Ego-Motion Compensated for Moving Object Detection in a Mobile Robot

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Abstract. This paper presents a moving object detection method using optical flow in an image obtained from an omnidirectional camera mounted in a mobile robot. The moving object is extracted from the relative motion by segmenting the region representing the same optical flows after compensating the ego-motion of the camera. To obtain the optical flow, image is divided into grid windows and affine transformation is performed according to each window so that conformed optical flows are extracted. Moving objects are detected as transformed objects are different from the previously registered background. In omnidirectional and panoramic images, the optical flow seems to be emerging on focus of expansion (FOE), on the contrary, it to be vanishing on focus of contraction (FOC). FOE and FOC vectors are defined from the estimated optical flow and used as reference vectors for the relative evaluation of optical flow. In order to localize the moving objects, histogram vertical projection is applied with specific threshold. The algorithm was tested in a mobile robot and the proposed method achieved comparable results with 92.37% in detection rate.

Keywords: Moving object detection, Omnidirectional camera, Mobile robot, Ego-motion compensated.

1 Introduction

Vision-based environment detection methods have been actively developed in robot vision [1]. Detecting moving object is one of the essential tasks for understanding environment. It is important to segment out and detecting moving objects in order to avoid an obstacle and control locomotion of the mobile robot in real-world environment. However, the vision system can provide not only a huge amount of information but also intensity and feature information in the populated environment. The omnidirectional vision system supplies a wide view of 360 degree, so they have been popularly used in many applications such as the motion estimation, environment recognition, localization and navigation of a mobile robot.

In the past few years, moving object detection and motion estimation methods for a mobile robot using the optical flow have been actively studied and developed [2].

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Fig. 1. An omnidirectional camera mounted on a mobile robot

A qualitative obstacle detection method was proposed using the directional divergence of the motion field. The optical flow pattern was investigated in perspective camera and this pattern was used for moving object detection. Also real-time moving object detection method was presented during translational robot motion. The optical flow pattern in a perspective camera is different from the pattern in an omnidirectional camera because of the distortion of an omnidirectional mirror.

Several researchers have been also developed for ego-motion estimation and navigation of a mobile robot with an omnidirectional image [3], [4], [5] and [6]. [3], [4] tried to measure camera ego-motion itself using omnidirectional vision, and [5] gave analysis related to translation and rotation motion using optical flow. They used Lucas Kanade optical flow tracker and obtained corresponding features of background in the consecutive two omnidirectional images. Use analyzing the motion of feature points, camera ego-motion was calculated, but it was not used for moving object detection. They set up an omnidirectional camera on a mobile robot and obtained panoramic image transformed from omnidirectional image. They obtained camera ego-motion compensated frame difference based on an affine transformation of two consecutive frames where corner features were tracked by Kanade-Lucas-Tomasi (KLT) optical flow tracker [6]. But detecting moving objects resulted in a problem that only one affine transformation model could not represent the whole background changes since the panoramic image has many local changes of scaling, translation and rotation of pixel groups. For this problem, each affine transformation of local pixel groups should be tracked by KLT tracker. The local pixel groups are not a type of image features such as corner or edge. We use grid windows-based KL T tracker by tracking each local sector of panoramic image while other methods use sparse features-based KLT tracker. Therefore we can segment moving objects in panoramic image by overcoming the nonlinear background transformation of panoramic image.

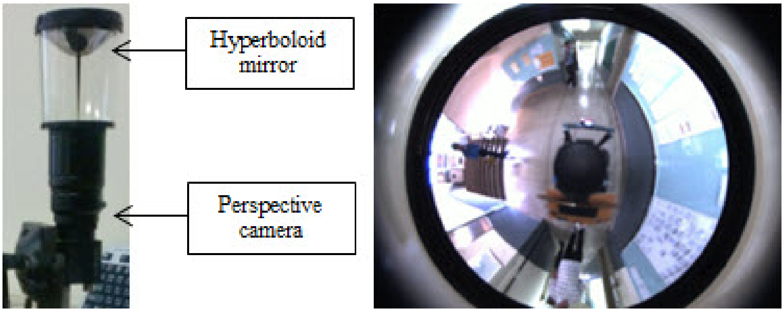

Fig. 2. The structure of omnidirectional vision and its image

In this paper, a method for detection moving object using ego-motion compensated was proposed in an omnidirectional camera mounted on a mobile robot. We focus on the optical flow in omnidirectional camera. First, an omnidirectional image converted into a panoramic image. The moving object is detected in panoramic image. In omnidirectional image, the length of optical flow becomes large according as the radial distance goes away from the center point. Otherwise, in panoramic image, the length of optical flow becomes is not affected from radial distance of omnidirectional image. Then, optical flow pattern is analyzed in panoramic images. The moving object is segment out through the relative evaluation of optical flows. The image divides as grid windows then compute each affine transform for each window. Moving objects can be detected from the background transformation-compensated using every local affine transformation for each local window. In order to localize the moving objects, we applied histogram vertical projection with specific threshold. The proposed algorithm was tested in mobile robot motions straight forward and rotation.

