ELSEVIER

Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Engineering 41 (2012) 911 – 916

Engineering Procedia

www.elsevier.com/locate/procedia

International Symposium on Robotics and Intelligent Sensors 2012 (IRIS 2012)

Moving obstacle avoidance of a mobile robot using a single camera

Jeongdae Kim, Yongtae Do *

Major of Electronic Control Engineering, Daegu University, 712-714, South Korea

Abstract

This paper presents some preliminary results of the detection of moving obstacles (particularly walking humans) by the use of a single camera attached to a mobile robot. When a camera moves, simple moving object detection techniques for a stationary camera, such as background subtraction or image differencing, cannot be employed. We thus detect objects that move near the robot by block-based motion estimation. In the method, an image is firstly divided into small blocks, and then the motion of each block is searched by comparing two consecutive images. If the motion between matching blocks is significantly large, the block in the current image is classified as belonging to moving objects. The method is verified by the indoor navigation experiments of a robot.

Keywords: Mobile robot; Obstacle avoidance, Block-based motion estimation; Robot vision.

Nomenclature

B	image block
S	size of image block
x, y	coordinates

1. Introduction

Since George Devol and Joseph Engelberger built the first practical robot more than half century ago, the vast majority of robots have been installed on factory floors to perform their tasks. The surroundings of the industrial robots, that we call manipulators, are well controlled so as to guarantee safe work. However, in recent years, many robots become mobile and navigate in uncontrolled dynamic environments, such as museum [1], city hall [2], airport [3], etc. Hence, the safety of a robot and surrounding objects including humans who reside in the same space with the robot becomes important.

There is a rich literature on the autonomous navigation of a mobile robot with obstacle sensing capability. Various sensors that can be usefully employed for a mobile robot are well described in [4]. The arrangement of a circular array of ultrasonic sensors around the body of a mobile robot is now one of the most popular methods of obstacle avoidance [5]. An ultrasonic range finder can be built in a low cost but suffers from low angular resolution. It may fail to identify a narrow open space like a doorway if its distance from the sensor is not close. An infrared detector provides another simple and cheap way of obstacle sensing [6]. As it is optical sensing, the measurement resolution can be higher than that of ultrasonic rangers. However, infrared sensors are sensitive to external light condition, and their detection range is rather short (less than

* Corresponding author. Tel.: +82-53-850-6625; fax: +82-53-850-6619.
E-mail address: ytdo@daegu.ac.kr

1877-7058 © 2012 Published by Elsevier Ltd. Open access under CC BY-NC-ND license.
doi:10.1016/j.proeng.2012.07.262

few meters and often some centimetres). Objects at long distances from a robot can be detected accurately by the use of a laser scanner [7], but the system is expensive and often bulky. Recently introduced time-of-flight (TOF) cameras have many advantages for the autonomous navigation of a mobile robot. In comparison to laser scanner, TOF camera provides 3D information with a real-time frame rate and is much faster [8]. However, camera calibration and data pre-processing are necessary to get stable measurement. In addition, TOF cameras are still expensive like laser scanners. Stereoscopic 3D sensing has been a long time topic for perceiving the space around a mobile robot [9]. It can be said a natural way of sensing because most animals and humans obtain information about their surroundings using two eyes. Stereoscopy, however, has a difficulty in providing reliable 3D information quickly due mainly to stereo matching problem.

Vision sensing has certainly high potential for a robot to perceive its surroundings. Recently, thanks to the rapid advance in solid state electronics, cameras become smaller and cheaper, and many mobile robots now possess visual sensing capability. When a single camera is mounted on a mobile robot for the autonomous navigation, it is often used for localization by detecting landmarks rather than obstacle detection because detecting obstacles usually requires at least two cameras to obtain depth information. Nevertheless, there are some attempts to find obstacles using a single camera. Ulrich and Nourbakhsh [10], for example, tried to detect obstacles based on colour cues. Image pixels that have different colour values to those trained with an empty trapezoidal area in front of the mobile robot are considered to belong to obstacles. This method is simple and can produce a high-resolution binary detection image in real time. However, we found that the method is quite sensitive to the colours of obstacles.

In this paper, we describe a method to detect moving objects using a single camera mounted on a mobile robot. If a site map is given, the robot needs to find only dynamic obstacles including humans who approach to the robot. The moving objects are found by matching the blocks in two consequent images. The camera image is divided into regular blocks, and each individual block is classified as belonging to either a moving obstacle or the stationary background based on its motion.

