Overloaded Ship Identification based on Image Processing and Kalman Filtering

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Abstract

To reduce water traffic accident, identification of overloaded ships has been of major importance for enforcing inland river management, especially in some developing countries. Driven by rising oil prices or other economic benefits, the ship overload phenomenon continued to occur in China. Therefore, overloaded ship detection has been of a key factor of shipping safety. This paper presented a robust method for detecting overloaded ship and the proposed algorithm included three stages: ship detection, ship tracking and overloaded ship identification. Ship detection was a key step and the concept of ship tracking is built upon the ship-segmentation method, in which the algorithm about background estimation, background updating, background subtraction and ship detection has been described. According to the segmented ship shape, a predict method based on Kalman filter has been proposed to track each ship. The described identification system included a video camera and a high definition camera, which led to a necessary coordinate transformation in system model of Kalman filter. The data of ship length and ship speed could be used to identify overloaded ship. The proposed method has been tested on a number of monocular ship image sequences and the experimental results showed that the algorithm was robust and real-time.

Keywords: Inland River, Kalman Filter, Overloaded Ship Identification

1. Introduction

Recently, increasing countries and groups have expressed concern about environmental protection and low-carbon life [1, 2]. As a part of green transport, inland river ships have been of increasing importance [3]. The trend of social development not only promotes the great development of inland river transportation, but also causes growing overloaded phenomenon of inland river ship [4, 5]. The overloaded phenomenon in inland river and access to the sea are represented in Figure 1, respectively.

![Figure 1. Examples of Overloaded Ship in Inland River and Access to the Sea](image-url)

With the development of information technology, video camera and high definition camera are considered as being a suitable sensor device for capturing and recognizing spatio-temporal aspects of inland river structures and traffic situations [6, 7], and have been introduced to many social systems for various purposes, especially transportation. It is well recognized that vision-based surveillance system are more versatile than the others for traffic parameter estimation and overloaded phenomenon identification [8, 9]. L. Eun-Kyung1 presented a fusion camera system combining one time-of-flight depth camera and two video cameras to generate multi-view video sequences. And Benetazzo A.2

presented a new six Degree Of Freedom (6 DOF) motion measurement technique for small-scale physical models of floating bodies, based on analysis of image sequence from one camera [10, 11, 12].

Ship detection and ship tracking can offer us a continuous description of vessel traffic flow. Therefore, it has been an important and challenging issue in video-based overloaded ship identification. However, there are several problems remain unsolved in this process [13, 14]. On the one hand, the tracking result strongly depends on the quality of ship detection. Apparently, it augments the instability of tracking system. On the other hand, overloaded ship identification is to be processed in real-time and it needs a simple and efficient approach to extract ship feature [15, 16].

In the last several years, an extensive research work has been done and many traffic monitoring systems have been exploited. Researchers have developed various algorithms to extract object feature and track moving object, but most of water transportation monitoring systems are focused on Synthetic Aperture Radar images, infrared cameras, AIS (Automatic Identification System), radar, or space-borne optical image, while little work has been done for optical image.

Kalman filter is a powerful tool to estimate the state of object. Considering the complexity of the Kalman filter, many researchers presented their own algorithms to construct imaging filters and achieve real-time operation. Li Peihua [8] applied a Kalman particle filter (KPF) and an unscented particle filter (UPF) to contour tracking to try to overcome the problem. Piovoso Michael [9] introduced a set of recipes for implementation of the Kalman filter to a variety of real-time imaging settings. Aiming at non-stationary and non-linear nature of the ship motion, Weng, Zhen-Ping [10] proposed an application of Kalman filtering in non-linear second-order Volterra series model. Fossen Thor [11] analyzed a control system which could process motion-related signals to infer the state of the ship, to filter disturbances, and to generate an appropriate command for the actuators. Wang Xiao-Fei [12] used UKF to estimate the states and uncertain parameters due to time-varying added mass matrices. And then the under-actuated ship with time-varying parameters can follow a desired straight path with help of the proposed UKF-based controller.

It is the final and most important stage to identify overloaded ships, in which the strongly jeopardizing effect of overloading could be researched [13, 19]. Many problems of detecting, tracking and identifying moving objects have been researched in some surveillance applications [14]. Some integrated solutions about the real-time operation, poor imaging conditions, decentralized architecture and relative pose selection for multi-camera self-calibration have been presented. The algorithms that are needed span from image processing to event detection and behavior understanding, and each of them requires dedicated study and research [17, 18].

