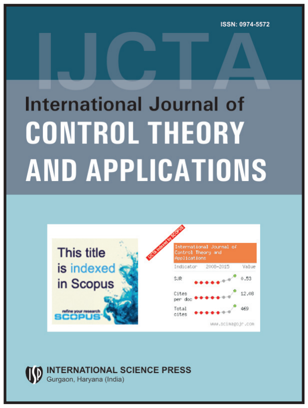

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Detection and Tracking of Marine Vessel Using Wavelet Analysis

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Abstract: For many object detection and its movement tracking has became a hot topic in computer vision research. These work present a automatic method for identifying the ship candidates by applying advanced image processing techniques. The input from a surveillance camera is undergone a wavelet decomposition to explore different frequency subbands that contain detailed and approximation coefficients. The spatial temporal and spectral features are extracted and then a sea land segmentation is done to cluster the similar pixels having same properties. For tracking a Kalman filter used to store the previous estimate, eliminating the need for storing the entire past observed data, and, thus is computationally more efficient. Extensive experiments by using maritime ship videos and images demonstrate that, in comparison with the existing relevant state-of-the-art approaches, the proposed method requires less detection time and achieves higher detection accuracy.

Keywords: Haar Wavelet transform, erosion, dilation, kalman filter.

1. INTRODUCTION

Image and Video detection and tracking has been an recent research topic in computer vision, which can be used for vehicle detection, object recognition, personnel monitoring and others. These detection of maritime vessels are mostly important in both civilian and military fields. It is not only for detecting illegal activities, but also for ensuring the safety in real environments. Traditional detection requires manual observations which consumes manpower and material resource greatly. With the development of remote sensing, satellite and artificial intelligence technologies, and image processing techniques fast and accurately detecting objects based on videos and images has been becoming an urgent issue.

Videos contains sequence of frames, each frame contains vital informations that are displayed in high frequency then only the human eye can view the videos with a continuity. The most common image processing techniques are applied to individual frames since each frames are closely related therefore can be applied to all frames. Visual contents can be represented as a different level of abstractions. At bottom level we can identify the colour information from the raw pixel values of image matrix. Then we can identify the shape of the object by yielding the edges, corners, lines, curves, and color regions. The followed by some techniques to confirm the detected object and highest level of abstraction layer may fuse and process these features as objects and their attributes then identify the relation of objects in each frames by successful tracking

Object detection in videos including identify the presence of an object in image sequences and locating it correctly for recognition. Object tracking is to monitor an objects with respect to the spatial and temporal changes in each frame sequence, including its presence, position, size, shape, etc. This is achieved by solving the problem in temporal domain that is identifying, the matching the target region in consecutive frames of a sequence of images taken at specific time intervals. These two methods are closely highly related because tracking initiate by detecting objects in frames, while detecting an object repeatedly in subsequent image sequence is often necessary to help and verify tracking.

The study of vehicle detection on land environment is relative simple and the algorithm can be easily devised than that for marine environment. For ocean maritime vessel detection with dynamic background of maritime environment, testing the images which are taken far away from the sea surface. The techniques of moving object detection for marine environment are still in the challenging stage because of the unpredictable or dynamic nature of ocean and natural weather conditions (such as wind, waves etc.) and the complex background of the marine environment. This paper proposes the moving object video detection techniques that can be applied to ship detection of marine background and successfully track that object in time domain analysis basis.

2. RELATED WORK

Most of the job in sea monitoring is done using radio radars [1].They rely on reflection of electromagnetic waves from a change in the dielectric or diamagnetic constants. A radar transmitter emits radio waves, which are reflected by the target. Reflected radio waves are detected by a radar receiver. Target objects are detected based on the latency between transmitted and received signals. Radar's ability to detect metal objects of various sizes depends on the choice of operating frequency. High (microwave) frequency marine radars are employed in most of the current vessels, aircraft and other object detection. They have properties of reliable detection that can detect small objects, however it is limited in operations that is 10-20 miles diatance.