2. Block-based motion estimation

The Block-Based Motion Estimation (BBME) method has been widely used particularly in video coding [11]. Video images have temporal redundancy, which is related to the spatial similarity that temporally correlated frames have. Thus, this information redundancy needs to be reduced for the efficient treatment of video images if the picture quality loss is acceptable. Similar advantages can be expected in stereo image matching as well. Since the block based matching has a regular algorithmic structure [12], it is possible to optimally implement the method for the real-time processing of the two slightly different images of stereo cameras.

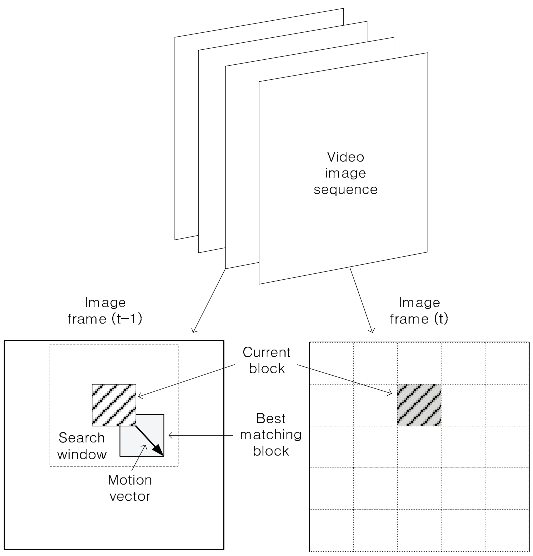

Fig. 1. Block-based motion estimation

In BBME, an image frame is divided into non-overlapping blocks of pixels. Then, the motion vector of a given block is determined by conducting an algorithmic search which tries to minimize the value of a matching criterion. The most commonly used criterion is the Sum of Absolute Differences (SAD), which is calculated between the current image block and a block in the previous image frame as follows:

$$SAD = \sum_{x=1}^{S} \sum_{y=1}^{S} | B_t(x, y) - B_{t-1}(x, y) | \tag{1}$$

The spatial distance between the best matched blocks represents a motion vector, and the vector can be regarded as a disparity if the motion is horizontal. The search for the best block is limited within a range, called search window, considering the possible range of the motion. Fig. 1 illustrates the BBME method.

3. Detection of approaching obstacles using BBME

The work of this paper has a purpose to avoid collisions between a mobile robot and dynamic obstacles. In many cases, the precise 3D reconstruction of obstacles is not necessary. Instead, some rough information, such as the approximate position of obstacles, is enough for a robot to proceed into free space (if any exists).

To narrow down the problem scope, we make the following assumptions:

- The map of the working space where a robot will navigate is given. It means that we know the properties of static obstacles, such as their positions and sizes. Then, only moving obstacles need to be detected.
- The robot is moving on a planar ground. This assumption is usually valid in indoor environments.
- Most dynamic obstacles are humans and their speed is slow or similar to that of a robot. Thus, it is possible to avoid approaching obstacles even if they are detected in a rather close distance.

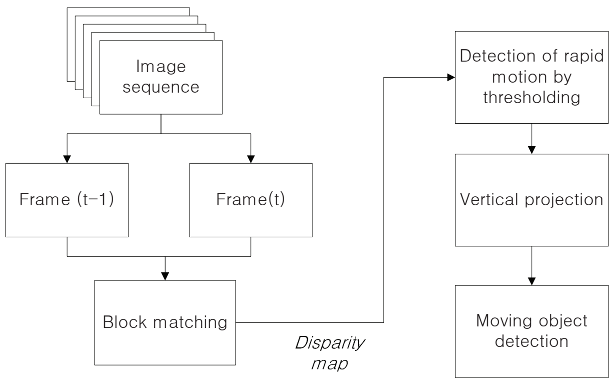

Fig. 2. Flow chart of the algorithm

If a camera is fixed, there are several effective and simple techniques to find moving objects in the scene, such as background subtraction [13]. However, if a camera is mounted on a mobile robot, such techniques cannot be used because, in the scene images taken by a moving camera, no entities look static. Then, the problem becomes rather complicated because we should find real moving objects among all that look moving due to camera motion. Particularly, detecting objects that move in the opposite direction to the navigation of a robot is important because it can cause a danger to both the robot and the approaching objects.

