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A Region Growing Based Segmentation for Recognition System Method Implement with Coin based Application

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Abstract

To analyze coin image has to be segmented into two regions once of the coin and the area belonging to the background. We focus on the segmentation task as a preprocessing step for any automated text localization and feature extraction system. Firstly, we present a simple and flexible method for coin segmentation, based on double seed of region growing of coin on Gaussian distributions that allow segmenting various style of coin such as holed coins, triangle coins. Secondly, in the second stage, an active model based segmentation approach extracts precisely the coin from the image with features extraction. Thus, the coin is identified to a monetary class represented by a template coin. The similarity score of two coins is computed from feature constructed by feature point's results with an identification accuracy of 94.4% on 2238 coin images of 120 classes.

Keyword: Coin identification, segmentation, feature extraction, pattern recognition**,** region growing, shadow detection coins. Nevertheless, both of approach is not suitable on coins which likely show no perfect circularity and holed Coins

- **Thresholding base approach**

Basically, Thresholding methods define a specify range of brightness values in the original image and select the pixels within this range as belonging to the foreground, any else it pertain into the background. [3] Developed a coin sorting system call Dagobert. This system is threshold based segment on the assumption that the coins itself are brighter than its background. However, it works well on perfect condition. This approach is no guarantee that the pixels identified by the threshold process are contiguous such as different lighting or image, which is assumed to provide higher responses at coin

INTRODUCTION

Nowadays automatic coin identification systems have been widely used in our daily life. With the development of computer vision, image-based approaches for coin identification and authentication have been investigated notably for the recent decade, and have shown strength over traditional systems based only on physical properties of coins such as diameter, thickness and weight. However, in professional numismatic services that still rely on expensive human investigation, to date; no automatic system has been applied successfully due to its complexity and high requirements. Developing an automatic image-based coin identification system that meets numismatic requirements will not only reduce time and cost for coin experts, but also fill the research gap. This article is organized as follows: Section 2 presents related publications. Section 3 is the overview of our method. Section 4 addresses the first segmentation stage. Section 5 describes the identification stage. Section 6 demonstrates and analyzes the results of the validation work on both segmentation and identification steps. In Section 7, conclusions are drawn.

RELATED WORK

Coin segmentation in the literature

- **Edge-Based Segmentation base approach**

This segmentation method partitions an image based on amplification of intensity changes in an image are assumed to represent object boundaries, and used to identify these objects. [1][2] Applies the Hough transformation segment the luminance. [4][5] applies a range and entropy filter[6] to the pixels than choose the best final segmentation with highest probability is close to a circle with form-factor[7]. this approach works very well with various coin even the coin imperfect such as ancient coin. Thus, it still can easily enlarge extraneous pixels that are not part of the desired region and we can just as easily miss isolated pixels that the region no similarity circularity, such as holed coins, triangle coins.

- **Region base approach**

The main idea of this category is to classify a particular image into a number of regions or classes, thus for each pixel in the image it decided or estimate which class it belongs to [8] applies K-Means Clustering algorithm in gray scale of image to segmentation. Unfortunately, the number of clusters from given image set must be the main problem. Our method falls into this category, but we proposed region growing to classify region

OUR APPROACH

Because of the above problems that we addressed of segmentation coin, we proposed a robust method base on region growing segmentation which is able to segment correctly a various style set of coin images. The only assumption we make is that the color region of coin itself different than background.

- **Region growing method**

The basic concept of region growing, the region is iteratively grown by comparing all unallocated neighbouring pixels to the region. The difference between a pixel's intensity value and the regions mean or initial seed value is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the region. This process stops when the intensity difference between region and new pixel becomes larger than a certain threshold. From the idea of region growing, it seems to be difficult to define the certain value of threshold for all coins given the variety unconditional by different luminance and initial seed points.

