PAVEMENT TEXTURE SEGMENTATION USING LBP AND GLCM FOR VISUALLY IMPAIRED PERSON

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Abstract: This paper proposes about a method for region segmentation and texture extraction to classify pavement and roadway region in the image that acquired from cameras equipped to the visually impaired person during a walk. First, detect a road boundary line through the line detections technique using the Hough transform, and obtain candidate regions of pavement and roadway. Second, extract texture feature in segmented candidate region, and separated pavement and roadway regions as classified three levels according to perspective scope in triangular model. In this paper, used rotation invariant LBP and GLCM to compare the difference of texture feature that pavement with various precast pavers and relatively a roadway being monotonous. Proposed method in this paper was verified that the analytical performance nighttime did not deteriorate in comparison with the results from the daytime, and region segmentation performance was very well in complex image has various obstacles and pedestrians.

1 INTRODUCTION

The rapid development of IT technology is precipitating the contemporary transformation of wired networks into wireless networks. Concomitantly, research is actively underway to develop various services using mobile terminal devices such as PDAs, mobile phones, smart phones, etc. which are adapted to the wireless network environment, and furthermore, to develop wearable computing devices and algorithms driven by various forms of nanotechnology. Among these, vision based systems are currently mainly applied for augmented reality applications using smart phones or navigations, etc. and numerous researches relevant to these areas are ongoing amid heightened international interest. However, the majority of such related research work is focused only on systems for use by non-disabled persons, while devices for assisting disabled persons are not being taken under consideration at present. Image processing and computer vision technology is a field with very high potential value for utilization as assistive devices for the visually impaired. This is an important technology for blind persons who had hitherto relied on assistive walking sticks or guide dogs for walking, offering the possibility of eliminating the risk factors that may arise when such disabled persons walk without separate guidance devices or guide persons. Most of the systems which had been developed in the past to serve as vision assistance devices that can be worn by the blind employed ultrasonic sensors, etc. to detect obstacles and transmit this information to the user, and hence they were limited in their capacity for information communication (Tuceryan and Jain, 1993).

Moreover, they were also hampered by the difficulty of identifying accurate information regarding the situational conditions or the environment during walking (Arvis et al., 2004). This paper has developed a system for enabling visually impaired persons to walk safely by using a camera mounted onto mobile computers or smart phones. Most of the pre-existing research into road detection and recognition had been constituted of efforts to develop applications for unmanned vehicles or navigation, and hence priority was not given to the subject of pavement detection and recognition from the perspective of the pedestrian's position. Also, as can be seen in Fig. 1, pavements are unlike roadways in that they are characterized by a wide variety of patterns created by the paving blocks, and they thus pose the problem that even the same pattern may pose a high possibility of being misrecognized depending on the perspective from which its image is recorded.

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Figure 1: Different images configurations in the same pavement situation.

To resolve the above problems, this paper proposes a method of segmenting regions of the road using LBP and GLCM, which are texture features invariant under rotation. To distinguish the boundary between roadways and pavement regions, the optimal road line is detected using the Hough transform, and this detected road line is used to derive the Local Binary Pattern (LBP), the Gray Level Co-Occurrence Matrix (GLCM) and the texture feature information of the segmented regions. Also, the segmented regions are distinguished into 3 stages of levels according to their distance, and the similarity of the texture features between each of the respective levels is measured, thereby distinguishing the roadway and pavement regions.

Fig. 2 presents the proposed pavement detection framework. The rest of this paper is organized as follows: In section 2, we describe about step for region boundary detection. Section 3 presents our pavement detection method based on perspective texture feature LBP and GLCM, and measure the similarity between each level within triangular model. Section 4 shows the experiment results and finally, this paper concludes and discusses our future research direction.

