GRID POINT EXTRACTION EXPLOITING POINT SYMMETRY IN A PSEUDO-RANDOM COLOR PATTERN

Zhan Song [1]*Ronald Chung*
Department of Mechanical & Automation Engineering
The Chinese University of Hong Kong
Hong Kong, China

ABSTRACT

Structured light system together with the use of pseudo-randomly coded pattern in the projection is an effective solution for 3D reconstruction; it requires only a single image capture to operate. In this article, a 2D pseudo-random pattern consisting of rhombic color elements is proposed, and the grid-points between the pattern elements as opposed to the centroids of the elements are adopted as the feature points. Two possible types of grid-point are described, and a scheme that allows each grid-point to be uniquely distinguished by a codeword and the grid-point type it belongs to is described. We also present a grid-point detector that is based upon a certain symmetry the grid-points of rhombic pattern own – the 2-fold rotation symmetry – which is largely preserved under pattern projection, reflection, perspective distortion, image noise, and image blur.

Index Terms – Grid point detection, 3D reconstruction, pseudo-random pattern, structured light system.

1. INTRODUCTION

Structured light based system together with the use of pseudo-randomly coded pattern in the projection is an important means of 3D recovery. Requiring only a single image capture to operate, it is particularly attractive to dynamic applications [1]. The performance of the system is however limited by how accurately the feature points can be extracted from the image data. Traditional methods use the centroids of pattern elements as the feature points. The extraction of such feature points requires accurate segmentation of the image into pattern elements in the first place, so that the centroids of each of these elements can be individually determined. The demand of segmentation however sets tight dependence between the individual centroid results. In checkerboard-like pattern for instance, every foreground pattern element shares boundary with four background elements, and vice versa. As a result, the segmentation result of a foreground (background) pattern element directly affects the segmentation results of the four neighboring background (foreground) elements. The determination of the various centroid points are thus heavily dependent on one another, and error in segmenting a foreground or background element will propagate and have effect on other centroids. This compromises the accuracy in localizing the points. Segmentation also operates directly on intensity values, which makes it particularly sensitive to albedo variation of the object surface, uneven illumination, image noise, image blur, and the influence will naturally be brought to the centroid results as well.

In this work the use of a 2D pseudo-random pattern comprising rhombic color elements, together with a particular choice of features points, is proposed. The colors of the pattern elements are designed according to a pseudo-random matrix, and the intersection points of every two neighboring pattern elements, which we refer to as the *grid-points*, are the feature points where 3D sampling is to take place. We show that grid-points of a checkerboard-like pattern can be divided into two types. We describe a scheme that allows every grid-point to be uniquely distinguished by its grid-point type and a codeword that consists of the colors of some pattern elements in its immediate neighborhood. As for the extraction of such feature points, unlike the centroid features, they can be determined independently of one another. We propose a grid-point detector that exploits a certain symmetry that the grid-points of rhombic pattern own – the two-fold rotation symmetry – for boosting the localization precision. Such a symmetry in the pattern projection is largely preserved in the image data, and quasi-invariant against perspective distortion, image noise, and image blur. The detection can reach sub-pixel accuracy.

2. PREVIOUS WORK

Feature extraction is 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 Harris [2], LoG [3], and SUSAN [4]

[1] Corresponding author

operators. While the use of direct image intensity can minimize pre-processing effort, it also makes the operators more sensitive to image noise, and degrades the accuracy in localizing the true feature positions in the image.

As for the localization of grid-points in image, it has been studied in the processing of calibration patterns like checkerboards [5-9].

Under the influence of the projector-camera system's optical ability (MTF, Depth of Field, sensor noise etc.) and of the imaged object's surface property (texture, reflectance etc.), adjacent rhombic elements in the pattern are often disconnected in the image. Traditional corner detectors such as Harris or SUSAN operator have difficulty tackling the issue. Since the object surface under operation can be a generic curved surface, grid-point extractors proposed for pattern-based calibration, which often assume planarity of the pattern, are not applicable either.

