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An Estimating Floor Region Algorithm based on Image Segmentation using FPGA for Smart Rovers

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ABSTRACT

By far most of the floor regions detection algorithms are still dependent on the depth or other additional sensors that consume more power relatively and increase the total weigh for smart land rovers. In this paper, a new framework that enable to estimate floor regions in single image for Unmanned Ground Vehicle (UGV) robots is presented. In general case, the cluttered indoor surroundings such as patterned floors, shadows and reflections, those surroundings are very difficult to differentiate floor regions. The proposed algorithm combines extracting surface texture characteristic with specific geometric area is able to find out from object boundary, and through SVM to distinguish between floor and non-floor regions. In experimental results, public MIT Scene dataset and indoor database were selected to verify the detection accuracy. The proposed algorithm accuracy can reach up to 94.72% in average without any other sensors for assistant.

Keywords: FPGA, UGV, Floor Estimation, Image Processing, Heterogeneous Computing

1. INTRODUCTION

An era of science and technology flourished in the 21st century, many hot topics like Artificial Intelligence, Robotic, Cloud Computing, Big Data are already and will soon be changing our lives. One of the big change, a variety of robots were developed such as quadcopter and Unmanned Aerial Vehicle (UAV) with camera or environment sensing features, Unmanned Ground Vehicle (UGV) robots have sweeping robot, machine dog, warehousing robot and Mars exploration rover etc. All of them require advances robotic vision processing such as 3-D positions in the stereo vision, object tracking or recognition, and ground detection.

Recently, there are many kinds of floor regions detection methods have been proposed for UGV robots. Chun et al. [1] and Wang et al. [2] proposed the methods are used camera and depth sensor to detect floor regions. The floor regions are obtained from the floor depth of characteristics. Kumar et al. [3] proposed a method of Markov Random Field with depth information. It can precisely segment the floor and detect obstacles which are extremely low. Seki and Sugaya [4] proposed a method is used camera and projector to detect floor-wall boundary. The green points are intersecting points of two ellipses. Floor-wall boundary will be detected as the green line segment.

However, additional depth sensor or projector will not only consume more power relatively but also increase the weight and cost. Therefore, recent researches proposed image algorithm for estimating floor regions base on RGB camera. Li and Birchfield [5] proposed a method for detecting indoor corridor floors. This method combines three visual cues for evaluating the likelihood of horizontal intensity edge line segments belonging to the floor-wall boundary for estimating floor regions detection. Hedau et al. [6] proposed a methods for recovering the spatial layout of cluttered room through a number of iterations to create a parametric 3D box that is able to distinguish a space and detected floor regions. Aggarwal et al. [7] proposed a method of estimating floor regions from first person camera view. This method integrates appearance cues, position density map and specific geometry cues in an iterative framework, and calculates floor regions.

In this paper, a new estimating floor algorithm based on image segmentation with a single camera is proposed. The proposed algorithm accuracy can reach up to 94.72% in average without any other sensors for assistant. On the other hand, the proposed algorithm has also been brief verified in ARM-FPGA platform, real-time floor estimating with high image segmentation efficient using FPGA heterogeneous computing acceleration for any type smart rovers.

2. THE PROPOSED ALGORITHM

The proposed new approach of floor region detection is component of extracting surface texture characteristic and specific geometric area to estimate floor and non-floor regions. Hence, it can process accurate estimation and reduce processing time. An overview of the proposed estimation algorithm framework is illustrated in Fig. 1, including segment superpixels, extract superpixels texture characteristic, boundary lines detection, label floor regions, classify floor and non-floor regions and specific appearance floor regions. The details are as following sub-sections.

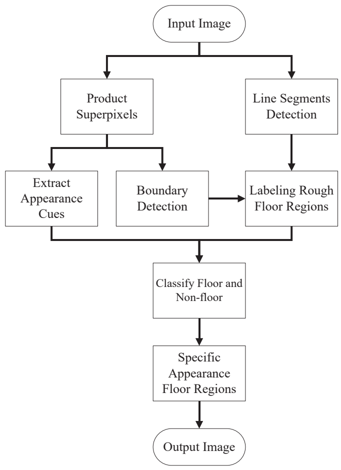


Fig. 1. The framework of the propose floor region estimating algorithm.

An image has many pixels. it takes a very long processing time to process each pixel. Therefore, a simple linear iterative clustering (SLIC) is used to generate superpixels form image [8]. The conventional k-means clustering method has to compare each pixel of the whole image, however, SLIC is limited a fixing region to cluster. Therefore, SLIC is easy for implantation and faster. Fig. 2 present an image segmented using SLIC into superpixels. The original image size is 400 x 300 pixels, and superpixels are only 400 pixels. In this way, using superpixels can help reduce a huge amount of computation time to the proposed approach. However, since superpixel has different texture information, we have to extract appearance cues from each superpixel. The proposed method is referred to Hoeim et al. [9] with following modifications.

- Color: RGB/HSV mean and Hue, Saturation and Value Histogram.
- Location: normalized x, y 10th, 50th and 90th percentile.
- Texture: mean absolute response using 48 Leung-Malik filter bank [10].

Fig. 2. Image segmented using SLIC into superpixels of size 400 pixels

In addition to using surface texture characteristic to classify superpixels into floor and non-floor groups, we add a specific geometric region cue to for additional information from the geometry. The image segmentation using SLIC into superpixels, and using RGB mean of superpixels will perform canny edge detector [11] that detect the boundary of object, it can help reduce some unnecessary noise. Next, Connected Component Labeling (CCL) [12] is used to generate a rough floor regions which is marked for the initial classification labels in PEGASOS. As shown in Fig. 3, red points are intersection points of inclined lines, blue of line segments are LSD detect line segments and yellow of line segments are selected line segments, while green regions are the rough floor regions.

