ROBUST AUTOMATIC SEGMENTATION OF ANCIENT COINS

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Abstract: Nowadays, ancient coins are becoming subject to a very large illicit trade. Thus, the interest in reliable automatic coin recognition systems within cultural heritage and law enforcement institutions rises rapidly. Central component in the permanent identification and traceability of coins is the underlying image recognition technology. Prior to any analysis a coin image has to be segmented into two areas: the area depicting the coin and the area belonging to the background. In this paper, we focus on the segmentation task as a preprocessing step for any automated coin recognition system. The objective is a robust segmentation procedure for a large variety of coin image styles. We present a simple and fast method for coin segmentation, based on local entropy and gray value range. Results of the developed algorithm are shown for an image database of ancient coins and demonstrate the benefits of our approach.

1 INTRODUCTION

Traditional methods to fight the illicit traffic of ancient coins comprise manual periodical search in auctions catalogues, field search by authority forces, periodical controls at specialist dealers, and a cumbersome and unrewarding internet search, followed by human investigation. Therefore, image-based methods to automatically recognize ancient coins have the potential to increase their traceability to a high degree and thus to help to combat their illicit trade.

For the image-based recognition of ancient coins, initially a segmentation of the coin region is of outmost importance. Especially for the identification of stolen coins a correct segmentation is a crucial step since the shape of the coin provides a substantial feature to identify a concrete coin specimen (Zaharieva et al., 2007). An automatic segmentation method is also of great benefit for the indexing of new coins since up to now numismatists have to perform this time-consuming task manually.

In the context described above, the methods have to deal with images from various sources (e.g. museum collections or public online databases). Therefore, no assumptions about image quality can be made and major challenges that have to be faced in the segmentation of coins are caused by an improper image acquisition procedure. Especially shadow casts caused by an insufficient illumination setup impede the correct determination of the coin border. Furthermore, tests have shown that image compression with chroma subsampling is often used when storing images of coins. The resulting compression artifacts preclude the use of color information, thus only the luminance can be used for a reliable segmentation of the coins.

In this paper a simple and fast method for coin segmentation based on local entropy and gray value range is presented. The remainder of this paper is organized as follows. Related work and the coin segmentation strategy itself are addressed in Section 2. Experiments on a set of 92 images are reported in Section 3. A conclusion is finally given in Section 4.

2 COIN SEGMENTATION

Coin segmentation deals with the division of the image into two regions: the region depicting the coin and the region belonging to the background. In (Zaharieva et al., 2007) segmentation of ancient coins was achieved using an adaptive thresholding method originally suggested by (Yanowitz and Bruckstein, 1989). The proposed method derives a threshold surface obtained by an interpolation of tie points placed at thresholded gradient values. However, as demonstrated in the experiments (Section 3), this method fails if the coin images show a high variability.

Segmentation of present day coins was done in various papers. However, all of them make special assumptions which are not satisfied in our image data: (Reisert et al., 2006) apply the Hough transformation for circle detection. By definition, this approach is not applicable on ancient coins which likely show no perfect circularity. The global thresholding methods presented in (van der Maaten and Poon, 2006) and (Nölle et al., 2003) are applied to images acquired under controlled conditions and are therefore not appropriate to segment images from many different sources.

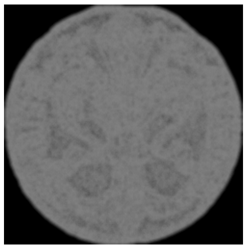
Because of the problems stated, we propose a robust method which is able to correctly segment a variable set of different coin images. The only assumption we make is that the coin itself possesses more local information content and details than the rest of the image, i.e. the background. For that reason, our method is based on two filters providing a local measurement of information content in the image: the *local entropy* and the *local range of gray values*.

Local entropy: Entropy is the measure of the information content in a probability distribution. For digital images the probability distribution is represented by the histogram of gray values (Kapur et al., 1985). If Ω defines a local neighborhood within the image with gray value frequencies $p_1, p_2, ..., p_N$ (i.e. the normalized histogram values), the local entropy is defined as

$$H(\Omega) = -\sum_{k=1}^{N} p_k \cdot \log_2(p_k) \quad (1)$$

Local range of gray values: The local range of gray values is defined as the difference of the maximum and minimum gray value of a local neighborhood.

The outputs of these two filters are summed-up to build the final intensity image where the thresholding is applied on. For both filters a circular neighborhood with a radius of 3 pixels is used and both filter outputs as well as the final intensity image are normalized to the range 0 to 1. For illustration on a simple example, in Figure 1 the particular results of the entropy filter (b), the range filter (c) and their summation (d), applied to a coin image (a), are shown. The output of both filters is higher for the region of the coin than for the region of the background, especially at the coin border.

(a)  (b) 

(c)  (d) 

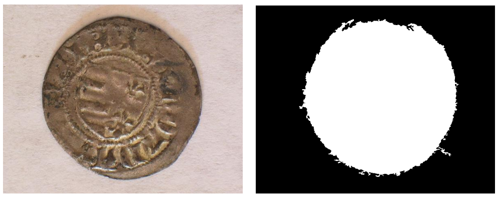
Figure 1: (a) original image, (b) output of local entropy filter, (c) output of local range filter, (d) sum of local entropy and local range (final intensity image).

