ESTIMATION OF SPECULAR COMPONENTS IN THE TASK OF PHOTOMETRIC RECONSTRUCTION

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Abstract

The drawbacks of photometric stereo reconstruction are shown. An estimation approach of specular components is described. Also it is proposed to select specular components features as the feature vector data in the problem of photometric stereo reconstruction.

Key words: 3D reconstruction, specular, image processing.

1 Introduction

The 3D reconstruction methods of the surface become the crucial steps in material analysis. Photometric stereo is the method of recovering three-dimensional shape of the surface from a series of images [20]. All images are captured from fixed viewpoint under different illuminations. The advantages of this reconstruction method may overcome advantages of different 3D reconstruction methods in sense of productivity, computability, and usability. Nevertheless the drawbacks of photometric stereo reconstruction narrows it's abilities in practical realization.

To reconstruct three-dimensional scene photometric stereo method require exact information about the reflectance of the surface. Theoretically the estimation of surface reflection is possible only in the case of the Lambertian surfaces, when diffuse reflection take place. In general case real surface reflection represented in mixture of diffuse and specular components. The specular components regions of the surface are making unknown or deformed reflection information.

Recently, a small number of surface reconstruction techniques have overcome these limitations by effectively decoupling shape and reflectance in images [21,22].

It is proposed that drawback of photometric stereo reconstruction can be prevented by the reduction of the specular components and previous recognition and classification. The reflectance function of the surface can be represented in the form of diffuse and specular components mixture.

As clear by equation a collection of vectors from a dichromatic material image under multiple view and illumination configurations lie in the dichromatic plane—the plane spanned by the effective source and body. In addition, it has been observed that these vectors often cluster in the shape, where the two limbs correspond to diffuse and specular reflection. When these limbs are sufficiently distinct, the diffuse component can be recovered, the two components can be separated, and the specular components can be removed thru classification of the last one.

This method works well for homogeneous, dichromatic surfaces in the noiseless case, there are three significant limitations that make it difficult to use in practice. First many surfaces are textured and violate the homogeneous assumption. Even when an image does contain homogeneous surfaces, a non-trivial segmentation process is required to identify them. In order for the specular and diffuse limbs the specular lobe must be sufficiently narrow (its angular support must be small relative to the curvature of the surface.) Finally when the diffuse and specular intensities are the same, there is no way to distinguish between the two components, and separation is possible. Some of these restrictions can be overcome by using additional cues such as multiple exposures.

2 Estimation of specular components

To process the image in the form of multi dimensional information and extract specular components, it is important to reduce the dimensionality of this information without substantial influence on discrimination properties of specular components information features.

The problem of specular components selection on the image is considered as division of an image in to the set of specular components that do not overlap. The regions of specular components should be homogenous, without inner abruption. Also those regions of specular components should be simple without cogged passage.

Estimation of specular components started from counting a preliminary threshold that strongly depends on the property of a given image. On the first step of the estimation algorithm all pixels are analyzed, where the luminance level overcome a preliminary level of a threshold value. On the base of connectedness model are created all sets of pixels that formed continuous regions and over the threshold value. Basing on this information a comparison of region size is making. Those regions are formed by pixels of the image and they compared to admissible limits of specular region size. After compare procedure a selection of small specular regions performed, when size of those is smaller than lower threshold value. For image pixels that form large regions, the threshold value is increased in some value and new reorganization of pixels that form small specular regions is performed. On final step a new reorganization is performed for each region and all pixels with values higher than threshold value are found. The iterative process finished by forming the array of specular components regions. Each specular component has center of mass that is responsible for location of this region on the image.

Inside the specular component each pixel value is larger than threshold value and the region can be presented at last by two pixels on the base of connectedness model. The connectedness model is applied to neighborhood pixels, corner neighborhood connectedness or full connectedness model. It exist district connectedness model to connect remote elements of an image.

Computation of the preliminary threshold value depends on the processed image. There are two levels of threshold value for upper and lower limits. For input image a primary threshold value H estimated as follow:

$$H = M + Vd,$$

where M is a mean value of image, V - threshold of pixel determination, d - mean square deviation.

When new iteration is made then M and d is recalculated with value of pixel larger then H from the previous iteration step. Iteration process continued until all pixels that result H is below threshold. In accordance to this new higher threshold will decrease specular region and or will separate the region in two regions. This threshold is computed apart for each region of image.