3. SYMMETRY-BASED GRID-POINT DETECTOR

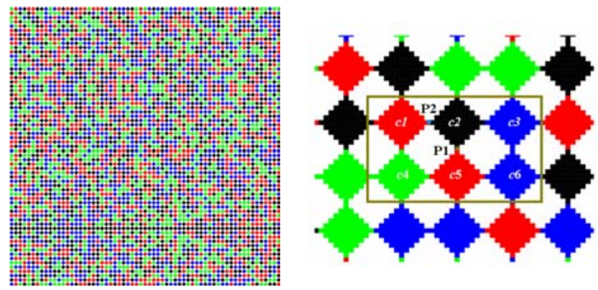
3.1. Grid-point Coding

The principle of pseudo-random array [10] can be used to design uniquely coded color pattern. In our system, a color pattern with rhombic elements, as shown in Fig. 1(a), is used. It is generated from a pseudo-random array of size 65×63. 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 pseudo-random array is constructed over $GF(4)$, we use 4 different colors (Red, Green, Blue, and blacK) for the foreground in the pattern, and the white color for the background.

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. As illustrated by Fig. 1(b), the grid-points can be classified into two types: P_1 and P_2, according to whether on the immediate left and right there are background or foreground elements. Grid-point of P_1 type can be encoded by the color profile of the 2×3 rhombic elements surrounding it, in the order of $c1$-$c2$-$c3$-$c4$-$c5$-$c6$ as shown in Fig. 1. As for grid-point of P_2 type, we search for the grid-point of P_1 type nearest it in the bottom right direction, and the codeword of P_1 will be adopted as the codeword of this P_2 grid-point. The type (P_1 or P_2) and codeword together uniquely distinguish a grid-point.

For convenience the projector-camera is configured so that the baseline between the camera and projector is almost parallel with the x- image coordinate axis of the projector's pattern generation plane and of the camera's image plane. That allows the descriptions "left" and "right" on the projector's illumination panel to be quasi-preserved in the camera's image plane. In our system, such "left" and "right" descriptions are used not for identifying pixel-level features but features as large as the rhombic pattern elements in the immediate vicinity of a grid-point, and thus small configuration errors do not matter.

With the above, the type (P_1 or P_2) and codeword of a grid-point are preserved in the image data, and they together uniquely distinguish every grid-point and allow easy correspondence of the grid-points between the projector side and the camera side.



(a) (b)

Figure 1. Our 2D pseudo-random color pattern comprising rhombic elements: (a) its 65×63 elements colored in Red, Green, Blue, or blacK; (b) the codeword of any grid-point which can be of either P_1 type or P_2 type.

3.2. Grid-point Detector

Suppose that the color image is looked upon as a monochrome image, with all the colored elements viewed as if owning the foreground intensity (label "1"), and the white elements the background intensity (label "0"). The image then becomes a checkerboard-like pattern with alternating foreground and background elements. From Fig. 1(b), 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 a symmetry is quasi-invariant against perspective distortion, image noise, and image blur for the reason that linearity of the edge segment that divides the circular disc into two symmetrical halves is preserved under the processes. If the circular disc is sufficiently small, even nonzero-curvature of the illuminated 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.

3.2.1. Pre-processing with a cross template

A grid-point in rhombic pattern is characterized by the presence of neighboring regions of drastically different intensities in the vertical and horizontal directions. We use this property to hypothesize candidate positions of grid-points in the image. A mask in the shape of a cross is used for convolution with the image $I(x, y)$. The absolute difference d as expressed below is defined as the response value of the mask at any image position (x, y):

$$d = \left| \sum_{i=-\varepsilon}^{\varepsilon} I(x+i, y) - \sum_{j=-\varepsilon}^{\varepsilon} I(x, y+j) \right| \tag{1}$$

where ε indicates the size of the mask. The image positions with high response values d are kept as candidates of grid-points. Such a template-based scheme is simple and efficient, but is used here only as a preliminary step to hypothesize possible grid-point positions.