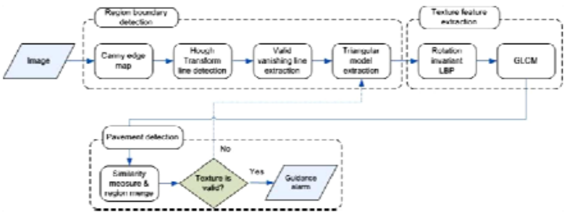

Figure 2: Pavement detection framework.

2 REGION BOUNDARY SEGMENTATION

2.1 Road Boundary Detection

Within an outdoor natural image in which roadways and pavements are simultaneously present, linear components exist due to the numerous obstacles. However, the road information conveyed by an edge image obtained through a canny edge operator has the characteristic of proceeding in the direction of the center of the image. Also, when walking while facing directly forward in accordance with the characteristic manner of blind pedestrians, the road is confirmed to be located within 60 % of the image, and the pixel information for the upper 40 % can then be eliminated. In order to secure edge detection that sustains strongly under lighting and illumination, first the edges for the specific RGB channels of the input image are detected, and the noise is removed using the logical disjunction (OR) operations and morphological closing operations. Then the results of the diagonal component edge detection are obtained by means of the elimination of the horizontal and vertical edge components. Fig. 3 shows the resulting image obtained in the edge detection stage.

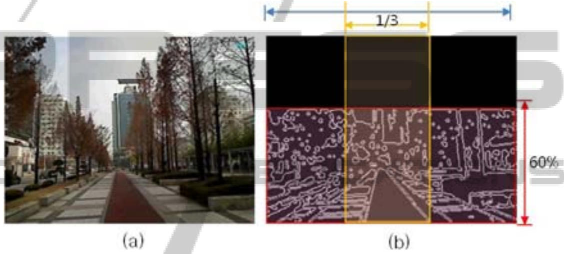

Figure 3: Resulting image obtained in edge detection step, (a) original outdoor image, (b) canny edge detection result within 60% of the image.

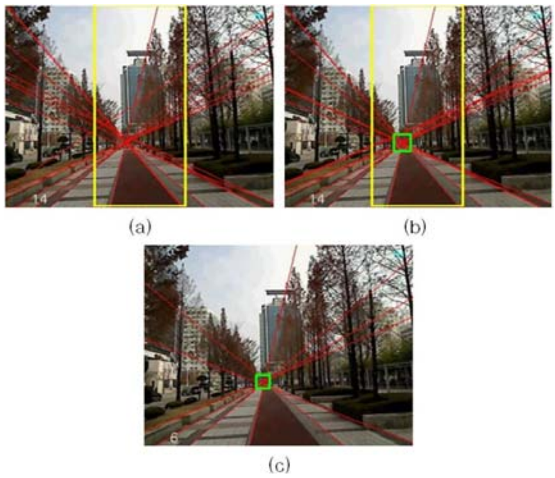

Figure 4: Process of detection for valid vanishing line, (a) the candidate region for the location of the vanishing point, (b) improved Hough line after eliminating invalid lines, (c) optimal valid vanishing lines.

The Hough transformation algorithm is performed to detect the boundary of the roads. Here, the valid line is the diagonal component, and hence the lines with slope of 20 or less are removed from among all the extracted lines. In the natural image, the pavement has a line parallel to the boundary surface and the vanishing point (intersection point) exists on the extension of the line according to the perspective. The valid line for detecting the boundary of the region is determined using these features. Also, the line that is located on the boundary of the pavement has a high probability of existing within the vanishing block which has a size of 20x20 and which is the candidate region for the location of the vanishing point. Hence, lines for which the vanishing point does not exist within this region are judged to be invalid lines and are eliminated. Fig. 4 displays the result of detecting the optimal valid vanishing line component by means of eliminating the invalid lines after generating the vanishing block.

2.2 Region Split and Triangular Model Extraction

The regions which have been separated by the valid road lines are regarded as the primary interested region. This paper designates all of these regions as the triangular model, and the separated regions are composed of an N number of small triangular models. In these triangular models, the regions which are determined to be identical by means of similarity verification are merged in cases where they lie adjacent. In the case of non-adjacent regions, the respective surface areas are calculated so that the regions which are smaller than the threshold value can be submitted to a stage of elimination to extract a single triangular model region. Fig. 5 shows the small triangular model generated by separating the extension lines of the valid lines of the pavement, and the final triangular model merged though the similarity verification stage.