To increase a flexibility of the approach it is proposed to use different types of thresholds like peakedness, simple and combine threshold.

Simple threshold can be computed:

$$H_s = M_l + Vd_l,$$

where M_l is a local mean value of image, d_l - local mean square deviation.

If analyzed region is shrinking on splitting, the threshold is recalculated for each region. If a number of pixels that belong to spelular region are constant, then for this region a center of mass is computed, even if the number of pixels in this region exceed maximal limit.

To the drawback of the simple threshold refer error of pixel ascribing to given region. Other drawback consist in weakness of the approach to separate two or more specular regions, which intensity level is much higher then irregular specular component.

Combine threshold is computed in form:

$$H_l = \sqrt{(P \cdot H_{\min} + M_l) \cdot M_l} \text{ ,}$$

where $H_{\min}$ - variance of previous threshold H and minimal brightness of the pixel image, P - number of threshold changing without effect on specular region.

The most flexible and efficient is peakedness threshold. In this case condition of region division is a condition of two and more peak pixels in the region. Peak pixel is a pixel with highest value of intensity on fixed radius region. For all regions it is computed the lowest peak value $G_{\min}$.

The threshold value H_l will defined in form:

$$H_l = G_{\min} - H_{\min} \text{ .}$$

If specular region is constant then the threshold will gradually increase according to the expression:

$$H_l = H_{\min} - \frac{H_{\min}}{P} \text{ .}$$

The increasing of the threshold proceeded until condition of the maxima is not reached. After that a center of mass is computed for specular component, the number of peak pixels is not important.

For specular components of the image the center of mass X , Y is computed:

$$C(x)_{mass} = \frac{\sum_i^n x(i) \cdot f(i)}{\sum_i^n f(i)} \text{,}$$

$$C(y)_{mass} = \frac{\sum_i^n y(i) \cdot f(i)}{\sum_i^n f(i)} \text{ .}$$

Rough features of the image could be the center of mass, coefficients of ellipticity and strain coefficient.

3 Specular component features

It is proposed to have I patterns as grayscale image I_i of size $N_1 \times N_2$ pixels, where $i = 1,...,I$. The image I is a square matrix which has N_1 pixels of rows from top to bottom and N_2 of columns from left to right.

For image intensity features we compute statistical moments such as central moments of the first (mean value) and second order (standard deviation). A mean value of gray level intensity of image I is:

$$X_1 = \frac{1}{N_1 N_2} \sum_{r=1}^{N_1} \sum_{c=1}^{N_2} I_{1,2} \text{ ,}$$

and a standard deviation of intensity level is:

$$X_2 = \sqrt{\frac{1}{N_1 N_2} \left(\sum_{r=1}^{N_1} \sum_{c=1}^{N_2} I_{1,2} - X_1 \right)^2} \text{ .}$$

This kind of statistical descriptors for surface images is able to distinguish, a specular component part of the image with a high intensity gray level from a dark part with low intensity. If consider geometrical features as that which describe geometrical properties of objects seen on the image, line segments and statistical properties of edges detected on the image. The resolution of surface images allows distinguishing specular componentes. Such objects have line segments of different length, angle and density. We want to benefit from such properties to have more rich set of features and to cover more image classes. It is proposed features of linear segments and edges. Let L_i be a length of the linear segment and α_i is its angle of rotation, where $i = 1,...,N$ and N - is the number of linear segments. Reduction of feature space dimension could be used to decrease over fitting and improve classification. One of these pruning techniques is Recursive feature selection. Recursive feature selection eliminates some of the original input features and retains a feature subset that provides best classification performance. The procedure stops when the desired number of features is obtained.

Geometrical features as that which describe geometrical properties of objects on the specular images formed line segments and statistical properties of edges detected on the image. Such objects have line segments of different length, angle and density. Such properties have more rich set of features and cover more specular image classes. Edges, edge approximation by line segments and extraction of geometrical features are tasks of geometrical feature extraction. An image is filtered by Roberts filter following thresholding and edge detection. Linear segments approximate edges using approximating algorithms. Features are extracted from both edges and line segments. For series of images edge detection should be adaptive because the image covers different specular components.

Conclusion

A problem of photometric stereo is analyzed. Specular components can be efficiently estimated by threshold approach. Feature vector selection is based in mean value and standard deviation.

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