New Ground Plane Segmentation Method for Electronic Cane

Jihen Frikha Elleuch, Imen Khanfir Kallel, and Dorra Sellami Masmoudi
Computer Imaging Electronic System (CEM Lab) University of Sfax, Tunisia
Email: jihen frikha4@yahoo.fr; imen.khanfir@betatex.com.tn; dorra.masmoudi@enis.rnu.tn

***Abstract*—In this paper, a new ground plane segmentation method is proposed for obstacle detection to improve the mobility of the visually impaired people by means of a novel electronic cane "Smartcane". Monocular camera was used which has the merits to get simple computation and cheap hardware and it's promising to realize real time navigation. The proposed method is based on an appearance-based approach by combining both color and texture information extracted from monocular image. The algorithm is tested with a challenging indoor image set. It gives better obstacle detection than available color based obstacle detection approaches.**

***Index Terms*—obstacle detection, ground detection, monocular vision, appearance based technique, electronic cane.**

I. Introduction

Many researchers have been performed to improve navigation autonomy of visually impaired people. Recently, Electronic Travel Aids (ETAs) were developed to assist the visually impaired and reduce the difficulty encountered in navigation [1]. They make use of sensors to acquire some attributes of the world in order to detect obstacles. Despite development of various mobility assistants [2], it is still difficult to find out a one which is ultra-portable, low cost, non-intrusive, and able to detect on-floor obstacles. In fact, best choice of sensors giving the required information, useful for obstacle detection is tremendously. Accordingly, two types of sensors can be used: active and passive ones. Popular active sensors used for range obstacle detection include laser, radar, lidar and ultrasonic sensors. Although these sensors can measure distance and speed of the target object in bad weather and poor lighting conditions, their use is limited by difficult interpretation of output signals, high acquisition price, poor resolution and inability to detect small obstacles. Passive sensors include stereo and monocular vision sensors. The major advantages of using passive sensors for obstacle detection are low power consumption and no interference with environment. It is to note that monocular cameras are the best sensors in term of range, accuracy, amount of usable data and cost.

The remainder of the paper is organized as follows: Section 2 introduces the related work. Section 3 explains the proposed ground plane segmentation method. Evaluation results are presented in Section 4 and finally conclusions are drawn in Section 5.

Manuscript received February 13, 2013; revised April 16, 2013.

II. Related Work

Obstacle detection is one of the major problems that need to be solved to ensure safe navigation for visually impaired people. The problem of obstacle detection may often be reduced to a problem of ground plane detection. When detecting the ground plane, remaining objects can be viewed as obstacles, if they protrude outside of the ground plane.

Existing Smart Cane systems based on monocular camera that could lead to the obstacle detection can be classified into two major categories: Optical Flow based approaches, and appearance based approaches.

In Optical Flow based (motion based) approaches, motion information is extracted from successive images, and can be computed from optical flow. Optical flow describes the motion with vectors at feature points in a captured image, and it can be used for calculating the time to contact with a surface. Various approaches have been proposed to address the problem of ground plane detection, such as [3] and [4]. Usually, a reference flow related to the motion of the ground is computed (or predicted) first, and then obstacles are identified in regions whose actual displacements (motions) differ from the ground plane flow. Recently Xue-Nan and al [5], has propose a new method to detect movable paths during visual navigation of a robot operating in an unknown structured environment. This approach detects and segments the floor by computing plane normal from motion fields in image sequences. The major problem with this approach is the time required to compute the plane normal.

Motion-based approaches work very well in finding moving objects, but they have difficulty in reliably detecting ground plane particularly when it does not have dominant motion against the surroundings, cannot be used to detect static obstacles with no motion and it is computationally intensive, often inaccurate (shocks and vibration of the camera can also influence the accuracy of motion information) and sensitive to noise. Also these techniques usually fail when there is no or little motion between the subsequent image frames.

Appearance-based systems detect the obstacles by making use of color [6]–[7], texture [8]–[9], edge [9]–

doi: 10.12720/joig.1.2.72-75

[10]–[11], and frequency [12] features to identify an area as belonging to the ground plane. Objects with different appearance from the ground may be classified as obstacles. Color information is computationally cheap to learn and process. While small objects are difficult to detect in range based system due to their poor angular resolution, they can in many cases be easily detected with color vision.

One approach to extract 'ground plane area' is to flood-fill the image starting from an estimated ground point [7]; the filled area is then classified as the ground plane. Another similar method involves segmenting the image into regions, and using color and position to identify one region as the ground [13]. Several methods that use vertical scan lines have been described. They run vertically upwards until an edge is detected [10]–[11], defining the area below the detected edge points as the ground. There are also several methods that work by comparing pixel colors against those from a ground sample [6]–[12], with some implementations using a machine learning approach to remember ground pixel appearances for new ground pixels classification [6]–[12]–[14].