3.2.2. Measure of two-fold symmetry

Strong two-fold symmetry is displayed by the circular neighborhood of a grid-point. To measure the strength of the two-fold symmetry, we used the coefficient of correlation between the circular window and the 180° rotation of it. Since the image intensity is usually normally distributed, *Pearson's Product-Moment Correlation coefficient* (*PMCC*) is adopted [11] in our method.

Suppose M_C is a circular mask centered at any candidate image position C, and M_C' the mask created by rotating M_C by 180˚ around C. By the definition of PMCC, we can write the correlation coefficient ρ_C as:

$$\rho_C = \frac{n\sum_{i=1}^{n} M_{Ci}M_{Ci}' - \sum_{i=1}^{n} M_{Ci}\sum_{i=1}^{n} M_{Ci}'}{\sqrt{n\sum_{i=1}^{n} M_{Ci}^2 - (\sum_{i=1}^{n} M_{Ci})^2}\sqrt{n\sum_{i=1}^{n} M_{Ci}'^2 - (\sum_{i=1}^{n} M_{Ci}')^2}} \tag{2}$$

where i here refers to individual element of the mask M_C or M_C', n is the size of the masks, and M_{Ci}, M_{Ci}' indicate image intensities of the ith elements of the M_C and M_C' masks respectively.

The operator is only applied to image positions C that pass the pre-processing step. The response values at these points are calculated, and a map named the response image ρ can be generated from the values. A threshold t is used on the ρ-map to extract image positions where the ρ value is a sufficiently strong local maximum. A small region of size say 3×3 pixels is then selected around every such position. The final grid position (x_g, y_g) at the vicinity of every such point C is then computed in sub-pixel accuracy as the weighted average of all positions in this 3×3 region, with the weight being the ρ value ρ_i of each ith position (x_{Ci}, y_{Ci}) in the region:

$$(x_g, y_g) = \sum_{i=1}^{9} \rho_i.(x_{Ci}, y_{Ci}) \Big/ \sum_{i=1}^{9} \rho_i \tag{3}$$

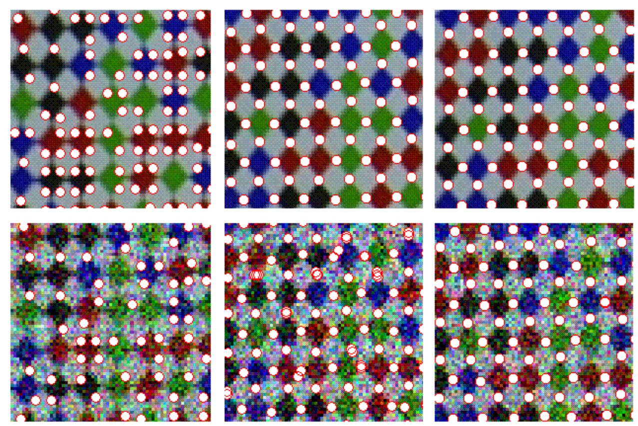
Since structure rather than raw image intensity at the grid-point is used, the described method has higher robustness than intensity-based methods against image noise, blur, surface texture, curvature, and projective distortions.

4. EXPERIMENTAL RESULTS

The structured light system we used in our experiments consisted of a DLP projector of resolution 1024×768 and a camera of resolution 1500×1000 pixels, both being off-the-shelf equipments. The system was first calibrated using the method described in [12] that made use of an LCD panel as the external reference object.

