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Image-based coin recognition using rotation-invariant region binary patterns based on gradient magnitudes ☆

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ABSTRACT

Most features of image-based coin recognition have been based on histogram information to achieve rotation-invariant property. However, discrimination of the features based on histogram information can be reduced by ignoring local spatial structure. In this paper, we propose a novel feature of image-based coin recognition that exploits a spatial structure. In order to consider the structure of a coin, rotation-and-flipping-robust region binary patterns (RFR) is adopted. The proposed method computes gradient magnitudes in a coin image, and extracts RFR using local difference magnitude transform to increase the accuracy of coin recognition. Comparative experiments with a number of state-of-the-art methods have been performed on the MUSCLE CIS-Benchmark Preview data set. The experimental results showed that the proposed method outperformed the state of the art methods in terms of recognition accuracy, smaller feature dimension, and shorter feature extraction time.

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1. Introduction

Coin recognition has been widely used in real life such as in vending machines, banks, and supermarkets. It is also very useful when classifying a huge amount of collected coins from charity organizations and ancient relics. A charity organization, 'Licht ins Dunkel' collected 300 tons of coins during two years from Austrian citizens who were asked to donate any spare coins they might have at home [1]. Moreover, museums have increased the demand on automatic systems to classify historical coins [2]. Thanks to the increased demand on automatic systems, coin recognition has been steadily improving to enhance classification performances.

Coin recognition systems began with electromechanical devices, which measured weight, radius, thickness, permeability and conductivity of coins [1]. However, these systems could not distinguish fake coins, which have similar properties of originals from real coins [3]. Several methods [4–6] detected coins from images using detection algorithms (Herris-Hessian or Otsu's Algorithm), and classify coins using their radiuses. Al-Zoubi [9] measured sizes and metal colors of coins. But, these approaches were very weak against fake coins having the same size and color as those of real coins.

Image-based coin recognition approaches have attracted many researchers as a way to handle the problem mentioned above [1,2,10]. These approaches usually extracted texture features from coin images and recognized them. In particular, edge information had been frequently adopted as features of coin images with Fourier transform. Huber et al. [1] and Van Der Maaten and Postma [2] extracted an edge map and divided it into several regions. Then, edge histograms were computed from the regions, and Fourier transform was applied to handle rotated coin images. However, edge features were not robust enough because they were easily distorted by noises such as abrasion, rust and dust [3]. Arandjelović [7] extracted the printed texts on coins and recognize them. But, this method was not suitable for coins having only symbols or pictures. Fukumi et al. [8] divided coins into several regions and extracted features. They adopted a neural network to classify coins.

Gabor filters were frequently adopted to recognize coins. Since Gabor filters generated many convolved images according to their phases and orientations, they used more information to extract features of coin images than edge approaches [1,2]. Usually, mean and standard deviation of Gabor coefficients were used as features from the convolved images. Bremananth et al. [11] and Shen et al. [3] generated convolved coin images using Gabor kernels, and they divided them into several regions. Then, mean and standard deviation of each region were computed and concatenated as 1-D feature vector. Additionally, Shen et al. [3] used circular shift technique to achieve robustness against rotation. Although the approaches using Gabor filters acquired high performance for coin

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recognition, the computational complexity due to convolution was high.

Recently, several approaches used local textures such as local binary pattern (LBP) for image-based coin recognition [3,12–14]. Since LBP features were extracted by comparing a center pixel and its neighbors in an image patch [12], the extraction time was much faster than that of Gabor filter approaches. Also, there were several rotation-invariant LBP approaches, which grouped binary patterns [15–17] or used Fourier transformation [18]. Most methods using LBP for image-based coin recognition [3,10,14] divided a coin image into several rings and extracted LBPs. Then, LBP histograms were computed from each ring by counting LBPs according to their pattern types, and they were concatenated as a final descriptor. However, the methods using LBP approaches generated a large dimensional feature since the size of histogram was related with the number of the pattern types.

In this paper, we propose a new coin feature based on the spatial structure of coin images by employing a rotation and flipping robust region binary patterns (RFR) [19]. Instead of luminance of RFR [19], we use gradient magnitudes in coin images to extract RBP because it is a more effective way to represent coin images [14]. Our gradient magnitude approach is different from the edge feature approaches [1,2]. Our approach is more robust than edge approaches from coin noises (abrasion, rust, and dust). Also, local difference magnitude transform is adopted [20] to extract intra RBPs. The proposed feature is defined as RFR-gradient magnitudes (RFR-GM). The main contributions of the proposed coin recognition method are summarized as the following:

1. *High discriminating capability*: Since the proposed features exploit the spatial structure (e.g., RFR), it achieves better discrimination for coin recognition than previous methods using histogram approaches do.
2. *Compact feature size*: The proposed features are extracted from rings in a coin image and stored as index numbers. Therefore, the size of feature dimensions is very small.
3. *Fast feature extraction*: Since the proposed feature is extracted from a coin image by comparing the means of sub-region's texture features, operations for feature extraction are very simple compared to those of Gabor or LBP histogram.