- **Image represents**

The first step of our approach is to make clearly between background and coin region, we considered then that the likeliness image of coin can be given follow by Gaussian distribution in RGB space. We first need to rough thresholding image in order to know an initial location and colour of coin information. Connected regions are then located and labelled. These regions can easily enlarge extraneous pixels and region effective from background. We then consider compute the connected region and represent as bounding box. In order to ensure obtain the colour information of coin we resize vertical and horizontal of bounding box with this equation.

$$R_{max}(x,y) = R_{max}(x,y) - \frac{dist(R_{max},R_{min})}{4} \quad (1)$$

$$R_{min}(x,y) = R_{min}(x,y) + \frac{dist(R_{max},R_{min})}{4} \quad (2)$$

Where R_{max} maximum point of the bounding box, R_{min} is minimum point of the bound box, dist is Euclidean distance between two points. Base of this bounding box we can ensuring the pixel with obtain from thresholding in bounding box consist coin color information neither coin with holes or rectangle. We then compute multivariate Gaussian probability for each original pixel assign with bounding box as

$$p(x) = \exp(-\tfrac{1}{2}(c(x)-\mu)^T \textstyle\sum(c(x)-\mu)^{-1}) \quad (3)$$

And diagonal covariance matrix $\sum$ in RGB color space for each pixel define as

$$\sum = \begin{bmatrix} \sigma_{RR}^2 & \sigma_{RG}^2 & \sigma_{RB}^2 \\ \sigma_{BR}^2 & \sigma_{BB}^2 & \sigma_{BG}^2 \\ \sigma_{GR}^2 & \sigma_{GB}^2 & \sigma_{GG}^2 \end{bmatrix}$$

where $\sigma_{IJ}^2 = \frac{1}{n-1}\sum_{(x,y)}(i(x,y)-\mu_i)(j(x,y)-\mu_j)^T \quad (4)$

Then, we used the Mahalanobis distance[8] to measure the dissimilarity/deviation between a point and the Coin Gaussian distribution.

- **Probability map**

The Mahalanobis distance is a statistic value which measures the distance of a single data point the mean or centroid of a simple in the space of the independent variables. The Mahalanobis distance D between at a pixel x and the coin sample can be formulated as Where D is Distance from the coin statistic to the closest current coin point, c is a color vector, and is the mean vector and the diagonal covariance matrix, respectively. The Mahalanobis distance is computed at each pixel in the image, generating a distance map as shown in Figure 1.

SHADOW DETECTION BASED ON CHROMACITY-BASED METHOD

We can obtain the coin object from image, but cast shadows are not treated explicitly. Automatic shadow detection on a single or a couple of images has been addressed in a variety of approaches[9] . Chromacity-based method, based on spectral features use colour information. It uses the assumption that regions under shadow become darker, but retain their chromacity. It is a measure of colour that is independent of intensity of invariant colour. The invariant colour features is invariant to changes in viewing direction, object geometry and illumination. We can be used to detect shadows in our framework. Our experimental results show that figure 1, compare colour model and invariant colour model. H, O_1O_2, $l_1l_2l_3$, $C_1C_2C_3$ and normalize rgb . Based on the illumination intensity highlight and illumination colour of our experiment the best results are obtained using the $C_1C_2C_3$ invariant color model. The $C_1C_2C_3$ invariant color models are proposed by Gevers et al. [10] in 1999, which is defined as follows:

$$c_1 = \arctan\frac{R}{\max(G,B)}$$

$$c_2 = \arctan\frac{R}{\max(R,B)}$$

$$c_3 = \arctan\frac{R}{\max(R,G)} \quad (5)$$

Where R, G and B representing the red, green, and blue colour components of a pixel in the image. The pixel becomes a candidate shadow if its intensity is smaller than that of the reference pixel for all three channels. For each pixel in the coin image, the pixel (x , y) can be considered, as a shadow pixel when it meets the condition in equation follow by

$$\left(\boldsymbol{c_1}^{B(x,y)} - \boldsymbol{c_1}^{I(x,y)}\right)\left(\boldsymbol{c_2}^{B(x,y)} - \boldsymbol{c_2}^{I(x,y)}\right)\left(\boldsymbol{c_3}^{B(x,y)} - \boldsymbol{c_3}^{I(x,y)}\right) < \mathbf{T} \quad (6)$$

