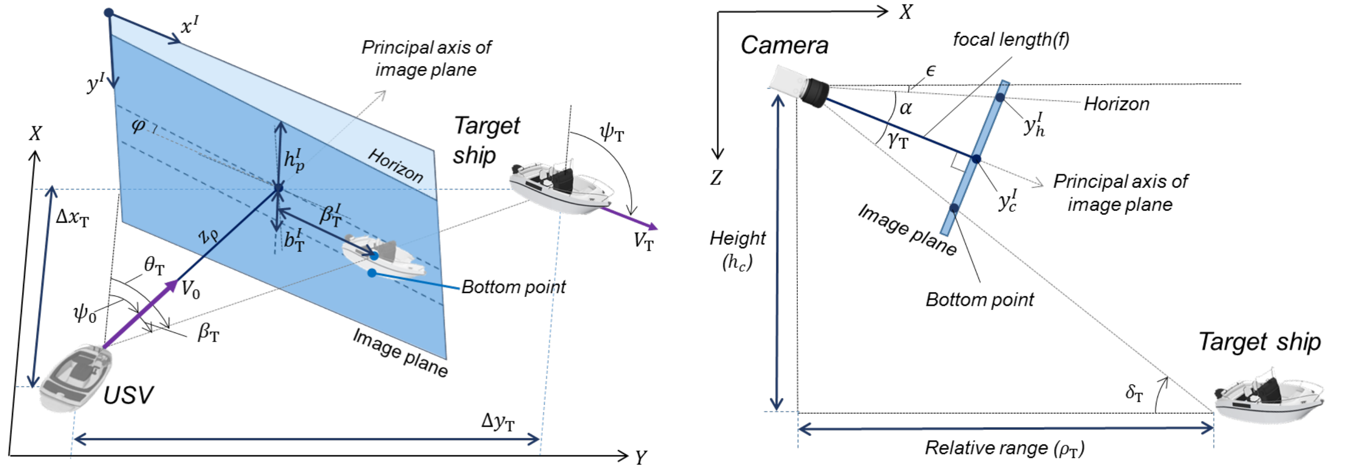


Fig. 2: Automatic detection of an approaching ship by the proposed image procedure: (a) Head-on situation; (b) crossing situation approaching from the own ship's starboard side.

B. Evaluation of relative measurements

For trajectory estimation of the detected target ship, relative measurements extracted from the camera image can be used in the tracking filter framework. The performance of a tracking filter critically depends on the accuracy and reliability of these measurements. Therefore, a reliable extraction method



(a) (b)

Fig. 3: Camera geometry and coordinate systems: (a) Coordinate systems in the horizontal plane for bearing measurements; (b) Coordinate systems in the vertical plane for range measurements.

is required to enhance the accuracy of bearing and range measurements. In order to extract relative measurements with respect to the global frame, the obtained pixel information is transformed into the sensor frame. These measurements are determined using the feature points of the target ship projected on the image plane considering the camera geometry and the relative coordinates in the observer's reference frame, as illustrated in Fig. 3.

The relative bearing to a target with respect to the observer's heading can be expressed as:

$$\beta_{\mathrm{T}} = (F_c/w_p^I)\,\beta_{\mathrm{T}}^I\,\cos\varphi \tag{1}$$

where F_c is the camera's field of view (FOV), w_p^I is the width of the image, β_{T}^I denotes the pixel distance in the lateral direction from the target ship to the center line of the image plane, and φ is the slope of the horizon. In order to determine the accurate location of the target in the current image frame, the feature points are re-extracted using the FAST corner detector on the detection region. The parameter setting of the FAST corner detector is adjusted to find the more features of the detected target. To accurately determine the center point of the detected target on the image, the density-based spatial clustering of applications with noise (DBSCAN) algorithm is used, as shown in Fig. 4. The DBSCAN determines the center point of the spatially distributed features by checking connectivity to other nearby features extracted within the detection region of the current frame [15].

