# Reliable Image Matching using Binarized Gradient Features Obtained with Multi-flash Camera

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Abstract: In this paper, we propose an object detection method using features describing information about a concavo-convex shape of an object that are obtained by using a small camera that controls the illumination direction. A feature image containing information about the shape of the object is generated by integrating images obtained by turning on, one by one, light emitting diodes (LEDs) annularly arranged around the camera. Our method can reliably detect a texture-less object by using this feature image in the matching process. Experiments using 200 actual images confirmed that the method achieves a 97.5% recognition success rate and a 4.62 sec processing time.

## 1 INTRODUCTION

Object detection using an image sensor is a useful technique in factory production systems. Most objects handled in a production system are intermediate workpieces having a slightly concavo-convex shape and few surface patterns such as characters or designs. Therefore, a practical object detection method that can be utilized for low-textured objects is desired.

Some object detection methods use edge pixels (Barrow et al., 1977) or distinctive pixels (Hashimoto et al., 2010) in the template image for detecting objects in general. These methods achieve reliable detection by analyzing the distinctiveness of the template image. They are also able to detect objects at high speed by using a small number of pixels in the matching process. For low-textured images, however, their detection performance is low since it is difficult for them to obtain effective pixels for matching.

To address this issue, in recent years keypoint-based matching methods such as SIFT (Lowe, 2004), SURF (Bay et al., 2006), and ORB (Rublee et al., 2011) have been proposed. However, these methods describe features on the basis of gradient distribution in the neighborhood of the key points, so it is difficult for them to describe effective features for matching with low-textured images. Therefore, there is concern that their detection performance will be lowered as well.

Three robust approaches for low-textured images that have been reported are the DOT method (Hinterstoisser et al., 2010) which uses the main gradient direction in local regions, the BOLD method (Tombari et al., 2013) which uses line segments of edge, and an object detection method (Akizuki and Hashimoto, 2013) using pixel pairs that are selected optimally in accordance with the intensity of the edge in the template image. However, if the surface of object is only slightly concavo-convex in shape, it is extremely difficult to obtain shading information about the surface. Since this information is an important clue in image matching, it is difficult for these methods to detect objects with sufficient accuracy.

The purpose of this research is to achieve a method that detects objects reliably even if the surface of the object has few or no patterns, which are important clues in image matching. We believe that if a concavo-convex shape of the object can be captured, it will be possible to detect an object even if its surface has few or no patterns. To achieve our purpose we propose an object detection method using features


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that describe the information about a concavo-convex shape of the object. The features are obtained by using a small camera that can control the illumination direction.

Using a multi-flash camera (MFC) (Raskar et al., 2004) with light emitting diodes (LEDs) annularly arranged around the camera, we obtain images by turning on the LEDs one by one. We consider that with these images, input images and template images are very similar at correct matching positions because they reflect the concavo-convex shape of the object for each illumination direction. Therefore, a reliable object detection method is achieved by using the images obtained with the MFC in the matching process. Moreover, the processing cost for matching can be reduced by integrating these images into a feature image that describes the information about the concavo-convex shape of the object.

Our method can also reliably detect texture-less target objects by using this feature image in the matching process.

In addition to the above mentioned methods, there are other methods (Hinterstoisser et al., 2012; Drost and Ilic, 2012) that use a 3-D sensor to obtain the concavo-convex shape of the object. However, while the sensor is quite a large device, the MFC we use is a compact device and thus is considered to be practical.

In the rest of this paper, section 2 describes the proposed object detection method and its use of the binary gradient features based on gradient information, section 3 presents experimental results to confirm the effectiveness of our method, and section 4 concludes the paper with a summary of key points.

## 2 THE PROPOSED METHOD

### 2.1 Basic Idea

The basic idea of our work is to use images obtained by turning on, one by one, $N$ LEDs (in this research, $N$=8) of the MFC that Rasker et al. proposed (Figure 1).

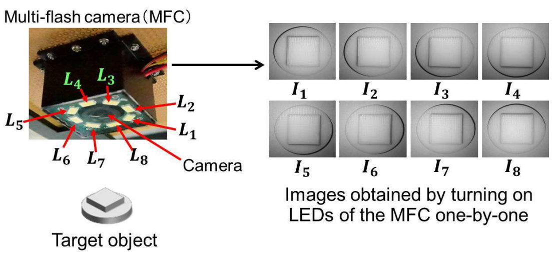


Figure 1: Example images obtained from the MFC.