4.1. Counter-noise Ability Check under Extra Noise

To evaluate the robustness of the proposed grid-point detector, zero-mean Gaussian noise with $\sigma=0.03$ was added to the image as shown in Fig. 2. From the results we can see that, even without extra noise, the Harris detector had trouble extracting all the grid-points correctly. With the noise added, the result by the template operator (presented in Section 3.2.1) degraded and the localization accuracy became worse. Using the proposed detector, all the grid-points could be extracted and their localization was only slightly affected by the extra noise, as shown in Fig. 2(c).

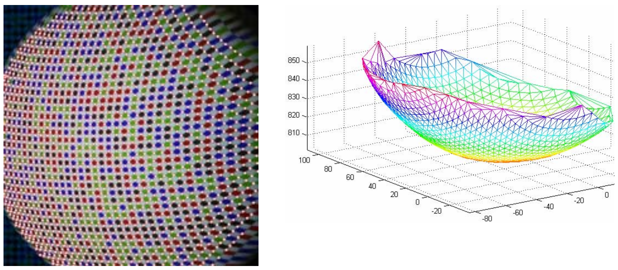


(a) (b) (c)

Figure 2. Grid-point detection results of three operators: (a) from Harris corner detector; (b) result by only using the cross template-based operator; (c) from the proposed corner detector.

4.2. Accuracy Evaluation

The pattern was projected onto a planar board with a distance of about 850mm. The planarity of a central small region about 60×60 mm^2 was measured. About 300 feature points were detected and reconstructed. To measure the planarity, a plane was fitted in the least square error sense to the reconstructed 3D points. An absolute mean error of 0.093mm, with a standard deviation of only 0.072mm, was obtained. By using only the cross template-based operator, an absolute mean error of 0.215mm, with a standard deviation of 0.151mm was obtained. The accuracy was improved substantially by the proposed grid-point detector. A spherical object as shown in Fig. 3 was also reconstructed. The cross template-based operator failed in grid-point detection. Using the proposed grid-point detector the result was much more reasonable. To measure the reconstruction errors under the proposed detector, a sphere was fitted in the least square error sense to the reconstructed 3D points. The absolute mean fitting residue was 0.182 mm, with a standard deviation of only 0.067 mm.

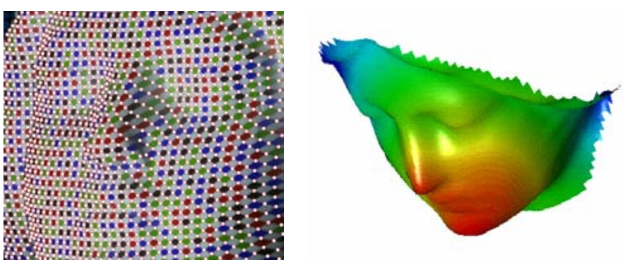


(a) (b)

Figure 3. Spherical reconstruction: (a) grid-point detection result; (b) reconstructed sphere.

4.3. Reconstruction of a Bust Model

A bust was also reconstructed as shown in Fig. 4. Most of the grid-points can be detected correctly. Though ground truth of this surface was not available for evaluating in precise terms the reconstruction quality, visual check showed that the reconstruction was of promising quality.



(a) (b)

Figure. 4. Reconstruction of a bust: (a) grid-point detection result; (b) reconstructed surface.

5. CONCLUSION AND FUTURE WORK

A 2D pseudo-random pattern comprising rhombic color elements is proposed that allows structured light system to achieve 3D reconstruction with a single image-capture. The grid-points between adjacent pattern elements are defined as the feature points in the system. A scheme that allows each grid-point to be uniquely distinguished by a type description and a codeword is designed, and a detector for the feature points is proposed. Exploiting a two-fold symmetry of the grid-points, the detector can extract the feature points in sub-pixel accuracy robustly and independently of one another of them. The detector uses structure, not raw intensities of the image, and is thus also more robust against albedo variation, uneven illumination, and image noise than centroid detector and other intensity-based methods.

A possible future work is the use of an adaptive size of the circular disc to improve the robustness of the grid-point detector further.

6. ACKNOWLEDGMENT

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