2 Mobile Robot with Omnidirectional Camera

This section presents the omnidirectional camera system which used in this work and how to detect moving object from an omnidirectional camera mounted on the mobile robot. The mobile robot shows in Fig. 1. The omnidirectional camera consists of perspective camera and hyperboloid mirror as shown in Fig. 2. It captures an image reflecting from the mirror so that the image obtains reflective scene and not perspective. It is easier to recognize whether image contains moving object or not, so it is necessary to transform the obtained image into panoramic image [7].

In order to perform the omnidirectional camera in mobile robot, before we apply in higher level task, it need to calibrate and investigated the accuracy. When it applied in structure from motion, we need to recover the metric information from environment [9]. In this work the omnidirectional camera was calibrated using checker board as a pattern with control points [8]. We used a flexible calibration method for omnidirectional single viewpoint sensors from planar grids. However this method was based on an exact theoretical projection function and some parameters as distortion were added to consider real-world errors.

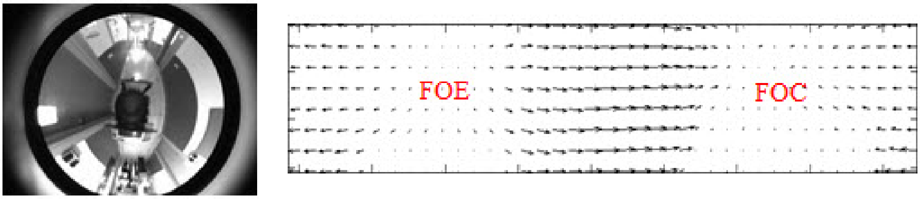

Fig. 3. In omnidirectional and panoramic images, the optical flow seems to be emerging on focus of expansion and to be vanishing on focus of contraction

The sphere model was used by [8] and didn't consider the image flip. This approach adds to this model distortion parameters to consider real world errors. This method is multi view, which means that it requires several images of the same pattern containing as many points as possible. This method needs the user to provide prior information to initialize the principal point and the focal length of the catadioptric system. The principal point is computed from the mirror center and the mirror inner border. The focal length is computed from three or more collinear non-radial points. Once all the intrinsic and extrinsic parameters are initialized a non-linear process is performed. From this step we got intrinsic and extrinsic camera parameter that is useful to apply this omnidirectional camera system in real application for mobile robot system [9].

3 Ego-Motion Compensated

In omnidirectional and panoramic images, the optical flow seems to be emerging on focus of expansion (FOE), on the contrary, the optical flow seems to be vanishing on focus of contraction (FOC) [5]. If mobile robot moves then the panoramic image changes like Fig. 3. The translational motion of mobile robot makes two scaling points, and pixels move from FOE to FOC making curve trajectories. The rotational motion of mobile robot makes all pixels move to left or right. These movements of pixels can clearly happen when there is no moving object. If both translation and rotational motions happens together, these pixel movements look quite nonlinear that is why only one affine transformation model cannot represents these motions.

3.1 Moving Object Segmentation

In order to obtain moving object from omnidirectional image in mobile robot, it is not easy to segment out only moving object areas when the camera also moving caused by camera ego-motion [10]. Using [6], we apply KLT Optical Flow Tracker in order to deal with several conditions. Brightness constancy which projection of the same point looks the same in every frame, small motion that points do not move very far and spatial coherence that points move like their neighbors.

The frame difference represents all motions caused by camera ego-motion and moving object in the scene. It needs to compensate this effect from frame difference to segment out only moving object motion, so how much the background image has