The relative range measurement is determined by the vertical pixel distance from the detected horizon to the lowest feature point of the target ship within the detection region. The range increases as this feature point approaches the horizon. The relative range can be calculated by $\rho_{\mathrm{T}} = h_c/(\tan\delta_{\mathrm{T}}\cos\beta_{\mathrm{T}})$, where h_c is the height from the horizon to the camera mounted on the vehicle. δ_{T} can be determined as follows:

$$\delta_{\mathrm{T}} = \begin{cases} \gamma_{\mathrm{T}} + \alpha + \epsilon \;\approx\; \gamma_{\mathrm{T}} + \alpha & \text{if } y_h^I \le y_c^I \\ \gamma_{\mathrm{T}} - \alpha + \epsilon \;\approx\; \gamma_{\mathrm{T}} - \alpha & \text{otherwise.} \end{cases} \tag{2}$$

Here, y_c^I and y_h^I represent the vertical coordinates of the image center and the horizon. $\gamma_{\mathrm{T}} = \tan^{-1}(b_{\mathrm{T}}^I/f)$ and $\alpha = \tan^{-1}(h_p^I/f)$ where f is the focal length of the camera. b_{T}^I and h_p^I denote the pixel distances from the center point of the image to the lowest feature point and to the horizon, respectively. ϵ is the angle between the level surface and the horizon.

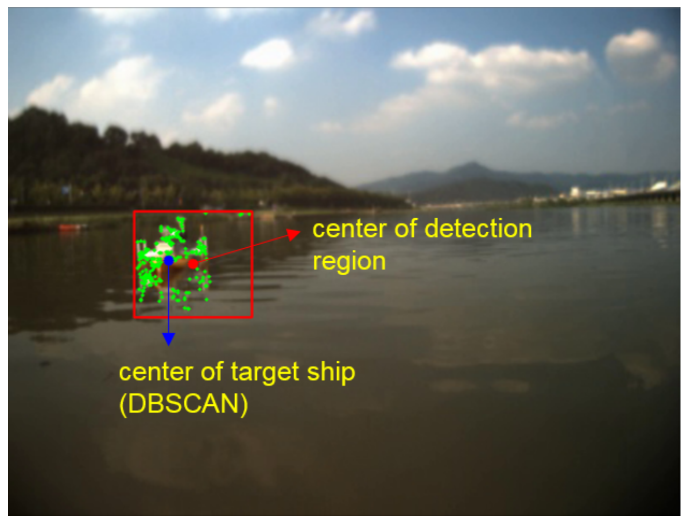


Fig. 4: Results of the center point of the detection region and DBSCAN. The green dots represent feature points extracted by the FAST corner detector in the detection region.

C. Target trajectory estimation

The state vector representing the motion of the observing ship is defined as $\mathbf{x}_0 = [\ x_0\ y_0\ \psi_0\ V_0\ ]^\intercal$, where x_0 and y_0 are the vehicle's position in the global frame, ψ_0 is the vehicle's heading, and V_0 is the speed in the longitudinal direction. The kinematic motion model of the observing ship can be expressed as:

$$\dot{\mathbf{x}}_0 = [\ V_0 \cos\psi_0 \quad V_0 \sin\psi_0 \quad 0 \quad 0\ ]^\intercal \tag{3}$$

The position, heading, and speed measurements of the observing ship are provided by onboard motion sensors. In order to estimate the motion of the target ship simultaneously, the state vector of the tracking filter is augmented by cascading the observer state vector $\mathbf{x}_0$ and the target state vector $\mathbf{x}_\mathrm{T} = [\ \mathbf{x}_{\mathrm{T}_1}^\intercal\ \mathbf{x}_{\mathrm{T}_2}^\intercal\ \cdots\ ]^\intercal$, where $\mathbf{x}_{\mathrm{T}_i} = [\ x_{\mathrm{T}_i}\ y_{\mathrm{T}_i}\ \psi_{\mathrm{T}_i}\ V_{\mathrm{T}_i}\ ]^\intercal$ represents the state vector of the ith target ship. Note that multiple traffic ships can be considered and thus the dimension of the target state vector may increase with the number of detected targets. The system dynamics can be expressed as an augmented vector equation consisting of the motion model of the observer and traffic ships, which can be written as

$$\dot{\mathbf{x}} = \begin{bmatrix} \dot{\mathbf{x}}_0^\intercal \\ \dot{\mathbf{x}}_\mathrm{T}^\intercal \end{bmatrix} + \mathbf{w} \tag{4}$$

where $\mathbf{w} \sim \mathbf{N}(0, \mathbf{Q})$ is the zero-mean Gaussian process noise and $\mathbf{Q}$ reflects the uncertainty of the motion model.