This paper presents a robust and real-time method to identify overloaded ship through a video camera and a high definition camera. The proposed algorithm includes three stages: ship detection, ship tracking and overloaded ship identification.

The rest of the paper is organized as follows. We first introduce the process of ship detection simply in Section II. The algorithm related to ship tracking is given particularly in Section III. Following that, overloaded ship identification and its experimental results are presented in section IV. Finally, the conclusion can be found in Section V.

2. Proposed scheme

2.1. Ship detection

It is a very important step to extract the ship shape out of the river background. The ship detection method requests to automatically segment every ship so that there can be a unique tracking associated with the ship. In this phase, we will solve several problems as follows:

- Extract the background image automatically from a sequence of river traffic images and update the background continually according to the change of ambient lighting, weather, etc.
- Select an adaptive filter to eliminate abnormal moving object in the binary background subtraction image so that the system can be more robust.
- Detect ship from the binary background subtraction image.

Apparently, it is desirable to extract the initial background image automatically from a sequence of road traffic images before background subtraction. Therefore, we propose a background extraction method based on moving object pixel detection, in which each pixel of image will be identified
whether its intensity had an obvious change or not. Moving object pixels could be extracted from current input image by performing a difference on three consecutive frames.

Firstly, it is need to calculate inter-frame subtraction image of two pairs of images, i.e. the first subtraction image between (k-2) frame image and the (k-1) frame image, and the second subtraction image between (k-1) frame and (k) frame. Secondly, two binary images could be transformed from the two subtraction images via a dynamic subtraction threshold. Then, we apply the bitwise logical AND operation to the two binary subtraction images, to clarify the moving object pixels. Finally, the original background image could be obtained through patching up non-moving object pixels from a sequence of input images. The same method could be used to update the background image, too.

Let \( I_{i,j} \), \( B_{i,j}^{k} \), \( B_{0,i,j}^{k} \) and \( B_{C,i,j}^{k} \) be input image, temporary background image, previous temporary background image and background image respectively, at frame \( k \), then:

\[
B_{i,j}^{k+1} = \begin{cases} 
0, & \text{if } \left| I_{i,j}^{k-2} - I_{i,j}^{k-1} \right| > T_D \text{ AND } \left| I_{i,j}^{k-1} - I_{i,j}^{k} \right| > T_D \\
255, & \text{otherwise}
\end{cases}
\]  

(1)

In above equation, \( T_D \) is the threshold of background subtraction and it can be determined via a dynamic threshold selection scheme based on MEC.

In view of the random of the input image, this paper defines \( C_{i,j} \) and \( \omega_{i,j} \) to enhance the stability of background image. First, through collecting grayscale of each background pixel, our method estimates previous temporary background image \( B_{0,i,j}^{k} \), \( C_{i,j} \) and \( \omega_{i,j} \). Then, according these arrays we may decide whether temporary background image \( B_{i,j}^{k} \) need to be modified. At last, our arithmetic will update the innovation and calculate the new \( B_{i,j}^{k} \), \( C_{i,j} \) and \( \omega_{i,j} \) in order to implement the next prediction recursively.

\[
\begin{align*}
&\text{if } C_{i,j} > T_C, \text{ then: } B_{0,i,j}^{k+1} = B_{i,j}^{k+1} = B_{i,j}^{k} + \frac{B_{i,j}^{k-1} \ast \omega_{i,j} + B_{i,j}^{k-1}}{\omega_{i,j} + 1}, \omega_{i,j} = \text{Max}(\omega_{i,j} + 1, M_{\omega}), C_{i,j} = 1. \\
&\text{if } C_{i,j} > 0 \text{ AND } C_{i,j} < T_C, \text{ then: } B_{0,i,j}^{k+1} = B_{i,j}^{k+1} = \frac{B_{0,i,j}^{k} \ast C_{i,j} + B_{i,j}^{k-1}}{C_{i,j} + 1}.
\end{align*}
\]  

(2)

\[
C_{i,j} = \begin{cases} 
C_{i,j} + 1, & \text{if } \left| B_{i,j}^{k+1} - B_{0,i,j}^{k} \right| < T_B \\
0, & \text{otherwise}
\end{cases}
\]  

(3)

In above equations, \( T_B \) and \( T_C \) are two thresholds and \( M_{\omega} \) is the destine maximum of \( \omega \).