We applied the BBME method to moving object detection in the video images of a moving camera. Fig.2 summarizes the proposed algorithm. Firstly, the current image frame was divided into small blocks. Then, a block which best matches the divided searching block was detected in the previous image frame within the search window using a block-based stereo matching function in OpenCV, *cvFindStereoCorrespondenceBM* [14]. The function is for finding the best matching blocks in the images of two cameras located at different positions while the search in this paper is for the two images snapped at different moments by the same camera. However, the search in both cases is commonly for finding corresponding blocks in the two slightly different images. In addition, the different picture-taking moments mean different camera positions if a camera moves. Further discussion about camera motion can be referred to [15-17]. The horizontal component of the motion vector is significantly larger than the vertical motion vector when both obstacles and a robot move on the same planar ground. Thus, the block search was done only in horizontal direction so as to increase the speed and accuracy of block matching. Secondly, the detected disparity (i.e., the length of the horizontal motion vector) between the matching blocks was converted to the grey value as exampled in Fig. 3(b). The brighter part in the image indicates the bigger motion. Thus, if an object approaches to the robot, the relative speed between the object and the robot is high, and the object looks bright in a disparity map. Thirdly, grey value distribution of the disparity map was examined as the histogram presented in Fig. 3(c). The threshold value to classify the grey pixels into those belong to the approaching objects or others was determined simply at the global peak of the histogram. A binary image obtained by thresholding is presented in Fig. 3(d). Fourthly, the binary image was projected vertically as shown in Fig. 3(e), and the position of the approaching person was estimated as shown in Fig. 3(f).

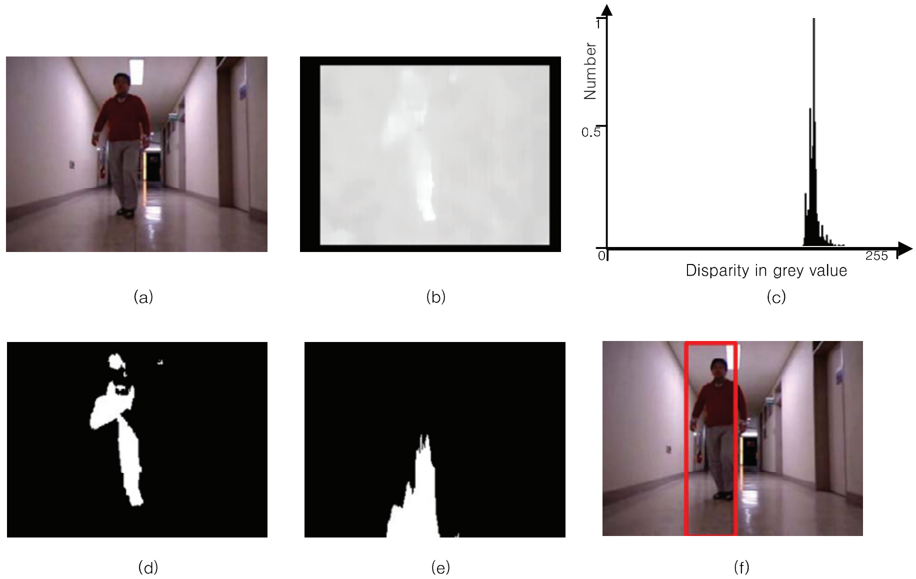

Fig. 3. Example of block-based moving object detection: (a) Scene image; (b) Disparity map; (c) Histogram; (d) Binary image of rapid moving blocks; (e) Vertical projection of (d); (f) Detected moving object.

4. Results

We implemented our method on a mobile robot that navigated in a corridor. The robot has a web camera producing colour images in the size of 640×480 pixels by 30 frames/sec rate. As highly accurate positioning of obstacles is not required, the image size was reduced by ½ before processing. Each image was then divided into blocks of 21×21 pixels and the searching window was set horizontally to 32×21 pixels.

Fig. 4 shows some experimental results of our moving obstacle detection algorithm. The top images show the cases of successful obstacle detection, while the bottom images show failure cases. Note that people in Fig. 4(e) and (f) are the same ones in Fig. 4(b) and (c), respectively. But they are at different distances, and the results are different. When people are at a farther distance, their motion in sequential images appears slower, and they may not be found as moving objects. Thus, the algorithm can be applied more successfully to objects at closer distances to the camera (i.e., robot). Colour also affects the performance of the algorithm because one of the two people in the figures was detected while the other in a different colour was missed. In Fig. 4(d), our algorithm detected the empty wall wrongly as a moving object. The motion of the light reflected brightly on the white side wall due to the camera motion might be the cause.