Where $c_1^{I(x,y)}$ is the value of c_1 at the pixel (x,y) in the background reference which is values given location by user. $c_1^{B(x,y)}$ is the value of $\boldsymbol{c_1}$ at the pixel(x,y) in the current image, $c_2^{B(x,y)}$, $c_2^{I(x,y)}$, $c_3^{B(x,y)}$ and $c_3^{I(x,y)}$ are similarly defined for $c_1$component. T is a Threshold value. The result shown in figure 3.

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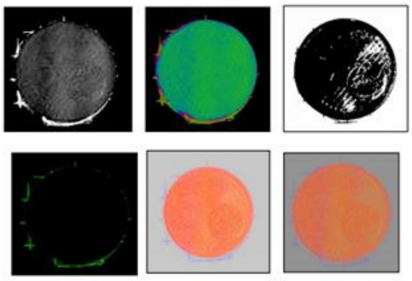

Figure 1. (left to right and up to down) H , $l_1 l_2 l_3$,S, $o_1 o_2$, $c_1 c_2 c_3$ and normalize rgb

Figure 2. Original image

Figure 3. Results of our approach

IDENTIFICATION BY GRAPH EDGE SIMILARITY

Feature based representation of coins

We employ the algorithms from [17] are query coins into template database. For the first step, the image of segmented coins from last section are converted into gradient magnitude images by Laplacian operator, for the purpose reduces noises caused by inhomogeneous illumination and texture. Let vector line $G^{I} = (V^{I}, E^{I})$and $G^{II} = (V^{II}, E^{II})$ represent respectively the query coin and the template coin. V^{M} and E^{M} are respectively the set of nodes and the set of edges in the vector G^{M}, where M is either I or II. The one-to-one correspondence between the i^{th} node v_i^{I} in the query coin and the j^{th} node v_j^{II} in the template image is denoted by $v_i^{I} \leftrightarrow v_j^{II}$, and the set of matched node pairs denoted by $C_v^{G^{I} \leftrightarrow G^{II}} = \{(v_i^{I}, v_j^{II}) | v_i^{I} \leftrightarrow v_j^{II}\}$.

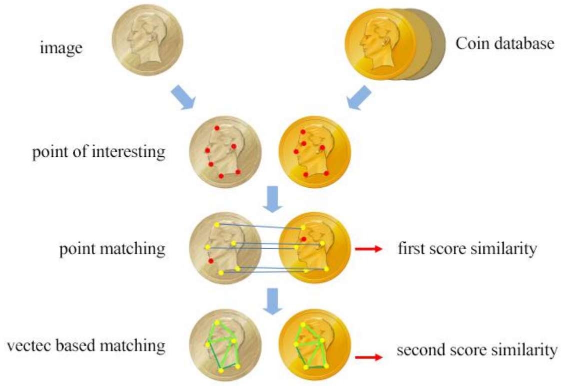

Figure 4. Overview of our recognition algorithms

To detect feature points construct vector based represent to recognize the pixel between both coin. For each node need to obtain feature points by algorithms of feature edge point as we mention in the literature, the beat algorithms that we test was ORB (Oriented Fast and Rotated BRIEF) operator [16] since it runs very fast than very famous feature points detectors such as SIFT(Scale-invariant feature transform). line distance of ORB features means that local patterns around those feature points are similar. Let us define P^{M} as set of feature points. The i^{th} feature point p_i^{I} in the query coin and the j^{th} feature point p_j^{II} could be a matched pair if Hamming distance of their ORB features is the smallest, denoted by $d(p_i^{I}, p_j^{II})$.

