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Location Estimation in a Maritime Environment Using a Monocular Camera

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***Abstract*— Maritime surveillance is a very important task in coastal areas, especially in harbour environments. The most popular such systems include components like Automatic Identification System (AIS) and Radar. Camera based visual surveillance can be used as an alternative to these systems in order to overcome the lacking features of them.**

Sea surface object detection and identification is a major need for such visual surveillance systems. Most of the current visual surveillance systems don't have the ability of identifying vessels in real time.

A vessel can be identified using information from other systems, if the location of the vessel is identified. Location estimation of sea surface objects is mainly explored in this research. Video stream from a single geo stationary camera is used as the input; however camera properties are not used for any calculation.

Mainly two distance measurements are considered and different approaches for estimating the distances are explored. Neural network approach gave considerably accurate results in vertical distance estimation and it was found that the shortest distance from camera to the object can be measured best using B-spline 3D curve fitting. Data taken from AIS is used for fitting curves and training neural network.

After calculating distances, latitudes and longitudes are calculated. An evaluation has been done comparing the calculated values and the values obtained from AIS data using various statistical tests. There, the different approaches are compared and accuracy levels are described. Vessel identification is done comparing the estimated location and the available location information from AIS data.

***Keywords*— Monocular Vision, Maritime, Distance Estimation, Location Estimation.**

I. Introduction

Surveillance systems are with great importance for any place where there are security concerns. In a maritime environment, surveillance is a major requirement. Considering a harbour as an example, surveillance and management of vessel traffic is highly essential for operations there. Real-time visualization of vessel's position, velocity, name and physical properties are important for military/ law enforcement authorities such as Sri Lanka Navy and Sri Lanka coastguard for their daily activities.

As stated before, there are systems like Radar and AIS for the task of tracking vessels on the sea. However, there are some drawbacks in these systems. When considering Radar, detecting non-metallic or small objects is not much easy with a normal Radar [1]. In an environment like a harbour, there are several static objects like buildings around the area. Hence picture which radar generates is much cluttered and it is difficult to identify the moving objects [2]. The classification power of the standard radar is very low which is another major problem [1].

The commercial ships should have AIS transmitters and receivers to broadcast their voyage information and to receive AIS information of other vessels. However, small fishing boats and other considerably small boats don't tend to keep AIS devices in their vessels. Vessels which are engaged with illegal activities such as smuggling, can broadcast fake AIS information [3].

However, the camera based visual data can be used to overcome these problems. Such objects can be detected and the locations can be estimated through live video streams taken from the harbour environment. There can be known objects such as lighthouses and buildings in a harbour environment. If such known objects are available, their location can be used to do relative distance estimation for the objects with interest.

Vessel Traffic Management Systems (VTMSs) like SIYARA-Harbour VTMS [4] and Transas [5] can use the outcomes of this research in automatically tagging vessels in live video streams taken from CCTV cameras. When a location of a certain vessel is calculated, the object can be identified using other information sources and then the identified objects can be tagged in the real time video. This enables users to easily recognize the vessels on the sea.

Other than these, a vision based method will be very useful in verifying the data gathered from similar systems. Data from AIS and Radar can be fused with information retrieved from the proposed method to create a common operating picture which is more precise.

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The major contribution of this research is proposing a novel way of location estimation of sea surface objects using only the video data from a single geo stationary camera without considering its properties such as focal length.

This research is done based on day time image streams and special environmental conditions or meteorological factors are not taken into account. The objects of interest here are the visible sea surface objects and objects which are occluded by others are not considered.

II. Previous Work

Previous work in literature has been studied under three main areas as described below.

A. Maritime Surveillance

Maritime surveillance plays a major role in security of coastal areas, especially in harbours. There are some literature related to visual surveillance in the maritime domain.

One such automatic maritime surveillance system is presented in [6]. Here, using a Haar-like classifier, the boats are detected. That enables the system to perform detections of objects robustly overcoming the problems like various sizes of objects, non-moving boats nearby the shore and wakes and reflection on water surface. The proposed system can deal with movements of cameras too.