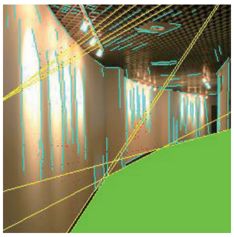


Fig. 3. The result of specific geometric area, the green regions are rough floor regions.

Next, Support Vector Machine (SVM) is used to compute a hyperplane which distribute superpixels into two regions of floor and non-floor from the extracted appearance cue of superpixels. In our approach, Primal Estimated sub-GrAdient SOlver for SVM (PEGASOS) is selected [13]. It is an online learning algorithm of SVM. PEGASOS is calculated in a random simple, in order to project the vector onto a sphere that radius is $1/\sqrt{\lambda}$. After each iteration, we enforce performing update as shown in Eq. (1).

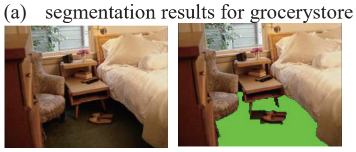
$$w_{t+1} \leftarrow \min\left\{1, \frac{1/\sqrt{\lambda}}{\|w_{t+1}\|}\right\} w_{t+1} \tag{1}$$

Where w_{t+1} is a new vector, λ is a custom parameter. When λ is the larger, the adjustment range is the smaller, and when λ is the smaller, the adjustment range is the larger relatively. Since the run-time does not depend directly on the size of the training set, this method is effective and faster than other SVM.

3. EXPRIMENTAL RESULTS

The proposed floor region estimating algorithm was evaluated with various indoor surroundings from public MIT scene dataset and indoor dataset [14], such as bedroom, nursery, classroom, closet space, market aisle, garage and corridor. On the other hand, the proposed algorithm has been implemented on a Multi-Core SOC-FPGA embedded system platform. Fig. 4 presents the results of the proposed algorithm on dataset. Fig. 5 shows the system implementation architecture.

(a) segmentation results for grocerystore



(b) segmentation results for bedroom

Fig. 4. The results of the proposed algorithm on public MIT scene dataset and indoor dataset [14].

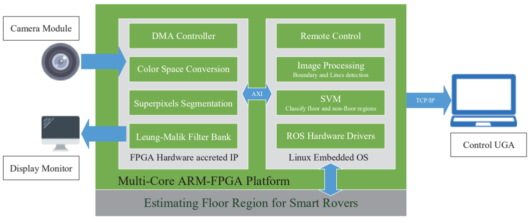


Fig. 5. The system architecture of algorithm on an SoC-FPGA heterogeneous computing platform.

Compare to Li et al. [5], although it can estimate indoor corridor floors fast and accurate floor regions, it is limited to the indoor corridor and could not be applied in the general room or the places with many obstacles. Hedau et al. [6] achieved the floor region detection in a complex environment, but the accuracy is poor. Aggarwal et al. [7] estimated floor regions in cluttered indoor scenes, however, the computation is too complex. Therefore, we integrated SVM for appearance cues, geometry cues and horizontal intensity edge line segments as a new framework so that the proposed algorithm can exact estimate floor regions in cluttered scenes such as patterned floors, shadows and reflections. Furthermore, in order to make the algorithm calculation faster, the texture of Leung-Malik filter bank and color space conversion are accreted on FPGA part.

For comparison, all the image scenes were manually annotated with floor and non-floor regions with ground truth.

For evaluation the result of the proposed algorithm, true positives, false positives, true negatives and false negatives are calculated. Besides evaluate the well-known accuracy as shown in Eq. (2), another G-Mean reliability of accuracy has also been evaluated as shown as Eq. (3).

$$\text{Accuracy} = \frac{TruePositive + TrueNegative}{TotalPopulation} \quad (2)$$

$$\text{Sensitivity} = \frac{TruePositive}{TruePositive + FalseNegative}$$
$$\text{Specificity} = \frac{TrueNegative}{FalsePositive + TrueNegative} \quad (3)$$
$$\text{G-Mean} = \sqrt{Sensitivity \times Specificity}$$

Table 1 shows the comparison of the proposed algorithm. It is obviously that the proposed algorithm's Accuracy and G-Mean are better than other methods. It is very suitable for UGV robots and segmentation accuracy is up to 95.02% in average. The proposed algorithm has been implemented on SoC-FPGA platform using FPGA heterogeneous computing acceleration and UGV rover robot is using TurtleBot-II as shown in Fig. 6Fig. .

Table 1. Segmentation Accuracy and G-Mean comparison results.

Method	Accuracy	G-Mean
Yinxiao and Birchfield [5]	89.10	N/A
Hedau et al. [6]	90.45	81.02
Aggarwal et al. [7]	90.08	87.85
Our Propose	94.72	93.01

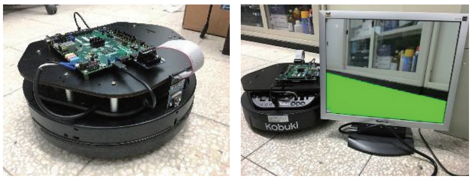


Fig. 6. The result of the proposed algorithm implemented on SoC-FPGA platform.

4. CONCLUSION

In this paper, an algorithm of floor regions detection that can precisely distinguish floor regions from complex indoor surroundings is proposed. The proposed algorithm is very suitable for UGV robots and segmentation accuracy is up to 94.72% in average. The complex surroundings including patterned floors, shadows and reflections, and these scenes are all detectable. In order to reach real-time computation, SoC-FPGA heterogeneous computing acceleration is implemented with the proposed algorithm. In overall, UGV robots will benefit better navigation and route planning from our approach.

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