At the starting time, each pixel of \( B_{0,i,j}^{k} \) is inexistent. Therefore, this arithmetic requires N frames of input video to construct initial background image and the above equations will be amended to adapt starting state of the system.

In our arithmetic, too low ship speed may cause errors background and failing detection. However, traffic jam event often bring on slower speed. To extract a robust background image, our group devises a new method based on multiple background images. In our method, three consecutive inter-frames is a group, whose difference can be used to detect moving object region. Then, the moving object region candidate would be calculated from these differences every some group. The intervals of group is defined \( A \). Of course, the value of variable \( A \) is three in our experimentation. Figure 2 sketch out the configuration about these groups, in which \( a > 0 \text{ AND } a < A, \ A = 3 \).
Now, the equation (1) would be changed as follows:

\[
B_i = \begin{cases} 
0, & \text{if } I_{i,j}^{p_{i,j}+3_{i,j}+1} - I_{i,j}^{p_{i,j}+3_{i,j}-1} > T_D \text{ AND } I_{i,j}^{p_{i,j}+3_{i,j}+1} - I_{i,j}^{p_{i,j}+3_{i,j}-1} > T_D, \|a| \geq 0, a < A. \\
255, & \text{otherwise.}
\end{cases}
\] (4)

In above equations, \( \{TB_i\} \) is temporary background image of group \( a \).

Accordingly, the equation (2) and equation (3) would be changed as follows:

\[
\begin{cases} 
\text{if } C(a)_{i,j} > T_C, \text{ then: } \{B\}_{i,j}^{k-1} = B_i^{k-1}, \ B(a)_{i,j}^{k-1} = \frac{B(a)_{i,j}^{k-1} \ast \omega(a)_{i,j} + B_i^{k-1}}{\omega(a)_{i,j} + 1}, \\
\omega(a)_{i,j} = \max(\omega(a)_{i,j} + 1, M_a), C(a)_{i,j} = 1.
\end{cases}
\] (5)

\[
\begin{cases} 
\text{if } C(a)_{i,j} > 0 \text{ AND } C(a)_{i,j} < T_C, \text{ then: } \{B\}_{i,j}^{k-1} = B_i^{k-1} \ast C(a)_{i,j} + B(a)_{i,j}^{k-1} \cr \text{otherwise, } C(a)_{i,j} = 0.
\end{cases}
\] (6)

In above equations, the \( \{B_i\} \), \( \{B_i^{k-1}\} \), \( \{C(a)_{i,j}\} \) and \( \{\omega(a)_{i,j}\} \) are the \( \{B_i\} \), \( \{B_i^{k-1}\} \), \( \{C(a)_{i,j}\} \) and \( \{\omega(a)_{i,j}\} \) of group \( a \), respectively.

At last, the statistic of \( \{B(a)_{i,j}\} \) would confirm the value of \( \{\omega(a)_{i,j}\} \).

\[
B_{i,j}^{k} = \begin{cases} 
\frac{1}{2} B_{i,j}^{k} + \frac{1}{A} \sum_{a=0}^{A} B_{i,j}^{k}, & \text{if } B(a)_{i,j}^{k} - B(a-1)_{i,j}^{k} < T_D \text{ AND } B(a)_{i,j}^{k} - B(a+1)_{i,j}^{k} < T_D \\
B_{i,j}^{k}, & \text{otherwise}
\end{cases}
\] (7)

After the update process, we calculate the difference between background image and input image for each pixel, and then apply binary filter to background subtraction image in order to clarify the moving object region. While the binary difference image of moving ships is obtained, we apply a block filter based on statistical to filter the noises and then adopt a simple seed-growing arithmetic to detect ship. The detailed results of our proposed scheme are represented from Figure 3 to Figure 5.
2.2. Ship tracking

Based on the segmented ship shape, which can be represented by a simple square model, we propose a Kalman filter method to track ship.

The Kalman filter is the minimum-variance state estimator for linear dynamic systems with Gaussian noise. In addition, the Kalman filter is the minimum-variance linear state estimator for linear dynamic systems with non-Gaussian noise.