A framework for camera based vessel recognition is proposed in [7]. What they propose is a framework which enhances the functions of current Vessel Traffic Services (VTS) systems with the use of electro-optical sensors. Classification of objects with no AIS data, and traffic monitoring in populated areas where radar systems perform weakly are some of the added features here.

A surveillance system using a set of video streams for securing ports is presented in [8]. This system is used to detect vessels which are moving within buffer zones and off-limit regions. Using MACH filter vessels are classified into various classes. A ships arrival needs to be reported 96 hours before and such data are stored in a database. A detected vessel is checked for entry permissions from that database. If no entries in the database is found for a particular vessel it is flagged as an intruder.

B. Object Detection and Tracking

Maritime surveillance plays a major role in security of coastal areas, especially in harbours.

1) Motion-cues: In literature related to object motion and detection, motion-cue generation has been studied widely [9]. The main two types of approaches for motion-cue generation are background subtraction and optical flow. However optical flow is a computationally expensive method than background subtraction. For the maritime domain which this research concerns on, a good performance is needed for processing high resolution images in real-time. Reviews on main background subtraction methods can be found in [10]–[12].

2) Background Subtraction: The main idea behind background subtraction is moving object detection by using the difference between current image frame and a reference frame which is referred as "background image" [10]. Some of the problems with background subtraction algorithms are illumination changes, image changes because of camera movements, moving background objects, foreground objects having similar features to background and foreground objects which become still after a movement [11].

A generic background subtraction algorithm consists of 4 main steps; Pre-processing (process the raw images taken from cameras in a way that is easy to be used for later steps such as noise removal and grayscaling), Background Modelling (or background maintenance), Foreground Detection and Data Validation [13].

A robust algorithm which can detect moving objects from a video containing complex environment is presented in [14]. It uses both the texture and colour features for performing this task. The main concerns of this algorithm are the problems such as background containing moving objects like tree branches, challenges of illumination variations over time and addition or removal of static objects.

This method consists of four main steps. As the first step they use colour measurement which is invariant of illumination to overcome the issues of local binary patterns (LBP) in areas of shadow boundary regions or poor or no texture areas. Handling the problem of moving background objects like escalators and tree branches is done using a weight updating method for background modes as the second step of the proposed algorithm. The third step tries to avoid the problem of adding or removing background objects using a layer based background modelling method. The final stage is removing noise and enhancing foreground objects using cross bilateral filter. Their test results show that this algorithm performs well overcoming the problems like illumination and background object changes.

Another background subtraction method using adaptive background models with shadow detection is presented in [15].

3) Object Tracking: A method of tracking ships in a dynamic background is presented in [9]. Authors present a good study on the problem and a proper solution for it. The characteristics of the objects that needed to be tracked using this method are material, size, direction, speed and visibility of the target. Here differentiation between animals and ships in detections are not taken into account. The scope is limited to contour extracting and tracking of moving objects. They assume that the camera used to take videos have pan and tilt functions.

In this method, for tracking purpose, background subtraction is used instead of optical flow due to computational expensiveness of optical flow. A probability density function is estimated per a pixel which is used to classify the pixel as background or foreground. If the pixel distribution is normal, mean and variance is enough for maintaining background model. If it is multi modal, a mixture of Gaussians is required.

In this method the first phase is a learning phase where the system learns from a predefined number of images. After learning classification of pixels is done. A post processing is needed for the generated motion-cues. It is needed in order to remove false positives and to recover false negatives. A fast heuristic spatial-regularization method is presented here which improves the motion-cue generation. With this technique some ocean waves are misclassified. However they don't effect on the tracking algorithm. Here even the very small targets are at least reconstructed partially.

For tracking purpose, image with motion-cues is segmented with a level-set based active contour. However this level-set based method is computationally expensive. As a solution authors propose a real time algorithm for approximating of level-set curve evolution.

The test results presented in this paper shows successful detection and tracking of targets. Some of the advantages of this method are ability to run in real time on high resolution images, ability of parallelism with less effort and detection, and tracking of even tiny objects. However this method fails when contrast between the ocean and the target is very low.