The most important advantage offered by appearance-based methods is that no motion is required in order to calculate a result [10]. This means that even when visual impaired person is motionless, obstacle information can be computed and used for path planning. Another major advantage is that the occupancy information is very high resolution [11]; ground planes can be discovered per-pixel. Appearance-based methods also work very well even on featureless surfaces [6]–[15], and have been described as faster than optical flow [16]–[17].

III. Ground Plane Segmentation Method

Ground Plane Segmentation refers to the process of extraction of the foreground (ground plane) from background (non-ground) regions respectively. So, our main task was to extract the ground plane from monocular image captured by a camera mounted on a Smart cane through the process of segmentation.

We are based in our ground plane segmentation on both color and texture features. The texture and color of a presumed clear area in front of the cane are used to generate a histogram which is then used to classify the pixels in the remainder of the image. This algorithm is both fast to execute and simple to implement.

This algorithm is based on the work of [6], who explored a purely color-based model. Here there work is extended by including texture. The texture is used specifically to enhance the performance of a color classifier and to detect the obstacle having a same color of the reference area. The algorithm consists of steps listed below and shown in Fig. 1.

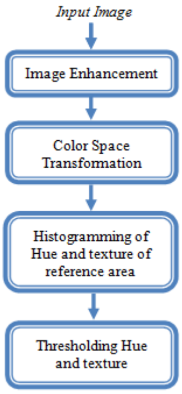

Figure 1. The block diagram of proposed method

In the following, a detailed description of the principle steps of the proposed method is developed.

A. *Image Enhancement*

a) Gaussian filter

In the first step, the matrix of RGB image is filtered with a 5×5 Gaussian filters to reduce the level of noise.

b) Texture filtering

Texture filtering is to filter an image using standard statistical measures, such as range, standard deviation, and entropy.

These statistics can characterize the texture of an image because they provide information about the local variability of the intensity values of pixels in an image. For example, in areas with smooth texture, the range of values in the neighborhood around a pixel will be a small value; in areas of rough texture, the range will be larger. Similarly, calculating the standard deviation of pixels in a neighborhood can indicate the degree of variability of pixel values in that region. Textural filtering was conducted based on Matlab toolbox. The functions all operate in a similar way: they define a neighborhood around the pixel of interest and calculate the statistic for that neighborhood [18].

The entropyfilt functions operate similarly, defining a neighborhood around the pixel of interest and calculating the statistic for the neighborhood to determine the pixel value in the output image.

B. *Color Space Transformation*

In the second step, color input image RGB values are transformed into the HSV (Hue, Saturation, and Value) color space. The latter is a cylindrical space, in which the H and S components contain the color information, in the form of a standard color wheel. The Hue is the actual color, or the angle of the point in the cylinder, the Saturation is the "purity" of the color, and is the radial distance of the point. The Value is the intensity, or brightness, and is the height of the point.

An appealing attribute of the HSV model is that it separates the color information into intensity and color components. As a result, the hue and saturation bands are less sensitive to illumination changes than the intensity band.

C. Histogramming Of Hue and Texture of Reference Area

In the third step, a rectangular area (assumed to be free from obstacles Fig. 2) in front of the Smartcane or blind person is used for reference in hue and texture, because the cane or blind person walk at first in ground that is surely background in images. Then the Histogramming of reference area is computed for both hue and texture.

Figure 2. The black rectangular area is used to construct the initial ground model.

D. Thresholding Hue and Texture

In the fourth step, all pixels of the input image are compared to Histogram of the hue and the texture. A pixel is classified as an obstacle if both of the two following conditions are satisfied:

- The hue value at the pixel's hue value is below the average of reference area in hue.
- The intensity value at the pixel's intensity value is below the average of reference area in intensity.
- The texture value at the pixel's texture value is below the average of reference area in texture.

If none of these conditions are true, then the pixel is classified as belonging to the ground.
After classification of a pixel a binary image is generated as follows:

- Black pixels correspond to ground
- White pixels correspond to obstacle.

IV. Results and Discussions

To illustrate detection results, the new algorithm color and texture histogram based approach is tested on sample image, which is set of 80 indoor environment grabbed from Olympus camera FE-370 with 640*480 pixels.
As shown in Fig. 3, the simplified version of our algorithm performs quite well. Independent of the depths of the reference area, the method detects the right and left corridor walls, the door on the left (Fig. 3b), and the table at the end of the corridor (Fig. 3a). In particular, the algorithm can detects easily the corridor walls which have the same color of the ground (Fig. 3a). Such result is due the difference of the texture feature. However, this method incorrectly classifies a highlight as an obstacle (Fig. 3b).

V. Conclusion

A new algorithm for obstacle detection that combines color and texture information extracted from monocular image is presented.

The algorithm is used in guidance system for visually impaired and helps them in navigating indoor environments.

For future work, we can extract information related to localized obstacles in order to apply recognition method to particular features namely: texture, color and shape.