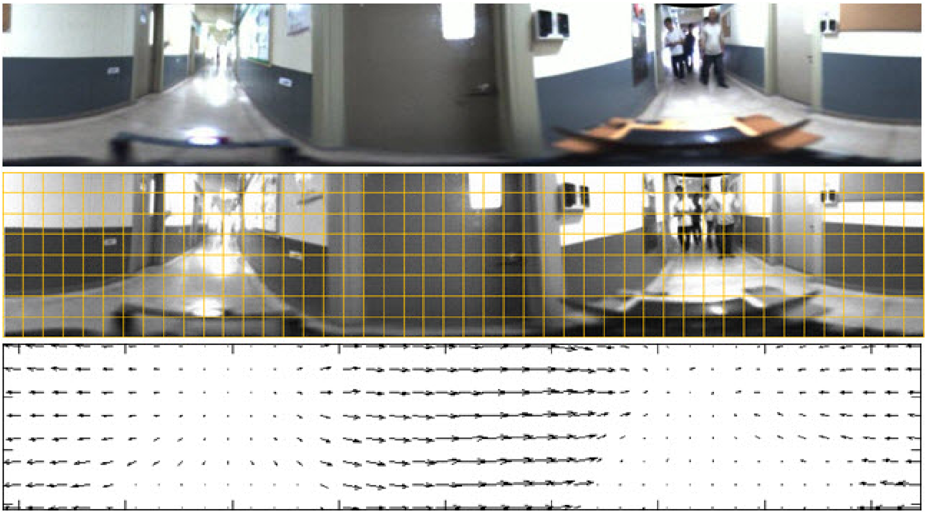

Fig. 4. From an omnidirectional image transformed to panoramic image (top image), we decide grid windows (middle image) and track each windows in the next image (bottom image)

been transformed in two sequence images. Affine transformation represents the pixel movement between two sequence images as in (1),

$$P' = \mathrm{AP} + \mathrm{t} \tag{1}$$

where P′ is pixel location in second image and P is pixel location in first image. A is transformation matrix and t is translation vector. Affine parameters can be calculated by least square method using at least three corresponding features in two images.

From the input omnidirectional image then transform to panoramic image, we decide grid windows and then compare and track each window in the next image, as shown in Fig. 4. Using method from [6], find the motion $d(i,j)$ of each group $g_{t-1}(i,j)$ by finding most similar group $g_t(i,j)$ in the next image.

$$g_{t-1}(i,j) = g_t(i + d_x(i,j), j + d_y(i,j)) \tag{2}$$

It represented as affine transformation of each group as (3)

$$g_t(i,j) = \mathrm{I}g_{t-1}(i,j) + d_x(i,j) \tag{3}$$

The camera motion compensated frame difference I_d is calculated based on the tracked corresponding pixel groups using (4)

$$I_d(i,j) = |g_{t-1}(i,j) - g_t(i,j)| \tag{4}$$

where $I_d(i,j)$ is a pixel group located at (i,j) in the grid.

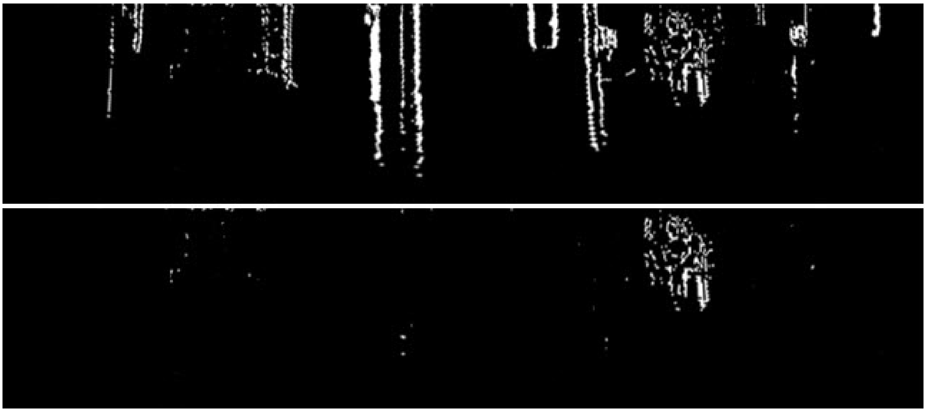

Fig. 5. From two consecutive images we applied frame difference (top image) and applied frame difference with ego-motion compensated (bottom image)

Suppose two consecutive sequence panoramic images shown in Fig. 4. It is not easy to segment out moving object using frame difference, then we apply frame difference with ego-motion compensate could obtain moving objects area shown in Fig. 5.

3.2 Object Localization

Each pixel output from frame difference with ego-motion compensated could not show clearly as silhouette. It just gives information of motion area from moving object. To obtain detected object, it is important to localize moving object area from the image. In this work, we define detected moving objects are represented by the position and width in $x-$ axis. Using projection histogram h_x by vertically project image intensities into $x-$ coordinate.

$$h_x = P_x I_d = [I, \dots, I] I_d \tag{5}$$

where P_x is a projection vector which size is same as the height of panoramic image. An obtained h, is shown in Fig. 5.