The measurement model can be expressed as

$$\mathbf{z} = \begin{bmatrix} \mathbf{z}_0^\intercal \\ \mathbf{z}_\mathrm{T}^\intercal \end{bmatrix} + \mathbf{v} \tag{5}$$

Here, $\mathbf{v} \sim \mathbf{N}(0, \mathbf{R})$ is the measurement noise, which is assumed to follow a zero-mean Gaussian distribution. The measurement vectors of the observer and the target are given by $\mathbf{z}_0 = [\ x_0\ y_0\ \psi_0\ V_0\ ]^\intercal$ and $\mathbf{z}_\mathrm{T} = [\ \mathbf{z}_{\mathrm{T}_1}^\intercal\ \mathbf{z}_{\mathrm{T}_2}^\intercal\ \cdots\ ]^\intercal$, where $\mathbf{z}_{\mathrm{T}_i}^\intercal$ represents the measurement vector of the ith target ship, which is defined as follows.

$$\mathbf{z}_{\mathrm{T}_i} = \begin{bmatrix} z_{\beta_i} \\ z_{\rho_i} \end{bmatrix} = \begin{bmatrix} \theta_{\mathrm{T}_i} - \psi_0 \\ \sqrt{[\Delta x_{\mathrm{T}_i}^2 + \Delta y_{\mathrm{T}_i}^2]} \end{bmatrix} \tag{6}$$

Note that the vision measurement $\mathbf{z}_{\beta_i}$ is the angle difference between the bearing $\theta_{\mathrm{T}_i} = \tan^{-1}(\Delta y_{\mathrm{T}_i}/\Delta x_{\mathrm{T}_i})$ and the heading of the vehicle, where Δx_{T_i} and Δy_{T_i} represent the distance between the vehicle and the ith target ship. The dimension of the measurement vector may vary depending on the number of target ships detected in the FOV. The Mahalanobis distance is used as a data association criterion for registering new target ships or identifying existing ships [16], [17].

D. Collision avoidance strategy

The COLREGs rules, commonly called "rules of the road", are defined for three situations: 1) overtaking, 2) head-on, and 3) crossing approaches. Three primary rules are as follows [13]:

- **Overtaking (Rule 13)**: Any vessel overtaking any other (give-way vessel) shall keep out of the way of the vessel being overtaken (stand-on vessel).
- **Head-on (Rule 14)**: When two power-driven vessels are meeting on reciprocal or nearly reciprocal courses so as to involve risk of collision each shall alter her course to starboard so that each shall pass on the port side of the other. (Both are give-way vessels.)
- **Crossing (Rule 15)**: When two power-driven vessels are crossing so as to involve risk of collision, the vessel (give-way vessel) that has the other (stand-on vessel) on her own starboard side shall keep out of the way and shall, if the circumstances of the case admit, avoid crossing ahead of the other vessel.

For evasive maneuver in these cases, the give-way vessel is required to alter its course to avoid the stand-on vessel, and the stand-on vessel should maintain its course and speed in accordance with the COLREGs rules.

Upon encountering a scenario for collision avoidance, if collision risk is not detected, the own ship maneuvers following a simple waypoint guidance by line-of-sight (LOS) considering a cross-track and along-track errors. In our strategy, when the relative range (i.e., separation distance) between two ships becomes smaller than the predefined minimum separation distance ρ_{th}, the own ship changes its heading towards the starboard side, as shown below:

$$\theta_d = \begin{cases} \theta_{los} + \theta_c & \text{if } \rho_\mathrm{T} \leq \rho_{th} \\ \theta_{los} & \text{otherwise.} \end{cases} \tag{7}$$

where θ_d denotes the desired heading angle of the own ship either to avoid collision or track the next waypoint, θ_{los} represents the LOS angle from the current position to the next waypoint, and θ_c is the command angle biased for collision avoidance.

