COIN RECOGNITION USING IMAGE ABSTRACTION AND SPIRAL DECOMPOSITION

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ABSTRACT

This paper presents a novel approach for coin image recognition. The approach enables measuring the similarity between full color multi-component coin images and needs no cost intensive image segmentation. A novel procedure, based on strong edges of the coin image, is exploited to derive an abstract image. Spiral decomposition of pixels in the abstract image is then used to extract a set of compact and effective features. The query set and the image database used in the tests are scanned, photographed, or collected from the web. The results are compared with three other well-known approaches within the literature. Experimental results show significant improvement in the Recall ratio using the proposed features.

1. INTRODUCTION

The recent explosion of digital images resulted from advances in imaging technology encompassing scanners and digital cameras. Moreover, the outbreak of Internet gives more people an opportunity to access vast amount of multimedia information at their fingertips. Image retrieval from multimedia databases is still an open problem. Traditional textual methods have been shown to be inefficient and insufficient for searching through visual data. Consequently, image and video content-based indexing and retrieval methods have attracted many new researchers in recent years. There are many papular image retrieval techniques currently being used with different technologies.

More specifically, most current coin recognition systems use one of the (a) statistical or (b) structural approaches. Statistical (or decision theoretic) coin recognition is based on statistical characterization of coin patterns, assuming that the patterns are generated by a probabilistic system. On the other hand, structural (or syntactic) coin recognition is based on structural interrelationship of features extracted from the coin. A wide range of algorithms can be applied for visual-based coin recognition from simple Bayesian classifiers to more complex neural networks. In any case, features extracted to describe the image of the coin play an important role in improving recognition rate of the approach [1, 2, 3, 4].

Thanks to Razi University for funding.

The work of Hirata and Kato, Query by Visual Example (QVE) [5], focuses on the problem of image matching. IBM has adopted a modified version of the approach in its QBIC system [6]. In this approach the query and the target images are resized to 64×64 pixels and measuring the similarity is performed using a block correlation scheme. The approach does not allow indexing and is computationally expensive. Although the method can tolerate small local rotations, it is not rotation invariant and does not allow for large global rotations.

The Dagobert system has been developed for coin recognition and sorting [4]. The system relays on a correlation method based on Canny edge operator. The correlation is calculated on a two dimensional edge density function restricted to the inner part of the coin. Coin image recognition is based on estimating a rotation angle and it is used to align the coin under process to master coins.

The 2-D Fourier transform in polar coordinates is employed for shape description [7]. Its supremacy over 1-D Fourier descriptors, curvature scale space descriptor (MPEG-7 contour-based shape descriptor) and Zernike moments (MPEG-7 region-based descriptor) has been shown in [8]. Polar Fourier descriptor (PFD) is extracted from frequency domain by exploiting two-dimensional Fourier transform on polar raster sampled image. It is able to capture image features in both radial and spiral directions [8]. Moreover, the edge histogram descriptor (EHD) was proposed in the visual part of the MPEG-7 standard [9]. An enhanced and more efficient version of the approach consists of a 150-bin histogram (i.e.; local, semi-global, and global histograms) [10]. A given image is divided into 16 sub-images (4×4) first, local edge histograms are then computed for each sub-image based on the strength of five different edges (vertical, horizontal, 45° diagonal, 135° diagonal, and isotropic).

In this paper we present a novel approach of feature extraction for matching purposes based on spiral decomposition of an abstract image obtained from multi-component images without computationally expensive segmentation. The abstract image is derived from the full color coin image and from the black and white image by similar procedures. Spiral distribution of pixels in the abstract image is then employed as the key concept for feature extraction. The extracted features are scale, translation, and rotation invariant. The major contribution of the paper is in invariance properties.

The details of the proposed approach are discussed in

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the next section. Section 3 exhibits experimental results and evaluation. Section 4 concludes the paper and poses some new directions.

2. SPIRAL DECOMPOSITION OF ABSTRACT IMAGE (SDAI)

The edge map of an image carries the solid structure of the image independent of the color attribute. Its applicability is well known in computer vision, pattern recognition and image retrieval. Edges are also proven to be a fundamental primitive of an image for the preservation of both the semantics and the perceived attributes [11]. Furthermore, in coin image retrieval, it is the most useful feature that can be employed for matching and retrieval purposes [1, 4, 2].

According to the assumption that overall structure of a given coin image can be recognized by its edge map, which contains only the perceptive and vigorous edges, we obtain an abstract image through the strong edges of the coin image and the proposed features are then extracted from the derived abstract image.

2.1. Image Abstraction

An abstract image is obtained for the coin image by the following approach. The full color coin image is initially converted to a gray intensity image I, by eliminating the hue and saturation while retaining the luminance. This step is bypassed for gray scale or black and white coins. The edges are then extracted using the Canny operator [12] with $\sigma = 1$ and Gaussian mask of size = 9 using the following procedure for depicting the most perceived edges.