Another algorithm for object tracking, Continuously Adaptive Mean Shift (CAM SHIFT) algorithm is presented in [16]. CAMSHIFT algorithm is based on mean shift algorithm which is based on finding the peak of probability distributions. CAMSHIFT is created by modifying mean shift to be able to handle colour probability distributions which are changed dynamically. This is a computationally efficient colour object tracker and it can work well in noisy environments.

C. Related work on depth finding using image processing

Depth estimation using a monocular video is considered in [17]. This paper presents a way of estimating the depth of static obstacles seen from a camera mounted in a moving vehicle. As a model free approach, obstacle detection is done based on the relative image motion. Depth estimation is performed with the use of scaling image regions. Detection of obstacles is done by hypothesis testing on the potential obstacles found in a distance histogram created in depth estimation phase. The authors have succeeded in detecting static obstacles but moving obstacle detection is not considered here.

Depth estimation using a single image is described in [18]. The idea is that with the use of an interpolation function, pixel count from the bottom edge of the image to the object location is mapped to the real distance represented by those pixels.

First an interpolation function is formed for a certain camera setting. Some lines are drawn in the ground keeping same distance between adjacent lines. Then pictures of these lines are taken. The pixel counts to these lines and related real distances are used to calculate the interpolation polynomial. Once the polynomial is completely derived, any distance to an object can be calculated by giving the pixel count related to that object in the image, as the input.

There are many advantages in this technique. This needs only a single camera and doesn't need camera properties like focal length. Using a single camera, the captured image stream can be wholly used in contrast to cases like stereo vision based applications which use only the intersected image areas. Here, the camera setup is also not complex like in multiple camera based approaches which need special arrangements.

The calculations are relatively simple. Other than the camera, devices like laser pointers are not needed for this method. The response time is constant because of the fixed number of calculations. The interpolation polynomial is unique for a specific height and a horizontal angle. If one of them is changed the polynomial has to be formed again.

III. Methodology

This section describes the proposed solution for the problem. A software prototype was created for the proposed solution to obtain results for analysis. First the objects in the image frames are detected. Then some relationships are formed between the pixel counts and real distances using known data. These relationships are later used for estimating distances to unknown objects. The distance estimations are used for calculating the GPS locations of those unknown objects. Finally the objects are identified by comparing the estimated locations with the known vessel locations in the considered time, obtained from AIS data.

A. Types of Input Image Sources

The software prototype supports two types of inputs; recorded video and image streams. The used videos were in AVI format with a frame width of 720 pixels and height of 576 pixels. The frame rate of the videos was 25 frames per second.

B. Vessel Detection

Vessel detection was done using two ways; manual detection and automated detection. Manual detection was done using a tool implemented in Matlab. Using that tool the vessel locations could be marked manually and the pixel coordinates of the marks could be obtained.

Fig. 1 An original image frame taken from a recorded video, to use in object detection

Fig. 2 Resulting image when Image shown in Fig. 1 is used for automated object detection (image is cropped from bottom)

Automated detection of objects was performed using the software prototype application. Various object detection methods were tested and later it was found that background subtraction method was not suitable for this particular task. The reason is that, the vessels move very slowly and the software applications can't detect the foreground objects from background. However an edge detection based object detection method gave considerably good results and that proposed method is described below.

First Canny Edge Detection was performed on raw images. After edge detection Probabilistic Hough Lines Transformation was done so that possible objects could be identified easily. Next dilation and erosion was performed in order to minimize false detections. The horizon of image frames taken from the videos were not exactly parallel to the image edges. Hence the images were rotated slightly as the next step so that the horizon was parallel to the horizontal image edges. The pixels must be counted from a known reference point in the bottom of the image. There was a buoy near the bottom of the considered images, and the images were cropped out keeping the bottom edge of the buoy in the bottom edge of the image. The final image contained objects in white in a black background. It was needed to identify the bottom edge of each detected object.

The pixels were checked one by one from right bottom-most pixel to left top-most pixel, column by column. When a pixel is found with an intensity value higher than 0 (non-black), it was considered as the right most pixel of an object and then the pixels in the next columns were searched and the bottom edge pixels of the object was filled into a vector. Vectors were created one per one detected object.