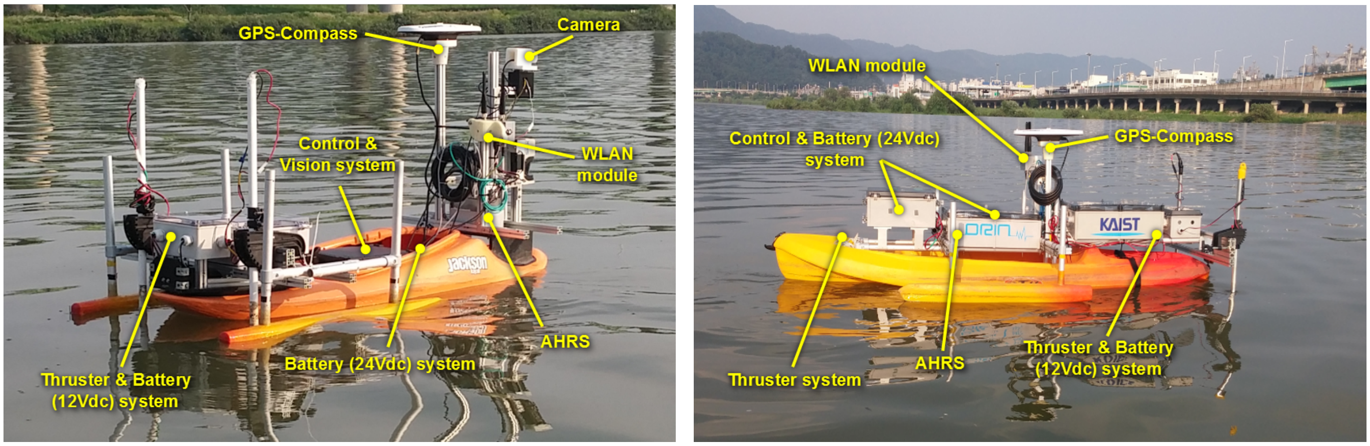
III. FIELD EXPERIMENT

Field experiments were carried out to demonstrate the feasibility of the proposed approach in an inland water environment. For these, two small kayak-based USVs developed by Korea Advanced Institute of Science and Technology (KAIST) were used. In addition, to clearly show the utility of the proposed approach under a low observability condition, a head-on scenario with a target ship was chosen.

A. USV system and experimental setup

The USVs were developed on commercial kayak platforms. A pair of floating pontoons were added to each ship on both sides for improved roll stability, as shown in Fig. 5. The observer was equipped with a suite of motion sensors including a Global Positioning System (GPS) compass for accurate position and heading angle sensing (see Fig. 5(a)). For detection of the target ship, a forward-looking camera was installed. A GPS was installed in a target ship as well to obtain the ground-truth trajectory data (see Fig. 5(b)). The observer and the target ship were commanded to approach each other head-on by waypoint-tracking control. The speed was set to be approximately 1.2 knots for both the observer and the target ship.

The proposed algorithm can process 5 frames per second (fps) on a computer with an Intel(R) CoreTMi7-4010U @ 1.7 GHz and 4 GB of RAM. It was fully implemented in C++ using the OpenCV library, the camera image had 800×600 resolution. The average execution time of our approach was within 127 ms for each frame.

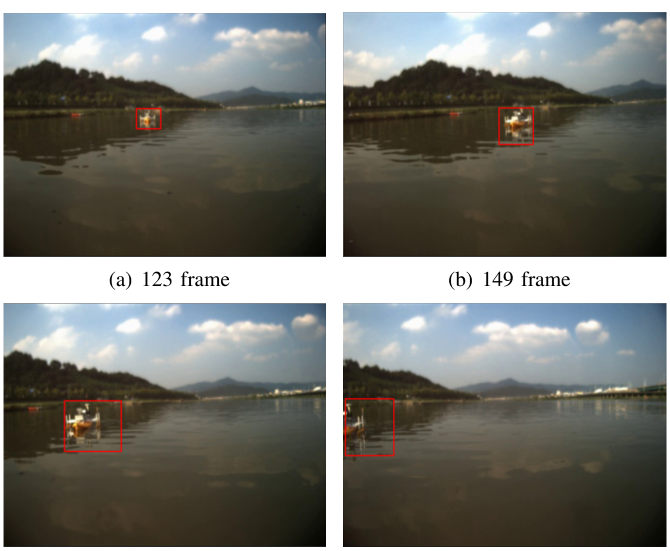


(a) (b)

Fig. 5: Two vehicles used in the on-water experiment: (a) Orange duck (Length 2.2 m), the observer; (b) Yellow duck (Length 2.8 m), the target ship

B. Experimental results

Figure 6 shows the detection results for the approaching target ship in the field test. In Fig. 6(a), the observer first detected the target ship approximately 25 m away in a head-on situation. At the first detection point, the estimated separation distance was far enough so that the observer simply treated it as a low-risk object. Note that the computer vision approach for detecting the target object depends greatly on the size and appearance of the object. As the target ship approached, the observer recognized the collision situation from the separation distance estimated by the tracking filter, as shown in Fig. 6(b). The observer avoided the target ship by further altering its path to its starboard. Figs. 6(c) and 6(d) show a turn maneuver toward starboard and successful avoidance of the target ship after it disappeared within the field of view of the camera.