The values of high and low thresholds for the magnitude of the potential edge points are automatically computed in such a way that only the strong edges remain. This improves the general resemblance of the resulted edge maps of similar coins. In order to depict strong edges, let G be the Gaussian 1-D filter and let g be the derivative of the Gaussian used in the Canny edge operator. Then

$$H(k) = \sum_{i} G(i)g(k+1-i)$$

is the 1-D convolution of the Gaussian and its derivative.

$$X(u,v) = [\sum_{j=1}^{V} I'(u,j)H(v-j)]'$$

$$Y(u,v) = \sum_{i=1}^{U} I(i,v)H(u-i)$$

for $u = 1, 2, 3, \ldots U$ and $v = 1, 2, 3, \ldots V$ that are the vertical and horizontal edge maps, respectively. Here, U is the number of rows and V is the number of columns in the image I. The magnitude of the edge points is then obtained as

$$\Gamma(u,v) = \sqrt{X(u,v)^2 + Y(u,v)^2}.$$

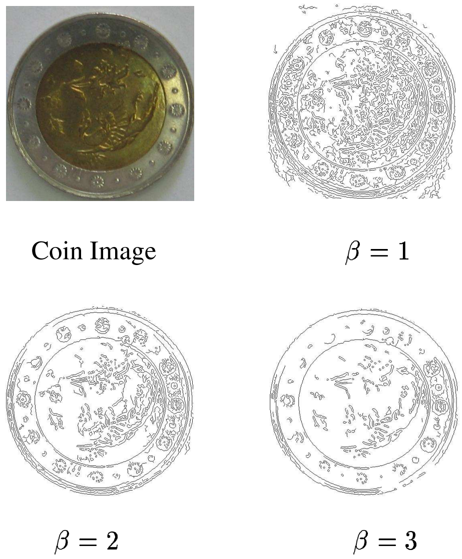

Fig. 1. The effect of β parameter on the Canny edges at one of the coin images

For efficient selection of the high and low thresholds, we then make a 64-bin cumulative histogram of the $\Gamma(u,v)$ values and find the minimum index ι in this cumulative histogram that is grater than $\alpha * M * N$, where α denotes the percentage of non edge points in the image ($\alpha = 0.7$ is an adequate choice for many images). To retain strong edges of the image, $\beta * \iota$ is selected as the high threshold value and $0.4 * \beta * \iota$ is used for the low threshold value in the Canny edge operator. β is a parameter that controls the degree of the strength of the edge points. Higher β's lead to lower number of edge points but more perceptive ones (see Fig. 1). Consequently, the gray image I is converted to edge image P using the Canny edge operator exploiting the above automatic extracted thresholds.

The bounding box of P are then normalized to $J \times J$ pixels, using nearest neighbor interpolation. The proposed normalization of P images ensures the scale and translation invariant properties. The resulting image is called *abstract image* Ω and used for the next feature extraction scheme.

2.2. Spiral Decomposition

Based on the fact that any rotation of a given image, with respect to its center, moves a pixel at (ρ, θ) to a new position at $(\rho, \theta + \tau)$, we define a circle of radius r at the center of the abstract image Ω and also $N-1$ spiral strips around the circle with width r. A typical strip S_i has the boundary concentric circles with radii ir and $(i+1)r$ respectively, for $i = 1, 2, 3 \ldots N-1$. The largest strip has the boundary circles with the radios of $R-r$ and R, where R is the radius of the surrounding circle of image Ω (see Fig. 2).

The number of edge points in the central circle and in each circular strip of Ω are chosen to represent the image. The scale and rotation invariant image features are then

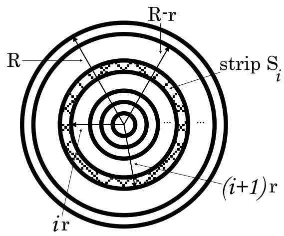

Fig. 2. The central circle and the $N-1$ circular strips used for spiral decomposition

$\{f(k)\}$ where

$$f(k) = \sum_{\rho=(k-1)R/N}^{kR/N} \sum_{\theta=0}^{\theta=2\pi} \Omega(\rho, \theta)$$

for $k = 1, 2, 3 \ldots N$.

The features extracted above are rotation invariant because the edge points in any circular strip S_i remain in the same strip with any rotation. The features are also robust against small translations as the inner edge points remain in the same circular strip with internal translations. The strip width $r = R/N$ is a discretionary variable which can be used for fine-to-coarse selection of the extracted features. Fig. 3 shows an example of Ω image, extracted from a coin image, and its spiral partitions.

The similarity between the model and the query images is measured by the ℓ_1 (Manhattan) distance between the two feature vectors. Experimental results (Section 3) confirm the robustness and efficiency of the method.

3. EXPERIMENTAL RESULTS AND EFFICACY EVALUATION

This section presents experimental results using the new proposed approach in comparison with three other methods known from the literature. We made a collection of different coin images called COIN BANK. Currently, it contains 4000 coin images of various sizes in the model part and 400 images are selected randomly as queries and put in its query part. For the experiments, we used a dataset of 100 coin images with different shapes and sizes ranging from currency coins in several countries, golden and heritage coins. These original coins are rotated using integer pixel shifts by a factor θ ($\theta = 90, 180, 270$ degrees) and added to the query part. This is to more precisely evaluate the rotation invariant property of different methods. Images in the database are either color or gray scale and in few cases in black and white. Approaches' independence to abrasion and dirtiness of coins are also considered to be evaluated. For this, identical coins with different levels of dirtiness, very new, used, and old coins have been added to the database. Furthermore, coins with extra parts (such as small rings attached to coins usually for hanging them) are included.