The position of the object in the image was considered in the following way:

- x coordinate : x coordinate of the left most pixel + (amount of pixels in the bottom edge/2)
- y coordinate : y coordinate of the bottom most pixel of the bottom edge

C. Location Estimation

As the first step of location estimation, needed data for distance estimation are prepared accordingly. Then there are two main phases of location estimation; training and calculation. In Training phase some relationships are obtained using known data. Here, AIS data are used as the source of location information. These relationships are used to estimate the unknown locations in the second phase.

1) Preparation of Data: The pixel coordinates output from the object detection component contains coordinates considering the left top of the image as the origin. Converting this to coordinates considering the bottom centre as the origin is done in order to make the calculations easy.

First the width and height of the image is identified. Then x and y coordinates are converted as follows.

```
xNew = (width/2)-oldX
yNew = height-oldY
```

Various calculations need the bearing from camera to the vessel. This is calculated as follows [16].

```
longitudeDiff = longitude2 - longitude1
y = sin(longitudeDiff)* cos(latitude2)
x = cos(latitude1) * sin(latitude2) - sin(latitude1) * cos(latitude2) * cos(longitudeDiff)
bearing = ((atan2(y, x)) + 360) % 360
```

Here GPS location of camera is represented by longitude1 and latitude1. Vessel's longitude and latitude is represented by longitude2 and latitude2.

When the GPS coordinates of the two locations, camera location and vessel location are known, the distance between these two points (See distance d in Fig. 3) can be calculated using Harvesine formula. How distance d is calculated is shown below. Here lat1 and lon1 refers to latitude and longitude of camera location in radians and similarly lat2 and lon2 refers to the latitude and longitude of vessel location.

```
dLat = lat2-lat1;
dLon = lon2-lon1;
lat1 = lat1;
lat2 = lat2;
a = sin(dLat/2) * sin(dLat/2) + sin(dLon/2) * sin(dLon/2) * cos(lat1) * cos (lat2);
c = 2 * atan2(sqrt(a), sqrt(1-a));
d = R * c;
```

R is the radius of earth in kilometres and the result d is also in km.

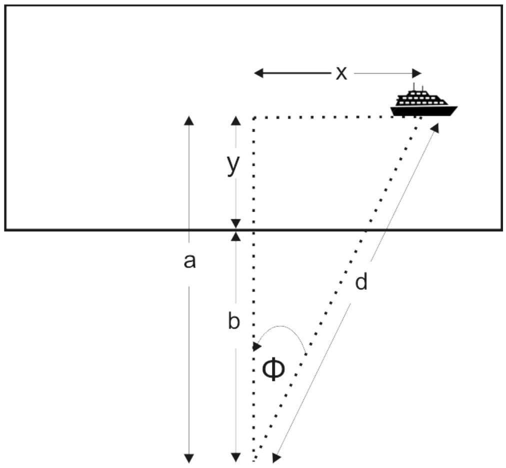

Fig. 3 In this figure "a" is the real vertical distance from camera to the vessel, "b" is the real vertical distance from camera to the bottom reference point, "d" is the shortest distance from camera to the vessel and "y" represents the pixel count from bottom edge of the image to the bottom edge of the vessel, vertically.

Distance "a" shown in Figure 3 refers to the real vertical distance from camera to vessel. The bearing of camera when faced to the sea must be known the difference between it and vessel's bearing is considered as angle Φ. Vertical distance from camera to vessel is calculated as follows. The real distance from camera to the vessel is referred by d.

```
cameraToVesselVDistance = d * cos (φ)
```

2) Obtaining Relationships: First a relationship is obtained for vertical distance estimation using following two measurements.

- Vertical pixel count or the number of pixels from bottom edge of the image to the bottom edge of the vessel - y coordinate of the ship location can be used for this
- Real vertical distance represented by those pixels in km. According to the Fig 3 it is a-b.

Obtaining this relationship is explored using several methods like Interpolation, Curve Fitting and Neural Networks. It was found that the Neural Network approach performs best, outperforming other methods.

Next another relationship for distance d calculation is obtained by using following three measurements.