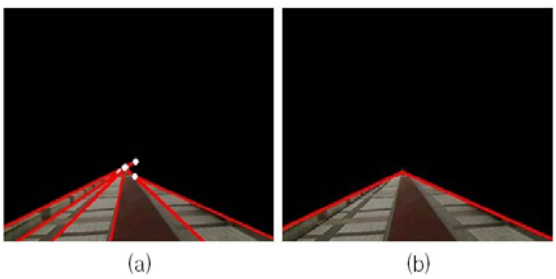

Figure 5: Separating the ROI and extracting a single triangular model, (a) primary interested regions, (b) the merged triangular model region.

3 TEXTURE FEATURE EXTRACTION

3.1 Perspective Texture Feature

The extracted triangular model is segmented into 3 levels according to distance to derive the texture information. This method is used to solve the problem arising from the fact that the texture of regions that are distant from the camera offer relatively less quantities of information and are inferior in clarity compared to the close regions. As seen in Fig. 6, the close region is designated as level 1 and the distant region as level 3 to extract the texture features for each respective level. Rotation invariant LBP and GLCM are used to distinguish the textures of the pavement and the roadway, and the image is segmented into window blocks of size 8x8 for processing to extract more textural features from the pattern.

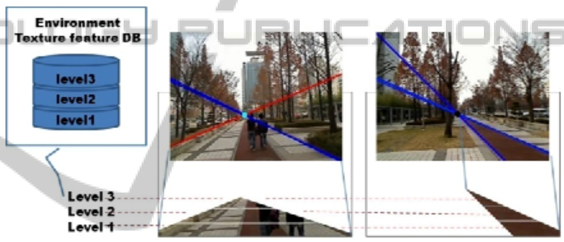

Figure 6: Perspective level of triangular model.

To address the problem posed by the transformation of the pattern of the paving blocks when the image is rotated or repositioned by the pedestrian, the texture features which hold up strongly under rotation are extracted. The first feature utilized for this purpose is the rotation invariant local binary pattern. The derivation of the LBP follows that represented by Ojala et al., g_c corresponds to the gray value of the center pixel of a local neighbourhood.

$g_p(p = 0, \cdots, P-1)$ correspond to the gray values of P equally spaced pixels on a circle of radius $R(R > 0)$ that form a circularly symmetric set of neighbors.

Fig. 7 illustrates three circularly symmetric neighbor sets for different values of P and R. And then, a binomial weight 2^p is assigned to each sigh $s(g_p - g_c)$, transforming the differences in a neighbourhood into a unique LBP code :

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c)2^p, \qquad (1)$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

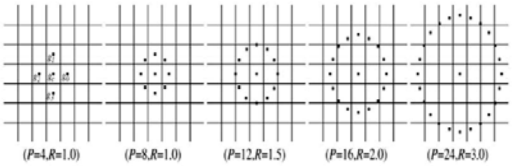

Figure 7: Local Binary Pattern(LBP).

The rotation invariant local binary pattern applied in this paper is one variant of the local binary pattern, and uses equation (2) to submit the LBP code to a circular rotation and generation is repeated until the minimum value is obtained. In short, the rotation invariant code is produced by circularly rotating the original code until its minimum value is attained. The LBPROT operator introduced by Pietikäinen et al. (Vadivel et al., 2007) is equivalent to $LBP_{8,1}^{ri}$. Rotation invariance here does not however account for textural difference caused by changes in the relative positions of a light source and the target object. So, we extract another texture extraction method to solve this problem using Gray level co-occurrence matrix(GLCM).