Other imaging sensors were used for ship detection as well. Forward Looking Infra Red (FLIR) cameras is often a good sensor[2] of choice because the images they provide are insensitive to lighting condition they used the principal component global features and similarity matching to classify ship silhouettes. The authors of[3] used neural networks applied directly to image pixels. Recent work on ship classification in uses a k Nearest Neighbor classifier on shape features extract using region base shape descriptor. A notable disadvantage of FLIR systems is the low resolution of the images obtained which requires a relatively small viewing distance of the imaging system to the target. It is also more power consuming and, thus, is less capable for autonomous operation. It is aimed for autonomous operation, under power and communication bandwidth constraints.

Another category of related work that should be mentioned includes horizon detection in images One research group, very active in vision-based navigation, has published a number of papers related to horizon detection [5, 6, 7, 8]. Their basic approach, a statistical horizon detection algorithm, attempts to minimize the intra-class variance of the ground and sky distribution. The horizon is considered a line with high likelihood of separating the sky from ground (or non-sky) regions. A considerably different technique is described in [9]. It uses an idea similar to skew detection in document image analysis, i.e. detecting the skew of the scanned documents. The original image is pre-processed and edges are extracted. Projection profiles of edges in the image for different angles are obtained and the horizon is found in the profile corresponding to the largest peak of such a projection.

3. PROPOSED WORK

A novel technique for the analysing the target object features and object is detected and track the object in spatial and temporal analysis.

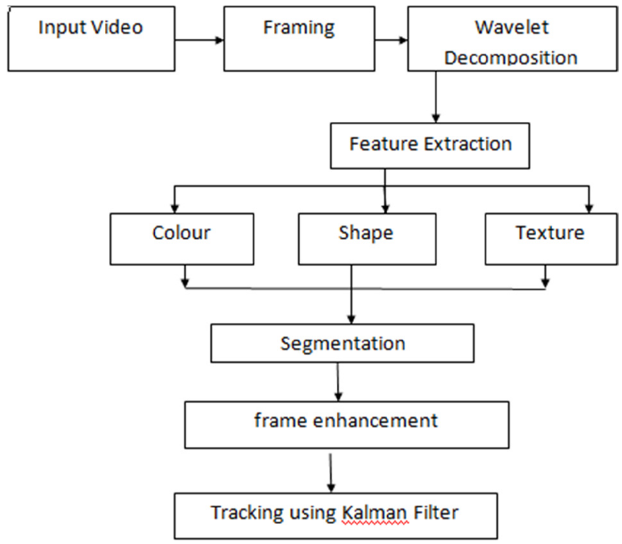

Figure 1: Basic Architecture of the system

Different frames can be obtained from videos by converting the videos into frames. These is achieved by using, the function 'frame2im' is used. Once frames are obtained, a haar wavelt decomposition is performed to extract the high level features of the images. The different frequency components show the sparse and different levels of features of the object. Once the decomposition is performed, further that image is processed by extracting different features of including color texture and temporal features. Then a image enhancement is performed to remove the unwanted illumination and followed by a sea land segmentation. The moving object tracking is performing a time series anlaysis using kalmaan filtering algorithm.

A. Haar Wavelet Decomposition

Inorder to identify different ship patterns the edge like informations need to be extracted. With the wavelet transform we can analyze the image in different resolution. Also differentiate the noise and actual corners are identified. As compared with traditional DCT,here there is no need of blocking the images. Instead a Haar wavelet transformation is applied to whole image which make the image more robust under the transmission error. The haar wavelet is the simplest wavelet which is not continous and hence it is not differentiable. Different subband frequency coefficients are explored by applying wavelet function on image pixel. These subbands contain coefficients that describe the horizontal and vertical characteristics of the original tile component. The haar wavelet mother wavelet function and scaling function is given as:

