

An Adaptive Grid-Point Detector by Exploiting Local Entropy Map

Xiaoting Zhang^{1,2} and Zhan Song^{1,2}

¹Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China

²The Chinese University of Hong Kong, Hong Kong, China

E-mail: {xt.zhang & zhan.song}@sub.siat.ac.cn

Abstract—This paper describes an adaptive grid-point detector for the feature detection task in a pseudo-random structured light pattern. In the algorithm, a local entropy map is firstly constructed to evaluate the distribution of the projected pattern elements in the captured image. A mask in the shape of a cross is then used for the preliminary detection of grid-point candidates. With reference to the entropy map, the size of the cross mask can be determined adaptively. With considering the local symmetry property around the grid-points, a correlation procedure is then introduced for the final grid-point localization with sub-pixel accuracy. Experiments on real human face and comparison with previous methods are used to demonstrate its high performance.

Keywords—grid-point; feature detection; structured light; image entropy

I. INTRODUCTION

Structured light system (SLS) using single pseudo-randomly coded pattern offers an efficient and affordable solution for dynamic 3D reconstruction [1]. Main advantage of such SLS is that it can finish the coding and decoding procedure via single projection and image capture. In its coding strategy, pseudorandom array or M-array [2] is the mostly used. Centroids of pattern elements are usually defined as the pattern features and then encoded by its surrounding pattern elements. The performance of the system is however limited by how accurately the feature points can be extracted from the image data.

Feature extraction is usually the first step of many visual reconstruction mechanisms including stereo vision and structured light systems, and a number of feature detectors have been proposed. The most widely used feature detectors in the literature are the LoG [3], Harris [4], and SUSAN [5] operators. In Harris detector, the second derivative of the Moravec's SSD (Sum of Squared Differences) [6] with respect to the shift is calculated for the corner detection. SUSAN (Smallest Univalued Segment Assimilating Nucleus) operator is another popular used feature detector. In the method, each image point p (of say grey level g) is associated with a local circular region C (of a certain radius r) centered at p . In C , the image points which have similar brightness as that of p will form a region named as USAN (Univalued Segment Assimilating Nucleus). The area of USAN is defined as the number of image points it contains. From the area, centroid, and second moments of each USAN, corners and edges in the image can be detected

using non-maximal suppression over the map. In [7], a corner detector is constructed based Hough transform. In [8], eigenvectors of covariance matrices and one-dimension wavelet transform is proposed to detect true corner and avoid false alarms on circular arcs. Rosten and Drummond [9] developed a FAST method which performs efficient corner detection at high speed. Simple thresholding method is used to judge the dark and bright areas in a circle around a candidate corner and that make it lack of robustness against complex illumination and surface texture. Generally, such image intensity based corner detectors are inapplicable to the pattern feature detection task in SLS, since the projected pattern elements are usually disconnected in the captured image due to projector-camera system's optical ability, e.g. MTF (Modulation Transfer Function), DOF (Depth of Field), sensor noise, surface textured and projective distortions etc. There are also some specialized methods for checkerboard-like corner extraction. In [10], the corners are firstly detected in the image using Harris corner detector. Such feature points then go through Delaunay triangulation to partition the image into triangular patches. Pairs of neighboring triangles are subsequently combined into quadrilaterals and a topological filter is then used to construct regular grids for the grid-point localization. In [11], a grid-point detector is constructed based on the characteristics of local intensity and the grid-line architecture of the planar checkerboard pattern image. But it's heavily dependent on the segmentation result of the pattern features. Simple threshold method is applied for the segmentation of pattern elements, which makes it particularly sensitive to albedo variation, uneven illumination, image noise and image blur etc.

In our previous work, a two-fold symmetry based grid-point detector has been proposed for the feature detection of a pseudorandom color pattern [12]. In the operator, local geometrical property but not image intensity is used and that makes it with strong robustness against projective distortion, surface texture and image noise and blur. However, the proposed grid-point detector may ineffective to the projection regions with big distortions because of its fixed parameters. In this work, we will introduce an improved grid-point detector with adaptive parameter determination.