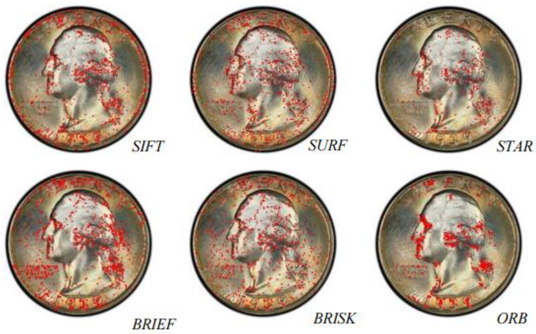

Figure 5. Compare feature point method

However, using only a most feature point of featur

e distance on coin often false matches, because local features represented by ORB feature are not always globally discriminate due to shiny effect. Therefore, we apply two position constraints for the nodes matching: the Neighbourhood constraints given by $\|p_i^{I}\text{-}p_j^{II}\|_2 < r$ where r is the radius of the neighbourhood, since it is assumed that matching points will be found around similar positions in professional photos in which coins are quasi aligned; and the Boundary constraints given by $\|p_i^{M}\text{-}O^{M}\|_2 < 0.90\ R^{M}$, where R^{M} is the radius of the segmented coin and O^{M} is the center of the image, since we calculate the canter of coin by first order moment. The two position feature on both coin allow us to minimize the false or uninteresting matches. To increase the retained matches, we set a high value for N_{kpts}, the number of total feature points, and apply k-nearest neighbour matching. Thus, the matched node pairs can be written as

$$C_v^{G^I \leftrightarrow G^{II}} = \{(p_i^I - p_j^{II}) \left| d_k(p_i^I - p_j^{II}), \|p_i^I - p_j^{II}\|_2 < r, \right.$$
$$\|p_i^M - O^M\|_2 < 0.95\, R^M\}, i, j \in [1, N_{kpts}], \tag{7}$$

Where $d_k(p_i^I\text{-}p_j^{II})$ is the best one-to-one correspondence in the frame of k-nearest neighbour matching N_{kpts} and k are two parameters defined by users. Our tests show that $N_{kpts} \approx$ 1000 and $\approx$ 10 result in stable and robust true matches for images of 500 * 500 pixels. From the matched node pairs, we then construct two vectors as follows. Firstly, we arrange the matched feature points in the two images by the same order, as $v_i^I \leftrightarrow v_j^{II}, i \in [1, N_v]$ where $N_v = \left|C_v^{G^I \leftrightarrow G^{II}}\right|$ is the total number of retained matches of nodes. Next, a Delaunay triangulation is performed on the set $V^I$to generate a connected vector G^I composed of triangles by maximizing the minimum angles. After that, for all directed edges $e_{ij}^I = v_i^I \rightarrow v_j^I$ in G^I, we line up the corresponding ends as $e_{ij}^{II} = v_i^{II} \rightarrow v_j^{II}$ on the set V^{II}I to construct G^{II}. The idea is to construct two connected vectors topologically equivalent whose nodes and edges are intrinsically in one-to-one correspondence.

Similarity score based on vector based

Normally, coins of the same template class have more likely pixel to matches of nodes than coins of different template classes. Then, the number of vector nodes $\left|C_v^{G^I \leftrightarrow G^{II}}\right|$ is the first similarity measurement between two coins, and we propose it Similarity Score based on vector Nodes (SSN)[17]. However, SSN is not as reliable as we expect in special cases where coins in comparison share a lot of local similarities but the main difference is omitted by selected local feature points. The point is then how to emphasize the importance of global similarity without weakening the local similarity already measured by feature points.