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2}, \\ -1 & \frac{1}{2} \le t < 1, \\ 0 & \text{otherwise.} \end{cases}$$

$$\phi(t) = \begin{cases} 1 & 0 \le t < 1, \\ 0 & \text{otherwise,} \end{cases}$$

Procedure for Haar Wavelet Transform:. (the Haar transform of an array of n samples)

1. Find the average of each pair of samples.
2. Find the difference between each average
3. Fill the first half of the array with averages. i.
4. Fill the second half of the array with differences.
5. Repeat the process on next datas

The advantages of Haar Wavelet transform as follows:

1. Best performance in terms of computation time since it need only addition and substraction.
2. Input and output are same length which is a power of 2
3. High compression ratio as lossless one
4. It is memory efficient, since it can be calculated can get our original data back and in the latter we can in place without a temporary array.

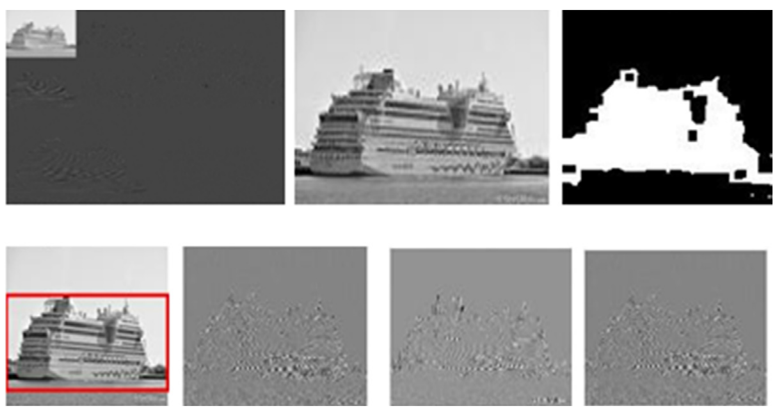

Figure 2: The result of Haar wavelet decomposition

B. Feature Based Object Detection

Feature extracted based object detection, standardization of image features that were extracted and alignment of reference points are important. The images that is to be transformed to another space for handling changes in illumination, size and orientation. Many of the features are extracted and the candidate objects which we are interested is modelled using these features. Object detection and recognition then can be transformed into a graph matching problem.

Image characteristics such as shape and spectral are the most useful features in images acquired at a high spatial resolution. Keeping their importance, it is difficult to successfully automate the detection of objects solely based on shape and texture features. Hence, based on *a* prior*i* knowledge of object' characteristics, we screen out spectral, shape features of the image is explored. A ship can be generally described by the following characteristic

- Bright pixels
- Large length to width ratio

- Symmetry between its head and tail, like a long narrow ellipse,
- a regular and compact shape

1. *Shape based approaches:* Shape based object detection very hard to achieve due to the difficulty of segmenting objects of interest in the images. In order to detect and determine the border of an object, an image may need to be preprocessed. The edge like informations are obtained in wavelet decomposition that is shown in Figure 2.The further shapes can be identified by applying the morphological operation like erosion and dilation is applied.

   Different object types such as persons, flowers, and airplanes may require different algorithms. For more complex scenes, noise removal and segmentation of sea and ship is performed. Once the object is detected and located, its boundary can be found by edge detection and boundary-following algorithms. The detection and shape identification of the objects becomes very difficult for complex scenes where there are multiple objects with occlusions and shading.

2. *Colorbased approaches:* As compared with shape feature, color is relatively constant under viewpoint changes and it is easy to be extracted. In colour histogram technique, it created a Gaussian Mixture Model to describe the color distribution within the frames and to segment the image into background and objects. This simple tracking method is based on tracking regions of similar normalized color from frame to frame. These regions are defined within the extent of the object to be tracked with fixed size and relative positions in a particular time. Each region is identified by computing a color vector sub-sampling the pixels within the region, which represents the averaged of pixels within this region. They even achieved some degree of robustness to occlusion by explicitly modeling the occlusion process.