Our proposed method was evaluated using a public coin recognition dataset, MUSCLE CIS Benchmark Preview [22]. The proposed method outperformed the state-of-the-art methods. Moreover, our proposed feature consisted of a very small feature dimension, and required only a short amount of time for feature extraction. In addition, our proposed feature had high robustness against rotation, and it showed much better performance than previous rotation-invariant features in the experiment section did.

The rest of this paper is organized as follows: Section 2 briefly reviews RFR, and Section 3 introduces the proposed coin recognition method using modified RFR. Section 4 outlines the experimental results compared with the previous methods. Finally, the conclusions are drawn in Section 5.

2. Review of the rotation and flipping robust region binary pattern

Rotation and flipping robust region binary pattern (RFR) has been proposed to detect rotated or flipped copy videos [19]. It uses region binary pattern template, which consists of several rings, and each ring is divided into several sub-regions. With the template, mean luminances of the sub-regions are computed and used to generate region binary pattern (RBP) features (shortly RBP). There are two kinds of RBP: intra RBP and inter RBP. Intra RBP is extracted by comparing mean luminance of sub-regions in a ring, and inter RBP is extracted from sub-regions between two adjacent rings. Each RBP type represents left–right and top-down spatial structure information.

Basically, a RBP forms a circular binary pattern since it is extracted from rings, and several RBPs could be equal to each other from rotation or flipping transformations. Fig. 1 shows examples of RFR and RBP when the number of sub-regions is 6. The RFRs in the left column become the left RBPs by rotation or flipping transformations. Suppose that there are two binary patterns, '010110', and '110100'. If '010110' is shifted in a circular way, the changed pattern can be '001011'. Also, if '110100' is flipped, the changed pattern also can be '001011'. Therefore, these two patterns are regarded to be the same after rotation or flipping transformations. Namely, RBP could have the robustness against rotation and flipping transformations by converting to RFR.

Fig. 2 shows all possible RFRs from 6 sub-regions [19]. The decimal numbers in RFRs denote their indexes, which are used to convert RBP to RFR. In order to assign the index numbers, RFR approach [19] uses an index table (e.g., look-up table), which is defined as **IND** [19]. For example, if a RBP is '010110', then it receives index 7 by **IND**(010110) [19]. If a RBP is '110100', then it also receives index 7 by **IND**(110100). Therefore, these two RBPs ('010110' and '110100') are equal to each other by the index table **IND**. For more details about RFR, please refer [19].

In order to minimize error of distances, RFR computed the minimum Hamming distance between two RFRs [19]. Suppose that x^q and x^r are indexes and they denote q-th and r-th RFR, respectively. Let $\mathbf{B}^q = \{\mathbf{b}_1^q, \mathbf{b}_2^q, \ldots, \mathbf{b}_N^q\}$ and $\mathbf{B}^r = \{\mathbf{b}_1^r, \mathbf{b}_2^r, \ldots, \mathbf{b}_M^r\}$ be RBP sets which are included in q-th and r-th RFR, respectively. Then, their distance is computed as

$$dist_{RFR}(x^q, x^r) = \min_{\mathbf{b}_n^q \in \mathbf{B}^q, \mathbf{b}_m^r \in \mathbf{B}^r} dist_H(\mathbf{b}_n^q, \mathbf{b}_m^r), \tag{1}$$

where $dist_H$ is the Hamming distance. In order to speed up the distance computation time, we employ the distance matrix of **DM** proposed in [19]. $\mathbf{DM}(x^q, x^r)$ is the same result as $dist_{RFR}(x^q, x^r)$ [19].

3. Image-based coin recognition using RFR based on gradient magnitudes

In this section, we present the proposed image-based coin recognition. Fig. 3 shows the overview of the proposed feature extraction using rotation and flipping robust region binary pattern (RFR). We apply RFR [19] to extract the proposed feature of image-based coin recognition. RFR has high discrimination with a spatial structure as well as robustness for rotation. Since a coin image has single color in general and is sensitive to brightness due to abrasion or rust [3], luminance value would not be enough to extract coin features. In this paper, the gradient magnitudes of a coin image are applied to extract RFRs. The gradient magnitudes represent the structure of the coin image because they are computed from boundaries of characters and symbols. In this paper, the differences of mean gradient magnitudes are used for intra RFR while the mean gradient magnitudes are used for inter RFR. This improved RFR for the coin recognition is defined as RFR-GM (RFR-gradient magnitude). The detailed feature extraction is explained in following sub-sections.

3.1. RFR-GM extraction

As shown in Fig. 3, a coin is segmented. We employ 2D Hough transform based segmentation algorithm [22], which is popularly used in many coin recognition [2,3,10]. The segmented coin image is denoted as **I**. The gradient magnitudes **M** can be written as

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