Here, our hypothesis, vector on the coins of the same class should cover similar patterns. Based on this hypothesis, we use vector to present the central pattern covered by vector, and apply a vector edge based descriptor to measure the similarity we define a vector edge descriptor for comparing gradient images. In the vector G^M, the length of the directed vector $e_{ij}^M = v_i^M \rightarrow v_j^M$ is given by $l_{ij}^M = \left\|v_i^M\text{-}\, v_j^M\right\|_2$. The patterns covered by e_{ij}^K can be represented by a gradient bar with the length of l_{ij}^M and the width of $\omega(\omega = 5\text{pt})$. Next, we divide the gradient bar of $0.8 l_{ij}$, from $v_i + 0.1(v_j\text{-}v_i)$ to $v_i + 0.9(v_j\text{-}v_i)$into s sections and calculate the mean of gradient for each section. By doing so, e_{ij}^M is converted into a feature vector composed of s elements. The reason of taking only 80% of central portion of $l_{ij}^K$is to make the descriptor less sensitive to the exact position of nodes. Then, we normalize the s meaned gradients into the range between 0 and 1. If the maximum and minimum elements are close, we normalize all the s elements to 0.5. Finally, we denote the normalized s-dimensional vector that encodes the transition of gradient along with the directed edge e_{ij}^M as the vector edge descriptor d_{ij}^M . After defining the vector edge descriptor, two matched edges $e_{ij}^I \leftrightarrow e_{ij}^{II}$are considered as similar, if the Euclidean distance of their descriptors is inferior to a threshold, given by$\left\|d_{ij}^I \leftrightarrow d_{ij}^{II}\right\|_2 < d_{th}$. The total number of similar edges in two vectors is the Similarity Score based on vector Edges (SSE) that we propose. However, we don't want to count similar edges if their length l_{ij}^M are too small, inferior to l_{th}. Let $S_e^{G^I \leftrightarrow G^{II}}$ be the set of similar matched edge pairs, SSE is denoted by,

$$\text{SSE} = \left|S_e^{G^I \leftrightarrow G^{II}}\right| = \{(e_{ij}^I, e_{ij}^{II}) \left| \left\|d_{ij}^I \leftrightarrow d_{ij}^{II}\right\|_2 < d_{th}, l_{ij}^K > \right. l_{th}\} \tag{8}$$

Two coins of the same class should have more similar edges, i.e., higher SSE, than two coins of different classes. It is worth to note that the similarity score is more or less sensible to unexpected reaction and inhomogeneous illumination that will intense on gradient images, but professional photos should guarantee the ideal conditions to apply our similarity score.

Figure 6. Vector line based similarity score

RESULTS AND DISCUSSIONS

Segmentation evaluation

A usually way but poorly motivated way of evaluating results of segmentation algorithms experiments is using Recall, Precision and F-factor. These measures are named for their original in Retrieval the pixel information and represent specific biases, namely that they ignore quality in correctly handling negative data, they propagate the underlying marginal Prevalence and biases, and they fail to take account the chance level performance. In term of Medical Sciences, Receiver Operating Characteristics (ROC) analysis has been employed to image processing to become a standard for evaluation and standard measure, comparing (TPR) True Positive Rate and (FPR)False Positive Rate. In the Behavioural Sciences, Specificity and Sensitivity are commonly used. Alternate techniques, such as Rand Accuracy and Cohen Kappa, have some advantages but are nonetheless still biased measures. We will recapitulate some of the literature relating to the problems with these evaluation measures, as well as considering a number of other techniques that have been proposed and argued within each of these tasks, aiming and claiming to address the problems with these simplistic measures.

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There is an increasing need for automated processing of massive amounts of visual information generated by video surveillance systems. The goal here is to verify that the automation of a number of tasks for image and video analysis is reliable, in order to reduce human supervision and to assist decision-making. The quantitative performance evaluation methods should make it possible to compare the results provided by different segmentation algorithms. The most commonly used methods in the literature attempt to find a compromise between Precision, Recall (also called Sensitivity) and Specificity. But most widely used representations only consider two of the three indicators: Precision/Recall space and ROC curves (which represent only the Sensitivity=Recall and Specificity). In the same way, the F-measure is a single value quality measure based on Recall and Precision only that completely ignores the Specificity of segmentation algorithms. In the context of segmentation quality evaluation, we used F-measure. The F measure is the harmonic mean of Precision and Recall.