   Accordingly, 12 spectral, shape features were computed for the image objects that is shown in Table 1.

Table 1
Different features extracted

Spectral	*Shape*
Number of pixels	Perimeter
Mean	Area
Standard deviation	Compactness
Min	Elongation
Max	Major minor axis ratio
Assymetry coefficient	Eccentricity

C. Image Enhancement

In order to remove uneven illumination, a morphological operator, i.e., top-hat transform (THT), is used for ship extraction and background suppression. As ships are usually brighter than their surroundings, the white THT is employed. The white top-hat transform is defined as the difference between the input image and its opening by some structuring element.

D. Sea Land Segmentation

Pre–screening of possible ship patterns is based on the contrast between sea (noise–like background) and target (a cluster of bright pixels) and the land pixels. These contrast mainly depends on the sea conditions and nature condition. A threshold based method is used for the detection of intensity peaks is based on the mean (μ_{oc}) and the standard deviation (σ_{oc}) of the sea background in the moving window. The steps of sea land segmentation is shown below

1. Binarize the input image by the Otsu algorithm[14, 15] and then label the connected regions
2. Find the geometrical center P of the largest connected region R.
3. Use point P as the starting point; traverse R to obtain another set of points P satisfying that the A × A neighboring regions of P', are inside the region R. Label the points P' as all-sea region S.
4. Compute the mean μ and variance σ of S, and use them as the statistical parameters of the Gaussian model, $T = \mu = \lambda\sigma$

Where λ is the weight of variation (σ) and set as three according to the Gaussian Distribution

E. Tracking

The Kalman filter KF [11] is an optimal estimation method of the state of a stochastic, non-stationary, dynamic and linear process. Kalman introduced the representation of linear dynamical systems by state equations. The process is governed by discrete and linear equations [12].

$$x(t+1) = \mathrm{A} \,.\, x(t) + \mathrm{B} \,.\, u(t) + w(t)$$

$$z(t) = \mathrm{C} \,.\, x(t) + \mathrm{D} \,.\, u(t) + v(t)$$

Where x is the process state vector, which may contain variables related to the object translation, scale and orientation and its first and second order derivatives, u is the control vector, z is the measurement vector obtained by a tracking algorithm, A is the state transition matrix, B is the state control matrix, C is the observation matrix, D is the measurement control matrix, w is the noise associated with the state and v is the noise associated with the measure. By hypothesis, w and v noise vectors are independent and have Gaussian multivariate probability distribution functions of zero mean and diagonal covariance matrix Q and R respectively

The Kalman filter provides a recursive solution to the linear optimal filtering problem. The solution is recursive; each updated estimate of the state is computed from the previous estimate and the new input data. The Kalman filter needs to store only the previous estimate, eliminating the need for storing the entire past observed data, and, thus is computationally more efficient than computing the estimate from the entire past observed data at each step of the filtering process. The algorithm works in a two-step process. In the prediction step, the Kalman filter calculate the current state of variables, along with their uncertainties. Once the outcome of the next measurement with some random noise is observed, these results are used for updated using a weighted average, with more weight being given to estimates with higher certainty. Since The algorithm is recursive, hence.

It can run in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required. For this work two different filters are defined to track the following two entities: the position of the center of the bounding box (centroid) and the bounding box dimensions. Each of these two filters tracks the behavior of the two variables. Two auxiliary variables for each filter describe the speed of change the main variables. For example for the first filter the pair of variables that describe the position of the centroid - namely the x and y coordinates are supplemented by auxiliary variables that describe the speed of movement of this centroid along the x and y axes; horizontal and vertical dimensions of the bounding box W and H are supplemented with the speed of changing of these variables in the horizontal and vertical directions. Equations show the implementation of the Kalman filter for visual tracking used in the thesis. The transformation matrix establishes the relation between the main and auxiliary variables in the current and next frames. That relation reflects the linear nature of the motion of the modeled object: the predicted value of the main variable (such as location of the corner) in the next state $k + 1$ is different from the previous state k on the amount of value of the corresponding auxiliary variable Δxk: $xk + 1 = xk + \Delta xk$. The measurement matrix shows correspondence between the state vector and measurement vector. Other important variables used in the model are state wk and measurement vk noises which are described by a normal distribution.