Consider the system model as follows:

\[
x_{k+1} = F \star x_k + w_k \\
y_k = H \star x_k + v_k
\]

(8)
(9)

where \( k \) is the time step, \( x_k \) is the state, \( v_k \) is the measurement, \( w_k \) and \( v_k \) are the zero-mean process noise and measurement noise with covariances \( Q \) and \( R \) respectively, and \( F \) and \( H \) are the state transition and measurement matrices. The Kalman filter equations are given as follows:

\[
P_k = F \star P_{k-1} \star F^T + Q
\]

(10)

\[
G_k = P_k \star H^T \star \left( H \star P_k \star H^T + R \right)^{-1}
\]

(11)

\[
x(k | k) = F \star x(k-1 | k-1) + G_k \star (y_k - H \star x(k-1 | k-1))
\]

(12)
for \( k = 1, 2, \ldots \), where \( I \) is the identity matrix. \( x(k \mid k) \) is the priori estimate of the state \( x_k \) given measurements up to and including time \( k-1 \). \( x(k-1 \mid k-1) \) is the priori estimate of the state \( x_k \) given measurements up to and including time \( k \). \( G_k \) is the Kalman gain, \( P_k \) is the covariance of the priori estimation error \( x_k - x(k-1 \mid k-1) \), and \( \xi_k \) is the covariance of the posteriori estimation error \( x_k - x(k \mid k) \).

When the noise sequences \( \{w_k\} \) and \( \{v_k\} \) are Gaussian, uncorrelated, and white, the Kalman filter is the minimum-variance filter and minimises the trace of the estimation error covariance at each time step. When \( \{w_k\} \) and \( \{v_k\} \) are non-Gaussian, the Kalman filter is the minimum-variance linear filter, although there might be nonlinear filters that perform better. When \( \{w_k\} \) and \( \{v_k\} \) are correlated or colored, (10) – (13) can be modified to obtain the minimum-variance filter. Our system schematic diagram is shown in Figure 6.

As we know, ship feature extraction plays an important role in the ship tracking. The extracted information must be robust and essential to the accurate visual interpretation of the image so that the tracking result isn’t dependent on parameters controlling thresholds, which is often established empirically to achieve acceptable performance. Our arithmetic extracts many ship features to characterize each ship, such as ship center of mass, average intensity, and ship speed etc.

Now suppose it satisfies the equality constraints. Let \( X_k \) be the ship feature vector of the time \( k \). then:

\[
x_k = \begin{bmatrix} x_i(k) & x_u(k) & x_j(k) & x_v(k) & x_e(k) & x_g(k) & x_h(k) \end{bmatrix}^T
\]

\[
y_k = \begin{bmatrix} y_i(k) & y_j(k) \end{bmatrix}^T
\]

Where \( x_i(k) \) and \( x_j(k) \) are the state values of ship center’s coordinates in the input image, \( x_u(k) \) and \( x_v(k) \) are their speed values, \( x_e(k) \), \( x_g(k) \) and \( x_h(k) \) are a series of ship image features extracted from edge image, gray image and hue image, \( y_i(k) \) and \( y_j(k) \) are the measurements values of \( x_i(k) \) and \( x_j(k) \).

According above definition and the system schematic diagram, we define the Kalman system model as:
In above equation, $\alpha, \beta, \gamma$ are coefficients of edge variation, intensity variation and hue variation, which reflects the influence of distance and lighting conditions.

3. Experimental results

The research in this step is primary on how to get the position of the waterline by digital image processing technology. In order to ensure the detection accuracy of waterline, another high definition camera will be used to shoot the ship photograph. Taking into account the difference of coordinate systems between the video camera and high definition camera, it is necessary to convert ship center’s coordinates and obtain the data about ship length, ship speed and navigation direction through the ship tracking result. This paper takes two steps to detect the waterline edge.

The first step is the edge detection approach based on the navigation direction. Compared to other operations, the canny operator gets the better results in detection. In order to find the exact waterline, the false edges are removed by navigation direction projection. At last, the waterline line is fitted by the least square method.

The second step is the edge pick-up approach based on the Hough transform. This paper adopts a voting method to choose the possibly true edges, in which the weight values of the following attribute are large: the hue grads, the saturation grads, the intensity grads, and the times of searching edges. According to the difference of the average values between the upside area and the downside, the method select the true edge of waterline. The horizontal line is fitted by the least square method.

Finally, the distance between the top of ship and the waterline will identify whether ship is overloaded or not. The detailed results of our proposed scheme are represented from Figure 7 to 9.

![Figure 7. Original Image](image-url)
4. Conclusion

In this paper, we present a new algorithm to ship tracking in a video-based ITS. The experiment results on real-world videos show that the algorithm is effective and real-time. The correct rate of ship tracking is higher than 85 percent, independent of environmental conditions.

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6. References