$$LBP_{P,R}^{ri} = \min\{ROR(LBP_{P,R}, i) | i = 0,1,\dots,P-1\} \quad (2)$$

Haralick suggested the use of gray level co-occurrence matrices (GLCM) for definition of textural features. The values of the co-occurrence matrix elements present relative frequencies with which two neighboring pixels separated by distance d appear on the image, where one of them has gray level i and other j. Such matrix is symmetric and also a function of the angular relationship between two neighboring pixels. The co-occurence matrix can be calculated on the whole image, but by calculating it in a small window which scanning the image, the co-occurence matrix can be associated with each pixel. Haralick suggests 14 features describing the two dimensional probability density function $p_{i,j}$. Four of the most popular commonly used are listed in [Haralick 73] (Leitão et al., 2003). They are Contrast, Correlation, Energy, Homogeneity, and Energy and Homogeneity features used to measure the uniformity of surface texture in this paper.

$$\text{Contrast} = \sum_{i,j} |i-j|^2 p(i,j) \quad (3)$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(i-\mu_j)p^2(i,j)}{\sigma_i \sigma_j} \quad (4)$$

$$\text{Energy} = \sum_{i,j} p(i,j)^2 \quad (5)$$

$$\text{Homogeneity} = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \quad (6)$$

3.2 Region Segmentation

The LBP and GLCM texture information of the extracted triangular model is calculated to measure the degree of similarity among the adjacent regions. The regions are separated initially according to the triangular model by merging the regions with high degrees of similarity and removing the regions with low similarity. By comparing the degrees of similarity among the texture features within the separated triangular model, analysis is performed on the regions where the pavement and the roadway lie adjacent or the regions that exceed the range of recognition during walking. Through this analysis, the secondary region is distinguished to guide the walking movement. In the proposed method, the local features which display the spatial information of the images can be reflected with high quality by comparing the respective pattern similarities of each block unit within the triangular model as in equation (7) as soon as the walking commences to measure the similarity of the stored texture features of the pavement and the query images that are input during walking. In equation (7), L and CM are the respective normalized values for the LBP and GLCM blocks, and α and β are their respective weighted values. The degree of similarity can be compared by varying the weighted values according to the information which is desired to be compared.

$$S_B = \alpha L + \beta CM, \quad \alpha + \beta = 1 \quad (7)$$

Equation (8) represents the method for calculating the similarity of the normalized LBP histogram between the query image Q and the compared image D. K is the number of bins, and N is the number of road region models. In the current image, the similarity between the LBP histogram and the stored road region model is identified as S, and the road model with the highest degree of similarity is thereby detected.

$$S_R = \sum_{k=0}^{K-1} \sum_{n=0}^{N-1} \min(Q(m), D(m)) \quad (8)$$

4 EXPERIMENT RESULTS

As for the image used for experiments in this paper, images sized 320 x 240 were input and processed in real-time. The average processing speed was measured to be 18 frames per second. For the experiment, outdoor images for both day and night were recorded, and the resulting extractions of texture features confirmed clear distinctions in texture for pavements and roadways in both LBP and GLCM. Fig. 8 presents the result of segmenting the image into 8 x 8 window blocks and then extracting the texture features of the valid blocks located within the triangular model. It indicates that while the unique pattern of the texture was able to be extracted in the pavement regions, almost no patterns could be extracted from the roadway regions.

Fig. 9 exhibits the experiment using experimental images in which the bicycle path and the pavement region are adjacently located, wherein the bicycle path was judged to be a roadway and the difference in the texture features when compared with the pavement region was sought. 3 stages of levels were distinguished within the region which had been segmented following the valid line, and the rotation invariant LBP and GLCM were extracted for the window blocks of each respective level identified according to distance. In level 3, the number of window blocks that remained valid was small and this posed a difficulty in comparing texture features. However, in the case of the bicycle path located in the center of the image, it was confirmed that sufficient extraction could be made of the texture features to enable a comparison of similarity even in level 3. Fig. 10 is the result of experiments on images recorded in the nighttime. Because LBP and GLCM utilize features which can express texture features well regardless of the conditions of lighting or illumination, it was verified that the analytical performance did not deteriorate in comparison with the results from the daytime. Also, Fig. 11 exhibits the results of experiments in continuous frames and