$$\begin{bmatrix} x_{k+1} \\ y_{k+1} \\ \Delta x_{k+1} \\ \Delta y_{k+1} \end{bmatrix} = \begin{vmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{vmatrix} \begin{bmatrix} x_k \\ y_k \\ \Delta x_k \\ \Delta_{yk} \end{bmatrix} + w_k$$

$$\begin{bmatrix} x_{m_k} \\ y_{m_k} \end{bmatrix} = \begin{vmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{vmatrix} \begin{bmatrix} x_k \\ y_k \\ \Delta x_k \\ \Delta_{yk} \end{bmatrix} + v_k$$

Here x and y represent the main variables such as the position of the center or dimension of the bounding box. Δx and Δy are auxiliary variables

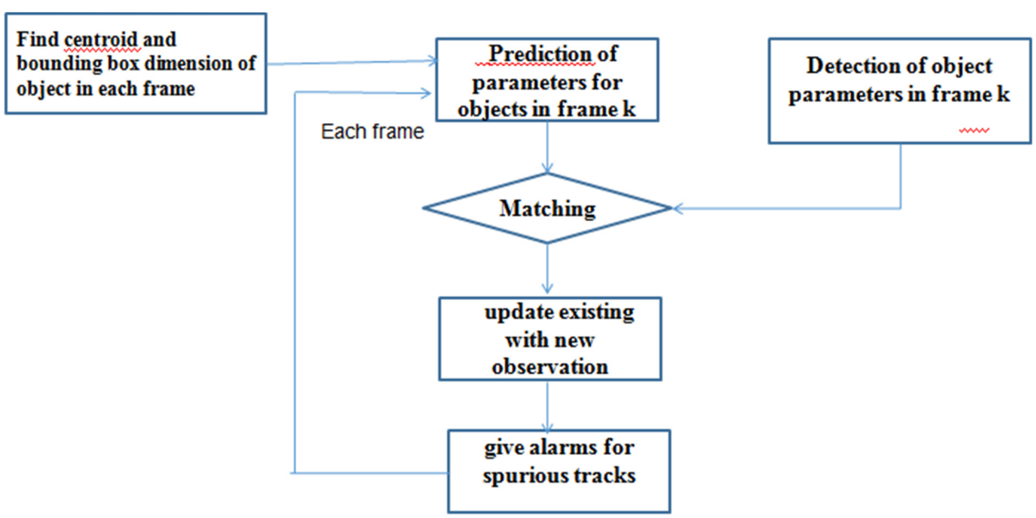

Figure 3: Kalman filtering process

Figure 3 shows the outline of the algorithm for tracking detected objects. The algorithm starts the iteration for the current frame by analyzing history of the previously tracked objects. It predicts the possible location and size of bounding boxes around objects by using a linear Kalman filter as described above. Independently the current frame is a subject of target detection by using the algorithm described in above. Parameters of detected objects are compared with predictions. Those tracks that had their object found in the vicinity of the predicted location are updated to reflect the detection in the current frame. Tracks that did not receive evidence of the object in the current frame use the predictions instead of detections to avoid possible occlusions in the image. New tracks are initiated for objects that enter the frame or in the beginning of the video sequence. Tracks are terminated when objects leave the frame and also when tracks are not long enough. Objects are considered to be marine vehicles if they have substantial tracking history. The track for a new object is initiated if the object that did not belong to any track was detected in two consecutive frames and the bounding boxes of such an object in these two frames intersect. Values for the state and measurement vectors for that track are initiated from these two frames. Such a simple initiation of a track creates many false alarms, but those false tracks are terminated quickly if the detection does not show consistency in the following frames.