(a)

(b)

Figure 3. Pixel classification a) Input color image with black rectangular reference area and corresponding obstacle detection result (pixels classified as ground are shown in black and pixels classified as obstacle are shown in white), b) Input color image with modified dimension of reference area and the corresponding obstacle detection result.

References

[1] D. Dakopoulos and N. G. Bourbakis, "Wearable obstacle avoidance electronic travel aids for the blind: A survey," *IEEE Transactions on System, Man and Cybernetics*, Part C, pp. 25, 2010.

[2] A. Sonda, F. Jihen, *et al*, "New electronic cane for visually impaired people for obstacle detection and recognition," in *Proc. IEEE International Conference Vehicular Electronics and Safety*, 2012, pp. 416 – 420.

[3] C. Braillon, C. Pradalier, *et al*, "Real-time moving obstacle detection using optical flow models," *IEEE Intelligent Vehicle Symposium*, 2006, pp. 466 – 471.

[4] A. Talukder, S. Goldberg, *et al*, "Real-time detection of moving objects in a dynamic scene from moving robotic vehicles," in *Proc. IEEE International Conference on Intelligent Robotics and Systems*, 2003.

[5] C. Xue-Nan, K. Young-Geun, *et al*, "Floor segmentation by computing plane normals from image motion fields for visual navigation," *International Journal of Control, Automation, and Systems*, pp. 788-798, 2009.

[6] I. Ulrich and N. Illah, "Appearance-based obstacle detection with monocular colour vision," *AAAI National Conference on Artificial Intelligence*, Austin, Texas, 2000.

[7] T. Taylor, S. Geva *et al.*, "Monocular vision as a range sensor," *CIMCA, Gold Coast*, pp. 566-575, 2004.

[8] V. C. Nguyen and M. Ian, "An efficient obstacle detection algorithm using color and texture," *World Academy of Science and Technology*, 2009.

[9] M. Blas, M. Agrawal, and al, "Fast color/texture segmentation for outdoor robots," *Intelligent Robots and Systems*, pp. 4078-4085, 2008.

[10] Q. Zhan and al., "Automatic navigation for a mobile robot with monocular vision," *IEEE Conference on Robotics, Automation and Mechatronics*, 2008.

[11] S. Lenser and M. Veloso, "Visual sonar: Fast obstacle avoidance using monocular vision," in *Proc. IEEE International Conference on Intelligent Robots and Systems*, Las Vegas, 2003, pp. 886-891.

[12] T. W. Ubbens and D. C. Schuurman, “Vision-based obstacle detection using a support vector machine,” *IEEE*, 2009.

[13] C.-H. Lin, and al., “Robust ground plane detection for obstacle avoidance of mobile robots using a monocular camera,” in *Proc. IEEE/RSJ International Conference on Intelligent Robots and Systems*, Taipei, Taiwan, 2010, pp. 3706-3711.

[14] D. Iakovidis *et al.*, “Color texture recognition in video sequences using wavelet covariance features and support vector machines,” in *Proc. Euromicro Conference*, 2003, pp. 199-204.

[15] Y. Chao and Z. Changan, “Obstacle detection using adaptive color segmentation and planar projection stereopsis for mobile robots,” in *Robotics, Intelligent Systems and Signal Processing*, 2003, pp. 1097-1101.

[16] R. Katz, O. Frank *et al.*, “Dynamic obstacle detection based on probabilistic moving feature recognition,” *Field and Service Robotics*, pp. 83-91, 2008.

[17] E. Einhorn, C. Schroter *et al*., “A hybrid Kalman Filter based algorithm for real-time visual obstacle detection,” in *Proc. 52nd Int. Scientific Colloquium*, 2007, pp. 353-358.

[18] L. Xiaoli, H. Yong *et al*., “Texture discrimination of green tea categories based on least squares support vector machine (LSSVM) classifier,” in *Proc. SPIE* , 2008, vol. 6625, no. 16.

Jihen Frikha Elleuch was born in tunisia in 1984. She received a master degree in 2009, in "New technologies for dedicated information systems" at "National engineering school of sfax tunisia".Since 2010, she is preparing a phd thesis in the same school. She is already affiliated to Control & Energy Management Laboratory (CEM Lab). Her research focuses on assisting the visually impaired: obstacle detection and recognition from monocular camera.

Dr. Imene Khanfir Kallel was born in Tunisia in 1979. She received her Electrical Engineering diploma in 2001, the Master Degree in Electrical Engineering in 2003, and the Phd Degree in Electrical Engineering in 2010 from the National Engineering School of Sfax - Tunisia. Now she is an assistant professor in Biotechnology Higher Institute of Sfax, a member of Control & Energy Management Laboratory in Sfax University and an associate researcher in Image & Information Processing (iTi) Dept in TELECOM Bretagne. She works on processing, analysis and fusion of information at various levels, and from various sensors. Her research works are applied on Biometrics and Biotechnologies. Since 2011 she manages a research team working on a smart white cane project.