We detect moving object based on the constraint of moving object existence that the bins of histogram in moving object area must be higher than a threshold and the width of these bins should be higher than a threshold as below

$$h_x(i \pm 10) > A\, max(h_x) \tag{6}$$

where A is a control constant and the threshold of bin value is dependent on the maximum bin's value. In order to get threshold of bin value, in this work using 10 omnidirectional images for training. Each image contains one or more moving objects shape with different shape and high, it is related to the distance from camera to object.

From Fig. 6 shows localization results. Top image show image result from frame difference with ego-motion compensated. Middle image shows histogram vertical

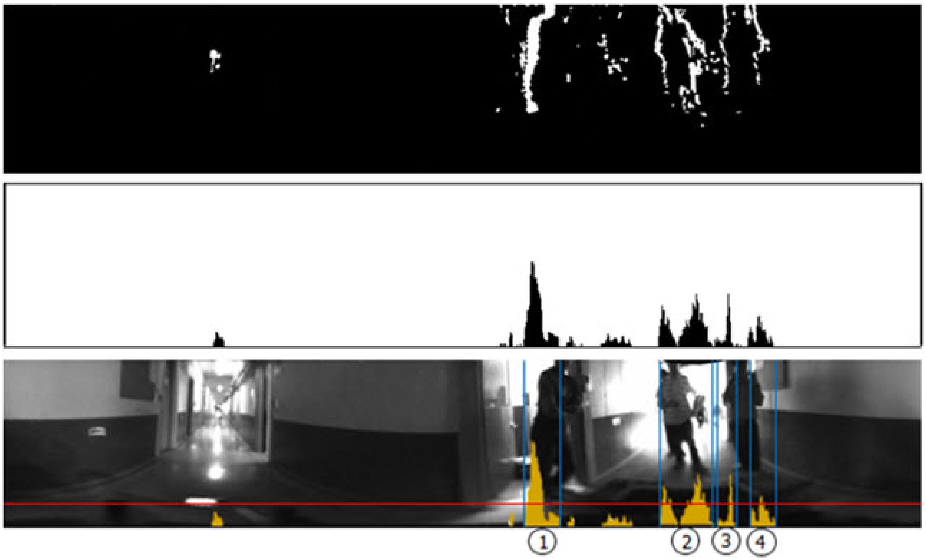

Fig. 6. Detection result

projection from above image, and bottom image shows there are four detected moving object, obtain from the region where have the number of bin above of the horizontal line as threshold value.

4 Experimental Results

In this work, our robot system is run in corridor with constant speed and detected moving object surround its path. Then evaluate our method from those image sequences. Proposed algorithm was programmed in MATLAB and executed on a Pentium 3.40 GHz, 32-bit operating system with 8 GB Random Access Memory

Mobile robot moves in constant speed at 20 centimeters per second. From omnidirectional camera it captured image sequences with frame rate 4 hertz in indoor environment. We perform two kinds of evaluation with difference of the number of image frames. The first we apply the system for around 800 image frames, for which is the number of moving objects are 2,335. The second, we conduct for 30 minutes of image sequence consist of 15,673 objects. In this case, all of moving object captured by omnidirectional camera is human walking in corridor. Evaluation process obtain from calculate the true positive detection and false positive detection.

In table 1, when the robot moving at constant speed for the first evaluation the accuracy of moving object detection result shown the system could detect 2,157 (92.37%) objects and 93 false positive detections. When we apply the system for long image sequences, the detection rate shown almost consistence with 92.33% and less than 4% in false positives detection rate. Fig. 7 shows detection results several images taken from omnidirectional camera.

Fig. 7. Successful moving objects detection results

Table 1. Detection comparison

Number of Image Frames	The number of human	True positives	False positive	Detection rate
800	2,335	2,157	93	92.37%
7,000	15,673	14,472	572	92.33%

5 Conclusions

This paper presents moving object detection applied in mobile robot which mounted by an omnidirectional camera. The moving object is segment out through the relative evaluation of optical flows to compensate ego-motion of camera. The image is divided as grid windows then compute each affine transform for each window. Moving objects can be detected from the background transformation-compensated using every local affine transformation for each local window. In order to localize the moving objects, we applied histogram vertical projection with specific threshold. The algorithm was tested in mobile robot motions straight forward and rotation. The proposed method achieved comparable results with 92.37% in detection rate and less than 4% in false positive detection.

In order to improve detection rate of the system, in the future work it need consider to combines object detection based on moving object detection with geometrical approach to calculate object position or kinematic model of robot movement relative to static objects environment.

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