4. EXPERIMENT ANALYSIS

In experiment for evaluating the performance of our proposed ship proposal extraction method, the test data set we used is comprised of image and videos captured on open sea. The performance of moving object tracking using the proposed kalman filter is compared with traditional histogram matching techniques. The results are shown in Table 2.

The Accuracy can be measured as the ratio of correctly detected object with total number of samples

Table 2
Overall performance comparison

	Histogram matching	*Kalman filter*	*Kalman filter with spatial temporal texture features*
Detection Accuracy	92.0%	95%	95.56%

5. CONCLUSION

Through this work we introduce a novel approach for the detection and tracking a moving object in series if frames. The system decomposes the input image into different subbands by applying a haar wavelet transform. The results shows that these wavelets have high accuracy in the presence of noise. The spatial temporal and spectral features of the ship candidates are extracted. The proposed kalman filter algorithm perform a time series analysis on object tracking which having high true positive rate. Hence it can run in real time using only the present input measurements and the previously calculated state and its uncertainty matrix that is no additional past information is required

REFERENCES

[1] R. Khan, B. Gamberg, D. Power, J. Walsh, B. Dawe, W. Pearson, and D. Millan. Target detection and tracking with a high wave radar IEEE Journal of, 19(4):540–548, 1994.

[2] V. Gouaillier and sL. Gagnon. Ship silhouette recognition using principal components analysis. Proc. SPIE Conf. on Applications of Digital Image Processing XX, 3164:59–69.

[3] L. Balmelli, J. Kovaevi, and M. Vetterli. Compressed domain ship detection on opticalspace borne images using deep nueral network and extreme learning machine.

[4] Christina Corbane, Fabrice Marre and Michel Petit using SPOT 5 Data in panchromatic mode for operational detection of small ships, Sensors 2008,8,2959-2973 DOI:10.3390/58052959.

[5] Todorovic. Statistical Modeling and Segmentation of Sky/Ground Images. PhD thesis, Master thesis, University of Florida, 2002.

[6] S.M. Ettinger, M.C. Nechyba, P.G. Ifju, and M. Waszak. Vision-guided flight stability and control for micro air vehicles. Advanced Robotics, 17(7):617–640, 2003.

[7] S. Todorovic, MC Nechyba, and PG Ifju. Sky/ground modeling for autonomous MAV flight. Robotics and Automation, 2003. Proceedings. ICRA'03. IEEE International Conference on, 1, 2003.

[8] S. Todorovic and MC Nechyba. A vision system for intelligent mission profiles of micro air vehicles. Vehicular Technology, IEEE Transactions on, 53(6):1713–1725, 2004.

[9] S. Todorovic. Statistical Modeling and Segmentation of Sky/Ground Images. PhD thesis, Master thesis, University of Florida, 2002.

[10] S.M. Ettinger, M.C. Nechyba, P.G. Ifju, and M. Waszak. Vision-guided flight stability and control for micro air vehicles. Advanced Robotics, 17(7):617–640, 2003.

[11] R. E. Kalman, A New Approach to Linear Filtering and Prediction Problems, Transactions of the ASME – Journal of Basic Engineering, Vol. 82, 1960, pp. 35-45.

[12] A. K. Bacho, F. Roux and F. Nicolls, An Optical Tracker for The Maritime Environment, Proceedings of SPIE, Signal Processing, Sensor Fusion, and Target Recognition XX, Vol. 8050, 2011.

[13] J. Li, Y. Wang and Y. Wang, Visual Tracking and Learning Using Speeded Up Robust Features, Pattern Recognition Letters, Vol. 33, 2012, pp. 2094-2101.

[14] X. You and W. Li, "A sea–land segmentation scheme based on statistical model of sea," in Proc. CISP, 2011, Vol. 3, pp. 1155–1159, IEEE.

[15] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 3rd ed. Knoxville, TN, USA: Gatesmark Publishing, 2007, pp. 742–745.