These images contain details about the concavo-convex shape (e.g., horizontal and vertical edges) that are emphasized in each illumination direction. In other words, they contain pseudo-3-D information. Therefore, an object that has few or no surface patterns can be detected by using these images, for which there is very high similarity between input images and template images at correct matching positions. However, the problem is that the processing cost is increased when the eight images obtained from the MFC are used in the matching process. In this research, we were able to reduce the processing cost in matching by integrating the eight images into a feature image that has the information about the concavo-convex shape of the object. This is because the integration makes it possible to achieve matching based on the pseudo-3-D information with a small amount of calculation.

### 2.2 Binarized Gradient Features based on Gradient Information

This section explains how we integrate the images obtained from the MFC into a feature image. Figure 2 shows the process for extracting binarized gradient features.

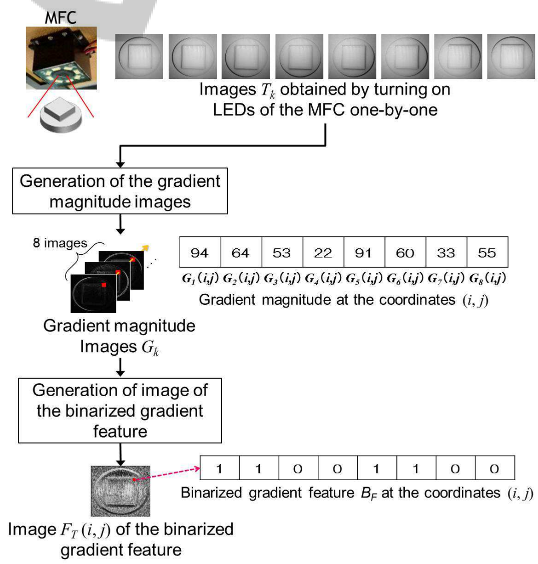


Figure 2: Method for extracting binarized gradient features.

Images $T_k$ ($k$ = 1,2,...,8) are obtained by turning on the LEDs of the MFC one by one, and images $G_k$ ($k$ = 1,2,...,8) of the gradient magnitude are generated from these images. The feature $B_F$ of each pixel is described as an 8-bit code using a gradient image $G_k$. The method of generating an image of the binarized gradient feature is to compare the gradient magnitudes of eight images at the same pixel. Next, the 8-bit binary code is described by assigning 1 bit for the four highest gradient magnitudes and 0 bits for the four lowest. The image $F_T$ is generated by the binarized feature $B_F$ of all pixels in the image. The processing cost of matching can be reduced by integrating the eight images into a feature image and designing a feature as the binary code.

### 2.3 Image Matching using the Binarized Gradient Features

This subsection explains a matching method we propose that uses the above mentioned binarized gradient features. Figure 3 shows a schematic diagram of the proposed algorithm.

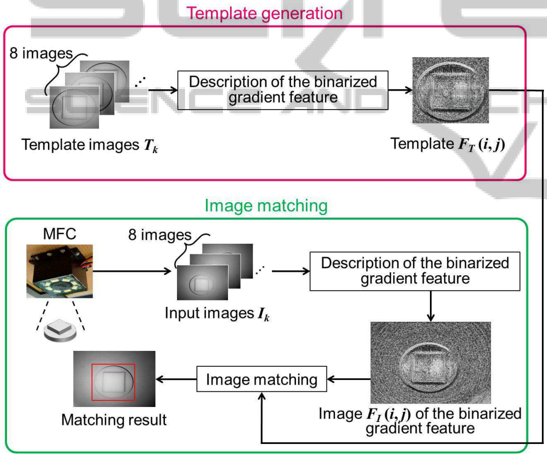


Figure 3: Schematic diagram of the proposed algorithm.

The proposed algorithm consists of template generation and image matching steps.

In template generation, the binarized gradient features are generated by the above described method, i.e., using template images obtained by turning on the LEDs of the MFC one by one. The image of the generated binarized gradient features is the template.

In the image matching process, the image $F_I(i,j)$ of the binarized gradient features is generated in the same way as the template. Next, the template scans the input image in the same way as in conventional template matching, and the position of the maximum similarity in the input image is detected as the final output. The high-speed matching is achieved by using the Hamming distance between the input image features and the template in the similarity calculation.

In this way, the proposed method is able to detect a texture-less object by using the binary features that reflect the concavo-convex shape of the object.