The paper is organized as follows. Section 2 introduces the underlying principle of the proposed adaptive grid-point detector. Extensive experiments including the comparison

with previous algorithms and the grid-point detection result on human face are given in Section 3. Conclusion and future work can be found in Section 4.

II. ADAPTIVE GRID-POINT DETECTOR

The structured light pattern is generated from a pseudorandom array of size 65×63 as shown in Fig. 1. By the property of the pattern, every window of size 2×3 in the pattern is unique upon the colored elements the window is composed of. Since the pseudorandom array is constructed over $GF(4)$ (*Galois Field with 4 elements*), we use 4 different colors (Red, Green, Blue, and Black) each of which is seemed as one pattern element for the foreground in the pattern, and the white color is used as the background color. While the traditional methods use the centroids of pattern elements as the feature points, in our system we use the grid-points between the neighboring rhombic elements as the feature points.

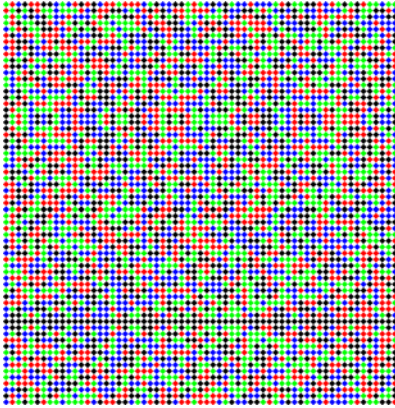


Figure 1. The pseudorandom pattern consists of 65×63 rhombic elements colored in Red, Green, Blue and Black. Grid-point between pattern elements is defined as the pattern feature and then encoded.

The proposed adaptive grid-point detection method can be summarized into the following steps:

- a) Compute the local entropy distribution over the whole image with a given window size.
- b) Decide the cross mask size according to the value in the entropy map, and then calculate the difference of the cross section intensity to get preliminary grid-point.
- c) Calculate the symmetry characteristic around the grid-point candidates and then use the weighted correlation coefficient to refine the grid-point position to sub-pixel accuracy.

A. Construction of Local Entropy Map

The idea behind local entropy method is to divide the target image into various regions and then to analyze each region separately as information source. In Shannon's information theory [13], entropy is a measure of the uncertainty associated with a random variable. The entropy of a random variable is defined in terms of its probability distribution and can be shown to be a good measure of

randomness or uncertainty. In image processing, local entropy can be derived from the ordering of the pixels intensity distribution and a measure of information containing in an image. Local entropy which reflecting the chaos of an image could be used to illustrate the pattern deformation type – compression, stretch or original shape. For two image regions which have the same size, the compressed one contains more pattern elements than the stretched one. In the sense of image entropy, compressed image regions contain more pattern elements and produce a higher entropy value accordingly. The entropy of an image with size $M \times N$ can be defined as:

$$E = - \sum_{i=1}^M \sum_{j=1}^N p_{ij} \log_2 p_{ij}, \quad (1)$$

$$p_{ij} = \frac{I(i, j)}{\sum_{i=1}^M \sum_{j=1}^N I(i, j)}$$

where I indicates the intensity at image position (i, j) , p_{ij} is the distribution probability of image intensity at (i, j) , E describes the entropy values within the $M \times N$ image region. With reference to E in different image regions, a cross mask with various sizes can be implemented for the grid-point preliminary detection.

B. Adaptive Cross Mask for Grid-Point Filtering

At grid-point position, the difference of cross section intensity could reach to a relatively high score. A cross shape mask is employed to measure the differences between the colored elements and the white elements along the cross arm. Normally, the cross mask size can be decided in advance based on the rhombic size of the pattern and the resolution of the camera. However, when the rhombic patterns are projected to an object with high curvature surface, the size-fixed cross mask may lead to an awful result. For regions being compressed, the routine size of cross mask may cross over more than two rhombic elements, on the other hands. For stretched regions, intensity from grid-point to pattern elements varies comparatively slowly, i.e. intensity difference between pixels is relative small. The routine cross mask is not able to contain enough information to distinguish the potential grid-point position. Therefore an adaptive cross mask is adopted here as shown in Fig. 2.