$$F = 2((PR * RE)/(PR + RE)) \tag{9}$$

Precision and recall are then defined as:

$$\text{Precision} = tp / (tp+fp) \tag{10}$$

$$\text{Recall} = tp / (tp+fn) \tag{11}$$

Recall in this context is also referred to as the true positive rate or sensitivity, and precision is also referred to as positive predictive value (PPV); other related measures used in classification include true negative rate and accuracy. True negative rate is also called specificity.

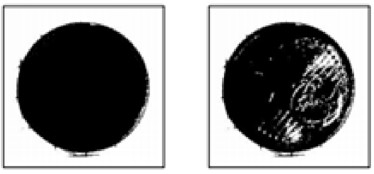

Figure 7. Example of segmentation: ground truth (left) segmentation results (right)

Table 1. Segmentation evaluation results

TPR	**FPR**	**Recall**	**Precision**	**F-measure**
0.8577	0.0024	0.8577	0.5862	0.6970

Coin database for validation

We selected USA Grading Database for validation our algorithms. USA Grading Database is standard Grading database of the American numismatics company. we have 2238 proper images partitioned into 2250 query coins and 128 template coins for the validation work, for 120 different classes (in our case both side of coin).

Figure 8. Example of over abraded coin (left) and "dark coin" (right).

In order to evaluated our method of coin recognition system. The success rates are listed in Table 2. The identification accuracy by the highest similarity score is 90.2% for all the total test set, and results for different datasets are listed in Table 2. Both similarity scores achieve high identification rates, and SSE performances slightly better than SSN except on the dataset of gold coins.

In a deeper analysis, we observe that coins with slight interclass difference, like those shown in Figure 1, contribute a lot to false identifications. It is really interesting to see that SSE reduces the confusion for similar coins that belong to different classes. Table 3 shows successful identification rates of two similarity measurements on four groups of coins that have confused class, where SSE proves its robustness over SSN. However, coins successfully identified by SSN but mistaken by SSE are not gathered into specific classes. The unstable quality of the image is the main reason that leads to false identification on SSE. Results of k-nearest neighbour classification show the right class has more than of 99% chance falling into the 3 (k = 3) top possible classes (see Figure 8).

Table 2. Performances on identification of coins

<table>
<tr><td></td><td colspan="2">Acceptance</td><td>Rejection</td></tr>
<tr><td>Valid coins
92.8%</td><td>Correct classification
85.64%</td><td>False classification
0.45%</td><td>False Rejection
6.67%</td></tr>
<tr><td>Invalid coins
7.2%</td><td colspan="2">False acceptance
1.56</td><td>Correct rejection
5.56%</td></tr>
<tr><td>All coins
100%</td><td colspan="3">Correct decisions
88.5%</td></tr>
</table>

It is worth to note that our current system is not rotation invariant because our neighbourhood constraints are used to limit false matches of feature points. Nevertheless, strict registration is unnecessary and small rotations caused by human error during the photographing process can be tolerated. We suppose that professional coin photos should be more or less aligned, otherwise a registration stage will be added in our system.

CONCLUSION

We proposed the algorithms for automatic coin recognition system which can provide to use for identification on coin industries. For our proposed , region based growing based use to segment the background for the class pre-selection combine with active parametric model .For the recognition, we selected the two step of recognition first we matched coin with feature point descriptor to select the best template then we constructed the vector based to filter the best match of coin. The results are promising very well on dataset of USA Grading Database. The result of coin recognition rate is 88.5%. For future work, we plan to implement image registration technical for photo that not fit well of rotation problem additionally, colour features of coins could be enhance with shape features in the templates pre-selection. Finally, compare segmentation and recognition algorithms with other method, larger database and more proper coin templates and also test on another dataset

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