## 3 EXPERIMENTS AND DISCUSSION

### 3.1 Performance Comparison of Proposed Method and Other Methods

This section explains the results we obtained in comparing the performance of our method with that of other methods. We used the following four methods as comparative methods.

(1) ZNCC: The Zero-mean Normalized Cross-Correlation method, which uses all pixels.

(2) Chamfer Matching (Barrow et al., 1977): A method in which edge pixels in the template image are used.

(3) SURF (Bay et al., 2006): A method in which the SIFT keypoints are used.

(4) OCPTM (Akizuki and Hashimoto, 2013): A method using pixel pairs that are selected optimally in accordance with the intensity of the edge in the template image.

We used 50 images taken of four objects (Figure 4) whose surfaces have different concavo-convex shapes in the experiment.

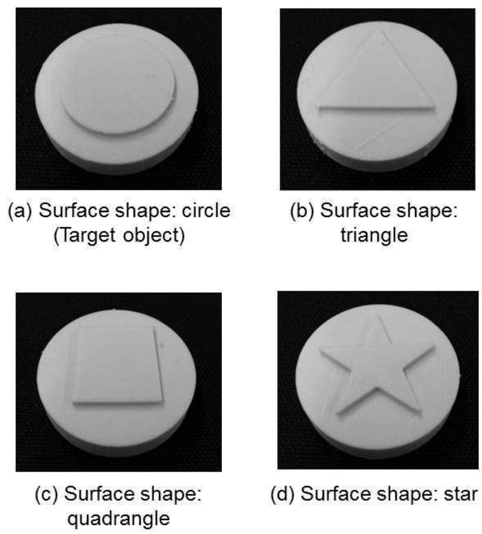


Figure 4: The four types of objects used in the experiment.

Figure 5 shows example feature images generated by the proposed method. While it is difficult to distinguish the objects in the grayscale images, it is easy to distinguish those in the feature images.

Table 1 shows recognition success rate $P_r$[%] and processing time for matching $T$[sec] of each method.

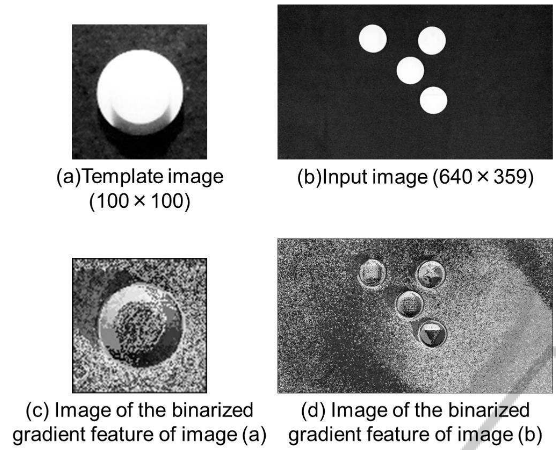


Figure 5: Image of the binarized gradient features generated by the proposed method.

The recognition success rate is defined by the value $P_r$ (the number of successfully matched images within accuracy of $\pm 2$ pixels) / the total number of images $\times$ 100. It should be noted that the comparative methods used images taken under environment light conditions.

Table 1: Recognition success rate and processing time for each method.

| Method | $M$ [pixels] | $P_r$ [%] | $T$ [sec] |
|---|---|---|---|
| (1) ZNCC | 10,000 | 22 | 2.13 |
| (2) Chamfer Matching | 230 | 18 | 0.07 |
| (3) SURF | 9 [points] | 0 | 0.18 |
| (4) OCPTM | 500 | 20 | 0.21 |
| (5) Proposed method | 10,000 | 94 | 4.62 |

(CPU: Intel ®CORE ™i5-2.50GHz, RAM: 4GB)

The proposed method achieved a 94% recognition success rate, considerably higher than the rates the comparative methods achieved. The comparative methods achieved much lower rates because it is difficult for them to distinguish a target object from other objects in grayscale images. On the other hand, the proposed method is able to detect target objects that do not have a surface pattern by using the features that reflect the concavo-convex shape of the object.

### 3.2 Evaluation of recognition Performance for Various Images

To test the general applicability of the proposed method, we performed matching experiments with 50 input images of each of three different types. The input image size was 640 pixels by 480 pixels. Figure 6shows the feature images of each object and their feature images, and Table 2 shows the recognition success rate achieved for each object. With regard to the experiment conditions, the ZNCC method and the proposed method used all pixels in the template image and the OCPTM method used pixels selected by the parameters described in reference (Akizuki and Hashimoto, 2013).