To determine the size of cross mask for various image regions, the local entropy value from last section is introduced to this step. Local entropy value at a pixel could not determine neither if it is a grid-point nor the deformation type. As a result, the summation value of local entropy in a square window whose size is decided by the local entropy window size and centered at every pixel is calculated firstly. By the summation value, the cross mask size could be controlled in inverse proportion robustly. Then a cross mask is employed on every pixel to calculate the intensity along x - and y -directions in the image.

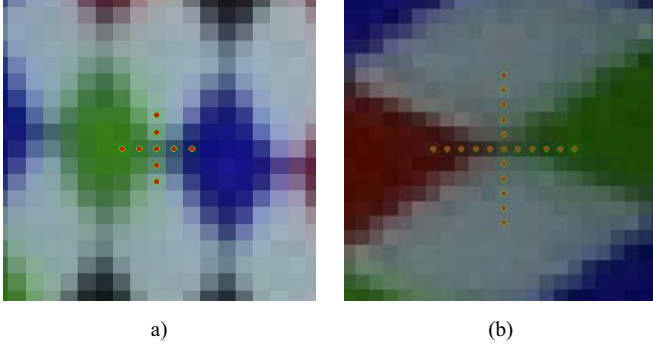


Figure 2. Different cross mask for various deformed images. (a) Smaller cross mask size for the compressed regions; (b) Bigger cross mask size are used for the stretched regions.

Once the size of the cross mask at $I(i, j)$ has been decided, the difference of the intensity d_p along cross section can be expressed as:

$$d_p = \left| \sum_{\alpha=-L_p}^{L_p} I(i+\alpha, j) - \sum_{\beta=-L_p}^{L_p} I(i, j+\beta) \right| \quad (2)$$

where L_p indicates the length of the cross arm centered at image point P . When the value of d_p is larger than a pre-specified threshold, the current position P is regarded as a grid-point candidate.

C. Grid-Point Extraction with Sub-Pixel Accuracy

From Fig. 1, it can be observed that any grid-point on the pattern generation plane of the projector then has a local circular neighborhood presenting perfect two-fold symmetry, in the sense that the circular window of intensity values overlaps exactly with the 180° rotation of itself in the image domain. Such symmetry is quasi-invariant against perspective distortion, image noise and blurs for the reason that linearity of the edge segment that divides the circular disc into two symmetrical halves can be preserved. If the circular disc is sufficiently small, even nonzero-curvature of the target surface in 3D has little effect to the symmetry, as locally at the location of the grid-point the object surface can be regarded as largely planar. To summarize, the two-fold symmetry of grid-point on the illumination side is largely preserved in the image data. This symmetry is what we exploit in precisely localizing the grid-points in the image.

Define W as the intensities in a circular window centered at grid-point candidate position P , and M the intensities under the window created by rotating W by 180° around P . By the definition of PMCC [14], the Pearson correlation can be expressed as:

$$r_p = \frac{\sum_{i=1}^{N_p} (W_i - \bar{W})(M_i - \bar{M})}{\sqrt{\sum_{i=1}^{N_p} (W_i - \bar{W})^2 \sum_{i=1}^{N_p} (M_i - \bar{M})^2}} \quad (3)$$

where N_p is the size of the window which is derived from the pre-processing step, setting to be equal to the length of the cross mask L_p , \bar{W} and \bar{M} indicate the average of all elements in the window and the rotated window respectively. The grid-point candidate whose correlation coefficient r_p is larger than a threshold would be kept as grid-point candidate for further processing.