(a) 123 frame (b) 149 frame

(c) 158 frame (d) 165 frame

Fig. 6: Snapshots of target ship detection in the head-on situation with the frame numbers.

Figure 7 shows the results of the on-water experiment. No communication between the vehicles was assumed during the field experiment. Figure 7(a) shows the actual trajectories of the observer and the target ship that were encountering each other head-on. The trajectories estimated by the proposed method were also plotted together for comparison. After evasive maneuver for collision avoidance, the observer continued its path toward the next waypoint which was predefined. Although the range measurement was not highly accurate, the filter uncertainty was considerably reduced by using the measurements obtained from images, as shown in Fig. 7(b). When the estimated separation distance became less than the predefined minimum separation distance, an evasive maneuver that changed the observer's heading according to the proposed strategy was initiated to avoid collision. The observer then changed its heading to track the next waypoint.

IV. Conclusion

This paper introduced the design procedure of a vision-based tracking filter that enables estimation of the trajectories of marine traffic ships and collision avoidance using an on-board monocular camera, even under low observability conditions. For improved state observability and filter performance, the vertical pixel distance between the detected horizon and the target ship in the image was introduced to the filter in addition to horizontal bearing angle measurements. A collision avoidance strategy was then proposed to implement an evasive action according to COLREGs. The feasibility of the proposed approach was demonstrated through field experiments.

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References

[1] S. Sivaraman and M. Trivedi, "Looking at vehicles on the road: A survey of vision-based vehicle detection, tracking, and behavior analysis," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 14, no. 4, pp. 1773–1795, Dec 2013.

[2] O. Gal and E. Zeitouni, "Tracking objects using phd filter for usv autonomous capabilities," in *Robotic Sailing 2012*. Springer, 2013, pp. 3–12.

[3] J. Larson, M. Bruch, and J. Ebken, "Autonomous navigation and obstacle avoidance for unmanned surface vehicles," in *Defense and Security Symposium*. International Society for Optics and Photonics, 2006, pp. 623 007–623 007.

[4] M. T. Wolf, C. Assad, Y. Kuwata, A. Howard, H. Aghazarian, D. Zhu, T. Lu, A. Trebi-Ollennu, and T. Huntsberger, "360-degree visual detection and target tracking on an autonomous surface vehicle," *Journal of Field Robotics*, vol. 27, no. 6, pp. 819–833, 2010.

[5] T. Huntsberger, H. Aghazarian, A. Howard, and D. C. Trotz, "Stereo vision–based navigation for autonomous surface vessels," *Journal of Field Robotics*, vol. 28, no. 1, pp. 3–18, 2011.

[6] Y. Kuwata, M. T. Wolf, D. Zarzhitsky, and T. L. Huntsberger, "Safe maritime autonomous navigation with colregs, using velocity obstacles," *Oceanic Engineering, IEEE Journal of*, vol. 39, no. 1, pp. 110–119, 2014.

[7] P. Shar and X. R. Li, "Practical approach to observability of bearings-only target tracking," in *SPIE's International Symposium on Optical Science, Engineering, and Instrumentation*. International Society for Optics and Photonics, 1999, pp. 514–520.

[8] E. Frew and S. Rock, "Trajectory generation for constant velocity target motion estimation using monocular vision," in *Robotics and Automation, 2003. Proceedings. ICRA '03. IEEE International Conference on*, vol. 3, Sept 2003, pp. 3479–3484 vol.3.

[9] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation with applications to tracking and navigation: theory algorithms and software*. John Wiley & Sons, 2004.

[10] E. Northardt, I. Bilik, and Y. Abramovich, "Bearings-only constant velocity target maneuver detection via expected likelihood," *Aerospace and Electronic Systems, IEEE Transactions on*, vol. 50, no. 4, pp. 2974–2988, October 2014.

[11] J. Park, J. Kim, and N. sun Son, "Passive target tracking of marine traffic ships using onboard monocular camera for unmanned surface vessel," *Electronics Letters*, vol. 51, no. 13, pp. 987–989, 2015.