- x coordinate of the vessel
- y coordinate of the vessel
- Distance d in Km

Similar to above, here also several methods were tested. From Polynomial Surface fitting, Neural Networks, and B-Spline 3D Curve Fitting approaches, the latter one outperformed others. Hence, B-Spline 3D Curve Fitting was used for further calculations. An online curve fitting tool was used to obtain the formula for the given data set [19].

Once these relationships are formed, they can be used to calculate real distances of an unknown object location using the pixel coordinates of the considered object.

3) Calculation: In this phase, the locations of unknown objects are calculated using the relationships formed earlier.

When the GPS location of the start point (camera location), the bearing to the location from the camera and the distance between the camera and the considered location is known, GPS location can be calculated using following formulas [20].

$$\varphi 2 = \mathrm{asin}(\sin(\varphi 1) * \cos(d/R) + \cos(\varphi 1) * \sin(d/R) * \cos(\theta))$$

$$\lambda 2 = \lambda 1 + \mathrm{atan2}(\sin(\theta) * \sin(d/R) * \cos(\varphi 1), \cos(d/R) - \sin(\varphi 1) * \sin(\varphi 2))$$

Definition of symbols: φ - latitude, λ - longitude, θ - bearing (given in radians, clockwise from north), d - distance, R - Radius of earth, d/R - angular distance in radians.

4) Vessel Identification: When the location of an object is detected in a certain time (t), details of the vessels in the sea at that time needs to be known in order to compare. Database table containing the AIS data is queried for AIS data which contain timestamps before time t. Distance from the calculated location to the locations contained in AIS data are calculated and put into a vector. Later the vector is sorted and the vessel with the minimum distance is chosen. That vessel is considered as the vessel represented by the considered object.

IV. Results

Results and evaluation is described in this section. It was stated above that several methods were explored for a considered calculation and one best method was selected from them. Only the results obtained from such selected methods are presented below. Several data sets were used for evaluation and results from few of them are described below.

A. Neural Network Approach for Vertical Distance Estimation

The neural network approach gave considerably good results in vertical distance estimation. 85 data items are used for forming the neural network. 70% of them were used for training, 15% for validation and the remaining 15% for testing. The neural network was trained with different number of neurons and the best result was obtained using 10 neurons. This network contained a single hidden layer. The performance measure was 0.0438. Some facts about the absolute error of the results obtained through this method using another test data set is shown below.

- Minimum : 0.00178
- Maximum : 0.11905
- Average : 0.04749

The number of data elements of the data sets used for testing is not much high. These results should be better if a larger number of data are used for training.

B. Distance d calculation using B-spline 3D Curve Fitting

Distance d refers to the real distance from camera to the object.

A B-spline 3D curve fitting was done using a training data-set. Some results were obtained using a set of test data with that curve. Figure 7 shows error values versus x coordinates and figure 8 shows error values versus y coordinates of the obtained results.

In both of the figures it is clearly visible that the error rates are randomly scattered and there is no clustering. Hence, it is clear that this model fits well with the considered data set. It also shows that there's no clear relationship between the measured distance and the occurred error.

The minimum error occurred was 0.00165 km and the maximum was 0.34518 km. On average there was an error of 0.08784 km.

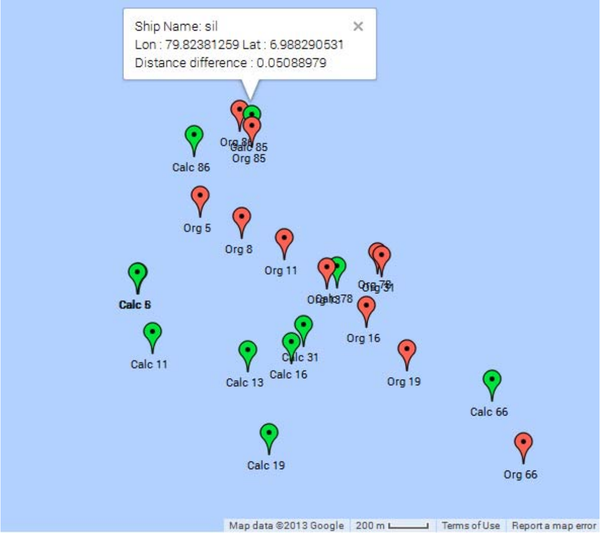

Fig. 4 Some estimated locations and their original locations marked on a map. Prefix "Org" denotes the original locations and "Calc" denotes calculated locations.