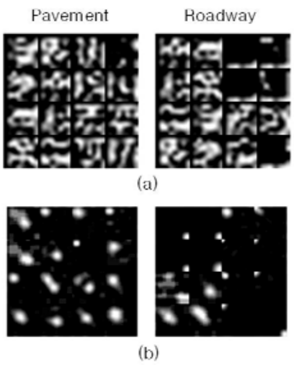

Figure 8: Texture feature of pavement and roadway, (a) 8x8 window blocks based rotation invariant LBP, (b) 8x8 window blocks based GLCM.

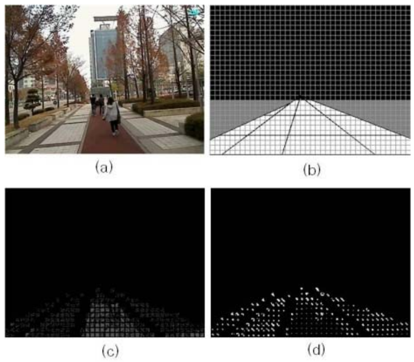

Figure 9: Result of texture feature extraction within triangular model, (a) original image, (b) triangular model based on 8x8 window, (c) rotation invariant LBP, (d) GLCM.

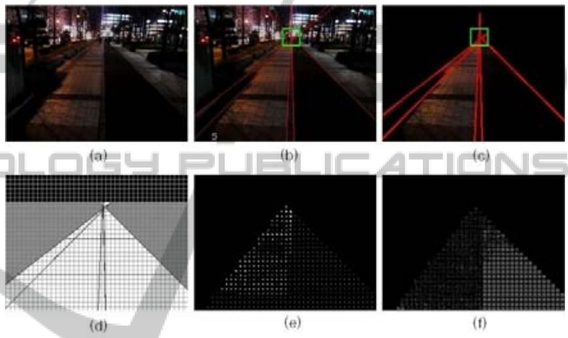

Figure 10: Pavement detection result with night outdoor image: (a) original image, (b) valid hough line, (c) and (d) region of triangular model, (e) rotation invariant LBP in (d), (f) GLCM in (d).

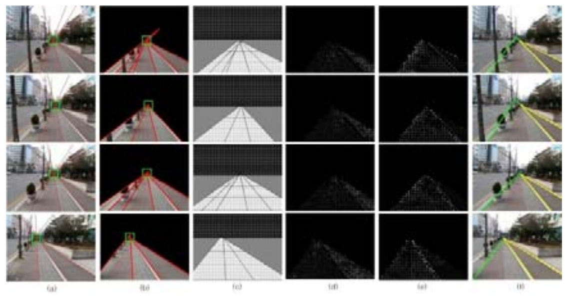

Figure 11: Process of texture feature extraction in real time image: (a) valid hough line detection, (b) region of triangular model, (c) separated according to 8x8 window block (d) rotation invariant LBP in triangular model, (e) GLCM in triangular model, (f) pavement and roadway detection result.

demonstrates that in this case, even if the distance texture of level 1 failed to be detected, because the quantity of texture information increased with the passage of time, the pavement situation could be determined by analyzing the texture in level 2.

5 CONCLUSIONS

This paper has proposed a probabilistic estimation method based on the rotation invariant texture features of LBP and GLCM as a method for distinguishing pavements and roadway regions in outdoor images. It was confirmed that pavement and roadway regions could be separated using a relatively simple form of similarity comparison between the regions when processing images in real-time using this method. However, because there is exists a great variety in the patterns of paving blocks, and because comparisons of similarity become challenging when a pavement region with a differing pattern is confronted, there are plans for additional research with the objective of resolving such problems by focusing on the stage of updating and recognizing texture features in real-time.

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