The COIN BANK was used as the test bed for the following four approaches: the proposed method (SDAI), the QVE approach, as it used in the QBIC system [6], MPEG-7 edge histogram descriptor (EHD) [9, 10], and the polar Fourier descriptor (PFD) approach [8]. All methods were tested using the same database. In the SPAI method (Section 2), we applied $\beta = 3$, $J = 129$ and $N = 90$, resulting in a 90-entry feature vector f. For the EHD method, *desired_num_of_blocks* was set to 1100 and Th_{edge} set to 11 (the default values) for the coin images. A 150-bin histogram was obtained in this approach employing local, semi-global and global histograms. We followed the algorithm given in [8] to obtain a 60-bin feature vector in PFD approach. The quantization stage in the EHD method was dropped to put all methods in a similar footing.

The ℓ_1 distance was used for measuring the similarity between image features of the MPEG-7 edge histogram descriptor (EHD) approach and of the proposed SDAI method. For the EHD method a weighting factor of 5 for global bins, as recommended in [10], was applied. Euclidian distance (ℓ_2) was exploited for measuring the similarity between PFD features [8] whereas global correlation factor was employed for measuring the similarity between images in the QVE method [6].

The queries were depicted from the following sets (each contains 100 images): the original coin images (Q_0), their $90°(Q_{90})$, $180°(Q_{180})$ and the $270°(Q_{270})$ rotated versions. This is to simulate different vertical and horizontal directions when posing a query coin to the retrieval system.

Recall ratio R_n [5] was used for the evaluation of retrieval performance. It shows the ratio to retrieve the original full color coin image in the best n-candidates. That is

$$R_n = \frac{\text{queries retrieved the target image in the top } n \text{ retrievals}}{\text{total number of queries}} * 100$$

The R_n was obtained for each approach using the four different query sets. Fig. 4 exhibits better performance of the proposed SDAI method over the other approaches. For the queries with the same direction as the model images (Q_0 set), the retrieval performance of QVE, PFD and EHD methods decline respectively compared to the SDAI method for all n's. The retrieval performance of PFD method is better than QVE and EHD methods in rotated sets that means it is more robust to rotation than the two others. The EHD and QVE methods show no significant rotation invariance property.

4. CONCLUSION

The approach presented in this paper (SDAI) enables measuring the similarity between full color coin images for the purpose of matching and retrieval. The images are arbitrary and may contain several complex objects in inhomogeneous backgrounds. The approach deals directly with the whole image and needs no cost intensive image segmentation and object extraction. An abstract image is defined based on the strong edges of the coin images and used for feature extraction. Spiral decomposition of the

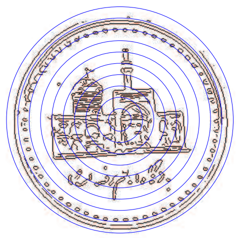

Fig. 3. An example of a coin abstract image Ω and the spiral partitions used for the feature extraction

abstract image is used to extract features that are scale, translation, and rotation invariant. Experimental results, using SDAI approach and the COIN BANK, as the test bed, show significant improvement in the Recall ratio over three other approaches known from the literature.

The decomposition scheme could be refined to improve retrieval performance. We also intend to investigate note (bill paper) recognition using modified versions of the SDAI approach.

5. REFERENCES

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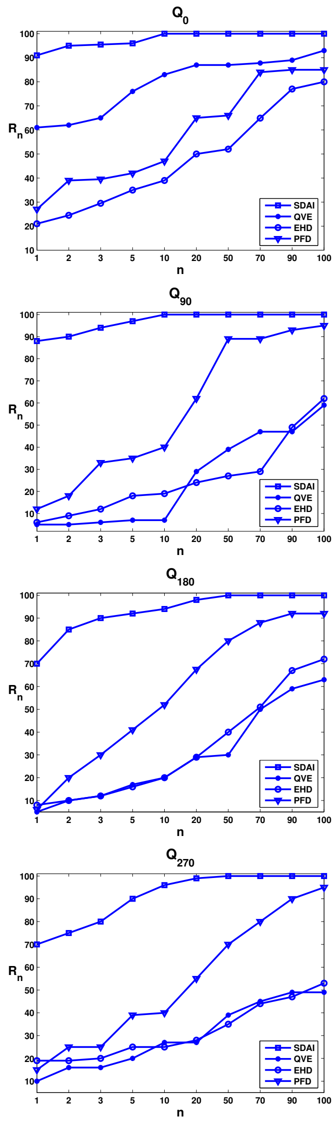

Fig. 4. R_n verses n for sets Q_0, Q_{90}, Q_{180}, and Q_{270} respectively

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