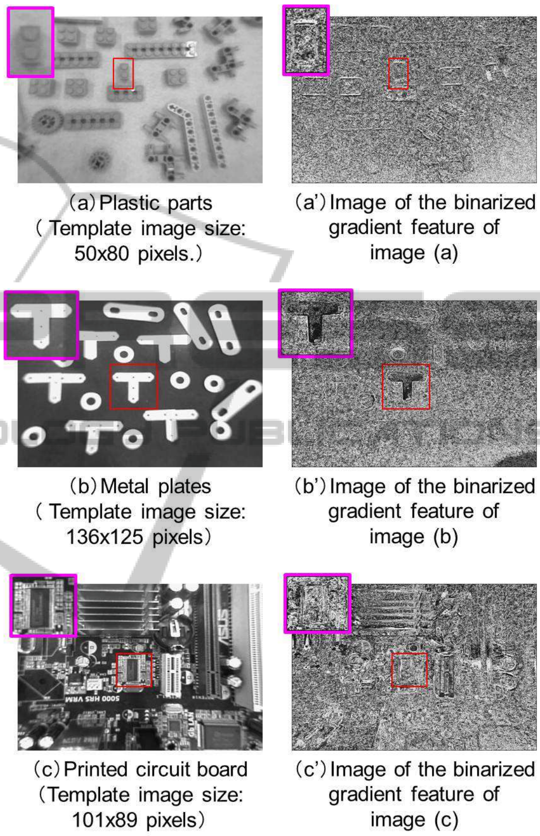


Figure 6: Example input grayscale images [(a), (b), and (c)] and images of binarized gradient features [(a'), (b'), and (c')]. Images enclosed in red frames are template images.

Table 2: Recognition success rate achieved for various objects.

| Method | Plastic parts | Metal plates | Printed board |
|---|---|---|---|
| | $P_r$ [%] | $P_r$ [%] | $P_r$ [%] |
| ZNCC | 58 | 58 | 100 |
| OCPTM | 84 | 98 | 100 |
| Proposed method | 100 | 98 | 98 |

The proposed method achieved a high (more than 98%) recognition success rate for all objects. On average this was 5% higher than that of the previous OCPTM method. These results confirm the proposed method has high general applicability.

### 3.3 Similarity Map Analysis

We confirmed the effectiveness of the binarized gradient features by analyzing the similarity map obtained for the proposed method. The experimental images used were images of the printed circuit board and plastic parts shown in Figure 6. The comparison method used was the OCPTM method. Figure 7 shows the similarity maps obtained for the proposed method and the OCPTM method.

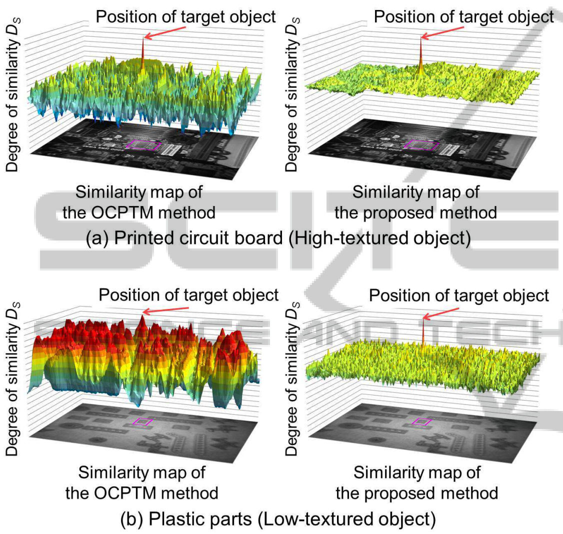


Figure 7: Similarity maps obtained for the proposed method and the OCPTM method.

In a high-textured object (the printed circuit board), the similarity maps obtained by the two methods showed a sharp peak at the position of the target object. However, in low-textured objects (the plastic parts), the similarity map of the OCPTM method showed a high degree of similarity in positions other than the position of target object, while the score map of the proposed method showed a high degree of similarity only in the position of target object. These results confirmed the effectiveness of the binarized gradient features.

## 4 CONCLUSION

We have proposed binarized gradient features that reflect the concavo-convex shape of an object and an object detection method using these features. By using the features in the matching process, we confirmed that our method is able to achieve reliable object detection even if a target object is low-textured. Experiments using 200 actual images confirmed that our method achieves a 97.5% recognition success rate and a 4.62 sec processing time. In future work, we will attempt to even further speed up the processing time.

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