C. Distances between original and estimated locations

When Neural Networks approach was used for vertical distance estimation and B-Spline 3D curve Fitting was used for distance d calculation, on average the estimated location was 0.461 km away from the exact location. The minimum error was 50m and the maximum was 0.8376 km.

D. Wilcoxon signed rank test for mean comparison

Wilcoxon signed rank test was done for mean comparison of the values obtained above. For all the following comparisons, the test proved that there's no significant difference between means of actual and calculated values.

- Vertical distance: Original Vs. values from NN approach
- Distance d: Original Vs. values from B-spline approach
- Longitude: Original Vs. Estimated
- Latitude: Original Vs. Estimated

E. Vessel Identification

The calculated GPS locations were compared with the known locations of the ships in the considered time periods and the best matching vessel to each unknown objects is chosen. On average each calculated location is compared with 59 nearby ship locations in the considered time. According to the results, 86.67% are correct identifications, which was impressive.

F. Causes for Errors

The accuracy of the final results can be improved by minimizing the influence of factors that caused the errors.

In the gathered data-sets most of the ships have broadcast AIS data once in twenty seconds. The rate of receiving the AIS data can affect for some of the errors.

There is a specific place in the ship where the GPS receiver is placed. However location of the vessels in the image is considered as the centre of the bottom edge. Most of the vessels are longer than two hundred meters and the location obtained from the GPS device in the ship may vary according to the location of the receiver. This can cause both the train and test data to prone to errors. On the other hand the GPS devices are not 100% accurate and the obtained location from a GPS device can vary for around 5 meters or more. This also affects the accuracy of the train data.

The clock time of each frame of a certain video is considered relative to the start time of the video. There may be minor errors on measuring the clock time when the video recording is started.

The ships considered in the data set have a length from 222m to 302m, hence most of the errors encountered in distance calculations can be negotiated comparing to the vessel sizes.

V. CONCLUSIONS AND FUTURE WORK

A novel way of location estimation of sea surface objects was introduced. This method uses only the video data from a single geo stationary camera and camera's properties such as focal length are not considered. The outcomes were successful and further developments can be done in a practical implementation.

The GPS location of a certain unknown object is estimated using two measurements, the shortest distance to the object from camera and the vertical distance. Calculations of these values are done using various methods by making a relationship with the real distance measurements with the pixel coordinates of the object. Vertical distance estimation was done using interpolation, curve fitting and Neural Network approaches, where the latter one outperformed others. Shortest distance from camera to the unknown object is calculated using Polynomial curve fitting, neural network and B-Spline 3D curve fitting approaches. Comparison of the three approaches showed that B-spline method is better than others in the considered conditions. The accuracy can be further improved if more data points are used as train data.

When considering the objectives and the accomplished work, the main objective has been achieved up to a satisfactory level. However the accuracy of location estimation needs to be improved. It is possible to identify the detected vessels by comparing estimated locations with the locations of the ships in the sea in the considered time. This vessel identification mechanism showed highly satisfactory results. Hence, the methodology proposed in this research can be used to develop relevant applications and the current accuracy is sufficient enough.

Further research should be carried out to investigate the effect of changes in factors such as camera position, height and angle to the accuracy of location estimation. Also the methods of physical properties extraction of vessels needs to be explored.

This concept can be improved to be used in automatic decision making systems in coastal surveillance systems. The objects can be automatically detected and identified when the proposed methodology is used along with another source of information. If unidentified objects are detected, users can be acknowledged. It would be a very useful tool for monitoring coastal areas.

On the other hand this can be used for vessel traffic management systems. The identified vessels can be shown in a real-time video itself and let the users view it. Users can be given ability to click on a specific vessel and view information about it. Rather than using computer generated graphics, viewing information on a real video will be very user friendly and make the decision making process easy.

The data retrieved from this system can be fused with data from other systems like AIS and Radar to generate a common operating picture with a better accuracy. A filtering technique like Kalman Filter can be used to obtain a better result in such applications.

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