[12] S. Nardone, A. G. Lindgren, and K. F.Gong, "Fundamental properties and performance of conventional bearings-only target motion analysis," *Automatic Control, IEEE Transactions on*, vol. 29, no. 9, pp. 775–787, Sep 1984.

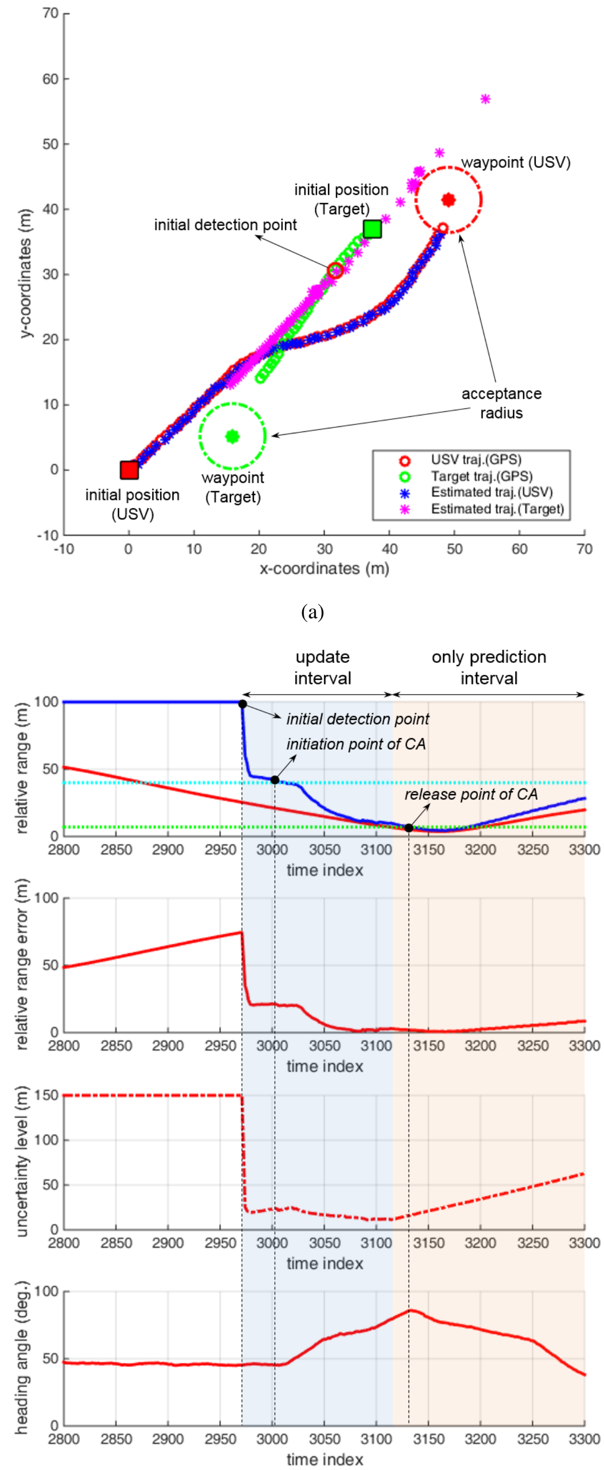
[13] U. Commandant, "International regulations for prevention of collisions at sea, 1972 (72 colregs)," *US Department of Transportation, US Coast Guard, COMMANDANT INSTRUCTION M*, vol. 16672, 1999.

[14] E. Rosten, R. Porter, and T. Drummond, "Faster and better: A machine learning approach to corner detection," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 32, no. 1, pp. 105–119, 2010.

[15] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise." in *Kdd*, vol. 96, no. 34, 1996, pp. 226–231.

[16] P. C. Mahalanobis, "On the generalized distance in statistics," *Proceedings of the National Institute of Sciences (Calcutta)*, vol. 2, pp. 49–55, 1936.

[17] Y. Bar-Shalom, *Tracking and data association*. Academic Press Professional, Inc., 1987.



(a)

(b)

Fig. 7: Field experimental results of vision-based collision avoidance in accordance with the COLREG rules: (a) the observer's overall path after a successful detection and COLREG maneuver; (b) the results for relative distance, distance error, uncertainty level ($\sqrt{[\sigma_x^2 + \sigma_y^2]}$ where σ_x and σ_y denote the standard deviations in x and y) and the change of heading angle.