Firstly, the whole grid-point candidates are divided into several clouds according to its eight-connectivity, and for each cloud, sub-pixel position mean \bar{C} is calculated. Secondly, a small square region of size $L_c \times L_c$ centered at \bar{C} is applied. The true grid-point is then computed in sub-pixel accuracy as the weighted mean of all grid-points in this square region, with the weight being the value of $r_{\bar{C}}$ at each position \bar{C}_i in the region:

$$grid = \frac{\sum_{i=1}^{L_c \times L_c} r_{\bar{C}_i} (\bar{C}_{i_x}, \bar{C}_{i_y})}{\sum_{i=1}^{L_c \times L_c} r_{\bar{C}_i}} \quad (4)$$

Since quasi-invariant local structure rather than raw image intensity at the grid-point is used, the described method has stronger robustness than intensity or gradient-based methods against image noise, blur, surface texture, curvature, and projective distortion etc., and can produce more accurate grid-point position as well.

III. EXPERIMENTAL RESULTS

The structured light system in our experiments consists of a DLP projector of resolution 1024×768 pixels and a DSLR camera of resolution 1500×1000 pixels, both being off-the-shelf equipments.

The first experiment is conducted on a spherical object as shown in Fig. 3(a), and its local entropy graph is showed in Fig. 3(b). The local entropy window is set to be the value of 7×7 pixels. From the result, we can see that the entropy value changes accordingly to the distribution of rhombic elements. For example, in the left image part, pattern elements are compressed. As a result, higher entropy values are produced.

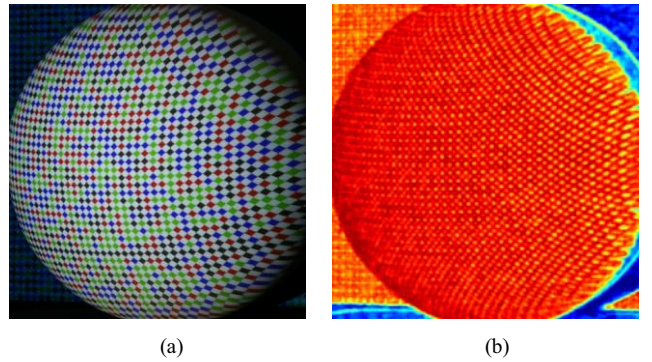


Figure 3. (a) A sphere with color pattern projection. (b) Local entropy map generated with the window size of 7×7 pixels.

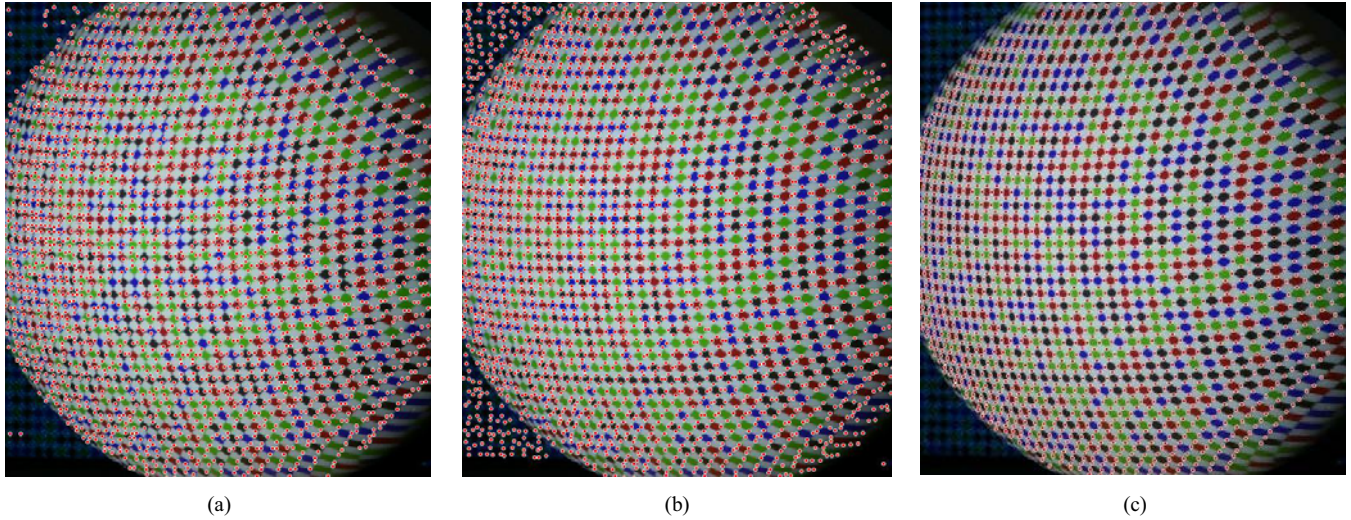


Figure 4. Grid-points detection results on the image of a sphere with color rhombic pattern projection by three methods: (a) Harris corner detector; (b) SUSAN corner detector; (c) the proposed method.