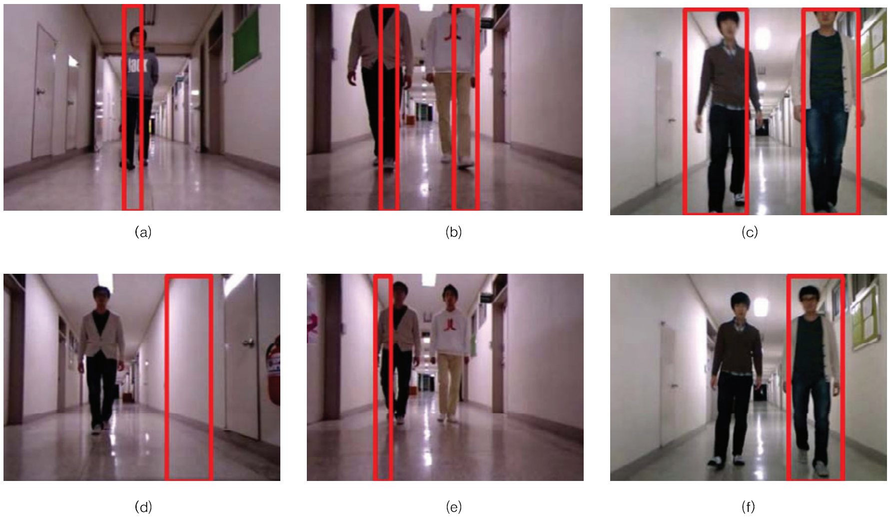

Fig. 4. Experimental results: Successful cases are shown in (a), (b) and (c), while detection failures are presented in (d), (e) and (f).

5. Conclusions

A vision-based moving obstacle detection method for the safe navigation of a mobile robot has been described. The method can quickly detect approaching obstacles like walking humans in an indoor space using a single camera which is mounted on the robot. In many cases of our experiment, the method detected moving objects well, but sometimes it failed by a number of factors, such as distance to objects, object's colour, and reflected light. Future work is thus improving the performance of the proposed algorithm against various practical environmental factors.

Acknowledgements

This research was supported by the MKE(The Ministry of Knowledge Economy), Korea, under the Core Technology Development for Breakthrough of Robot Vision Research support program supervised by the NIPA(National IT Industry Promotion Agency) (NIPA-2012-H1502-12-1002)

References

[1] Burgard W, et al. The interactivemuseum tour-guide robot. In: AAAI-98 Proceedings, Madison, Wisconsin; 1998.
[2] Kang J-G, An S-Y, Oh S-Y. Navigation strategy for the service robot in the elevator environment. In: Proc. Int. Conf. on Control, Automation and Systems, Seoul, Korea; 2007, p. 1092–1097.
[3] Capezio F, et al. The ANSER project: Airport nonstop surveillance expert robot. In: Proc. IROS, San Diego, CA; 2007, p. 991-996.
[4] Everett HR. Sensors for mobile robots. CRC Press; 1995.
[5] Kim S, Kim H. Optimally overlapped ultrasonic sensor ring design for minimal positional uncertainty in obstacle detection. Int. J. Control Autom. Syst. 2010; 8(6): 1280-1287.
[6] Alwan M, et al. Characterization of infrared range-finder pbs-03jn for 2-d mapping. In: Proc. IEEE ICRA, Barcelona, Spain; 2005, p. 3936-3941.
[7] Ye C, Borenstein J. Characterization of a 2-d laser scanner for mobile robot obstacle negotiation. In: Proc. IEEE ICRA, Washington, DC, December; 2002, p. 2512-2518.
[8] Werner B, Surmann H, Pervolz K. 3D time-of-flight cameras for mobile robotics. In: Proc. IROS, Beijing, China; 2006, p. 790-795.
[9] Chilian A, Hirschmuller H. Stereo camera based navigation of mobile robots on rough terrain. In: Proc. IROS, St. Louis, USA; 2009, p. 4571-4576.
[10] Ulrich I, Nourbakhsh I. Appearance-based obstacle detection with monocular color vision. In: Proc. AAAI; 2000.
[11] Nobie D, et al. Two novel algorithms for high quality motion estimation in high definition video sequences. In: Proc. SIBGRAPI, Maceio, Alagoas; 2011, p. 197-204.
[12] Piccardi M. Background subtraction techniques: a review. In: Proc. IEEE Conf. on SMC, 4; 2005, p. 3099-3014.
[13] Konolige K. Small vision systems: hardware and implementation. In: Proc. Int. Symp. Robotics Research, pages, Hayama, Japan; 1997, p. 111-116.
[14] http://opencv.willowgarage.com/documentation/camera_calibration_and_3d_reconstruction.html (Accesssed 25/05/2012).

[15] Williams TD. Depth from camera motion in a real world scene. IEEE Trans. Pattern Anal. Mach. Intell. 1980; 2: 511-516.
[16] Matthies L, Kanade T, Szeliski R. Kalman Filter-based Algorithms for Estimating Depth from Image Sequences. Int. J. Comput. Vision. 1989; 3(2): 209-238.
[17] Civera J, Davison AJ, Montiel J. Inverse Depth Parametrization for Monocular SLAM. IEEE Trans. Rob. 2008; 24(5): 932-945.