For comparison, Harris and SUSAN detectors are used for the grid-point detection as shown in Fig. 4. From the result, we can see that these two operators failed to discover the right grid-points not to say their localization accuracy. Fig. 5 shows the comparison between the proposed adaptive

grid-point detector and the original detector in [12]. In this application, according to the resolution of both projector and camera, the cross mask size is arranged from 1 to 8 pixels. From the result, we can see that by the proposed algorithm most grid-points at compressed and stretched regions can be detected correctly with higher accuracy.

Fig. 6 shows the experiment on a real human face. From the result, we can see that most grid-points can be extracted correctly even under the influence of surface color and shape variation.

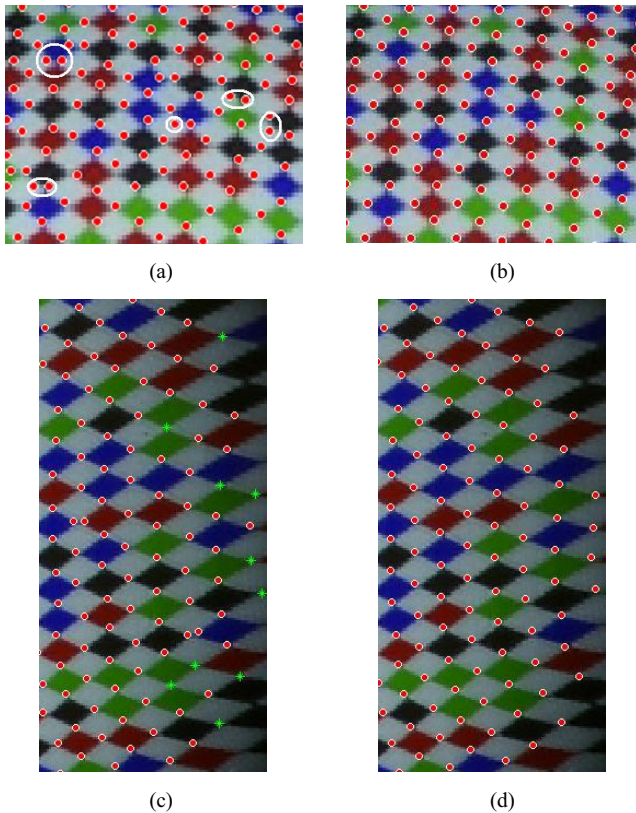


Figure 5. Comparison of grid-point detection results between previous work and the proposed method. (a), (c) Result by previous method on the compressed and stretched region. (b), (d) Result by the proposed detector on the compressed and stretched region. The incorrect and missed grid-points are marked in (a) and (c) by circles and stars.



Figure 6. Grid-point detection result on a real human face with pattern illumination.

IV. CONCLUSION AND FUTURE WORK

In this article, we have presented an adaptive grid-point detector for the feature detection task in a rhombic pseudorandom structured light pattern. In the algorithm, a local entropy map is firstly constructed to evaluate the distribution of the projected pattern elements. With

reference to this entropy map, the size of the cross mask can be adjusted adaptively. With considering the local symmetry property around the grid-point, a correlation procedure is introduced for the grid-point extraction in sub-pixel accuracy. The detector uses structure, not raw image intensities of the image, and is thus more robust against albedo variation, uneven illumination, and image noise. In the experiment, by comparison, the proposed detector can outperform previous operators in a large scale even big distortion exists. Promising results are also obtained with the experiment on a real human face.

The future work can address the optimization of the algorithm, and put the system into real-time and practice.

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