To obtain the final coin segmentation from the intensity image shown in Figure 1d, a simple way would be to apply a global threshold and close all holes in the binary mask caused by homogeneous regions inside the coin. However, tests have shown that such a manually defined threshold does not perform well on the overall given test set. Therefore, a more sophisticated approach is used: we apply seven thresholds T_i ($T_i = 0.3, 0.35, ..., 0.6$) to the normalized intensity image and compute a score for each achieved segmentation that represents the confidence to the given segmentation. Afterwards the segmentation with highest confidence is chosen. Since the shape of a coin is close to a circle, we use the *formfactor* (Russ, 2006) of the binary segmentation mask as confidence measure. The formfactor of a binary mask is computed as follows:

$$\text{formfactor} = \frac{4\pi A}{P^2} \quad (2)$$

where A is the area and P the perimeter of the binary mask. The formfactor is sensitive to both the elongation of a region and the jaggedness of its border. The higher the jaggedness of the border, the less the formfactor. The formfactor is equal to 1 for a circle and is less for any other shape. Since the final shape of the segmentation should be close to circle with a regular border, the formfactor provides a convenient measure for the confidence of the segmentation.

Since low thresholds can produce a coin segmentation that is near the rectangular shape of the whole image (providing a comparatively high formfactor), a segmentation is furthermore only accepted if the area of the segmented region is lower than 90 % of the



(a) Original image. (b) $T_1 = 0.3$, formfactor = 0.280

(c) $T_3 = 0.4$, formfactor = 0.708 (d) $T_5 = 0.5$, formfactor = 0.812

Figure 2: Four segmentation masks according to different thresholds T_i applied to the intensity image.

image area. In the case that thresholding produces more than one connected component in the image, the one with highest formfactor covering at least 5 % of the image area is selected. An example for different segmentations obtained with different thresholds is shown in Figure 2. The segmentation obtained with $T_5 = 0.5$ shown in Figure 2d has the highest formfactor and is therefore chosen as the final segmentation.

The discretization of $T_i = 0.3, 0.35, \ldots, 0.6$ was chosen empirically. Tests have shown that a finer discretization does not improve the accuracy of the method.

3 EXPERIMENTS

The proposed method was tested on a set of 92 images acquired at the *Kunsthistorisches Museum Vienna*, Austria, the *Fitzwilliam Museum*, Cambridge UK, and the *Romanian National History Museum* representing a wide range of different coin images. The images differ in various ways (resolution, background, coin size relative to image size, illumination conditions).

For the experiments presented here, all color images were converted to gray-level images. Compression artifacts due to chroma subsampling are highly present in the data and make the use of color information infeasible.

For each image a ground truth segmentation was manually obtained by means of a commercial image editing program. For the evaluation of the segmentation the mutual overlap (MO) (Bowyer, 2000), also known as dice coefficient, is measured:

$$\mathrm{MO} = \frac{2 \cdot |A_1 \cap A_2|}{|A_1| + |A_2|} \tag{3}$$

where A_1 is the set of pixels in the segmented region and A_2 the set of pixels in the ground truth segmentation.

To demonstrate the appropriateness of the proposed method for the segmentation of coin images, the results are compared to the outputs of various other segmentation methods: (1) the adaptive thresholding method used in (Zaharieva et al., 2007) for the segmentation of ancient coins, (2) the mean shift method proposed by (Comaniciu and Meer, 2002) for a comparison with a state-of-the-art method in image segmentation and (3) our method when the thresholding is directly applied to gray values instead of the sum of entropy and gray value range.

It must be noted that the output of the mean shift segmentation method is not implicitly a partition into foreground and background, as needed here. Mean shift partitions the image in a set of disjoint regions without labeling the foreground and background. From our point of view the segmentation has to extract the single most salient object in the image, which is in our case the coin. Therefore, to make the mean shift segmentation results comparable, the parameter M for the minimum allowable region area has to be manually adapted for each image to produce a two-segment partition of the image. Evaluation was performed on the mean shift implementation of the EDISON system[1].

In Table 1 the average and median MO for the different methods are listed. The average MO of 0.517 and median MO of 0.720 of the adaptive thresholding method indicate its low robustness. Although the parameters of the method can be adjusted to perform well on a given type of coin image it is not able to handle the wide range of different images contained in the test set. A second conclusion of the results is that the local entropy and range filtering is a reasonable preprocessing step to provide a more appropriate intensity image for the thresholding. This can be seen by the lower average and median MO when the original gray values are used. From the results in Table 1 it can also be seen that our method achieves a similar performance than the state-of-the-art mean shift segmentation. The average MO is equal (0.983) and the median MO of our method is even higher (0.993 to 0.988 of the mean shift method). However, our method has two advantages: firstly, in contrast to mean shift no parameter has to be adapted manually. And secondly, our method is computationally faster:

[1] http://www.caip.rutgers.edu/riul/research/code/EDISON/index.html, last visited: November 18th 08


(a) MO = 0.9973 (b) MO = 0.9981


(c) MO = 0.9970 (d) MO = 0.9441


(e) MO = 0.9500 (f) MO = 0.9904

Figure 3: Results of the proposed segmentation method.

our method (written in MATLAB 7.1) takes 0.38s for a 178×184 image and 8.40s for a 1154×866 image, whereas the means shift implementation (written in C++) takes 0.73s for the 178×184 image and 29.37s for the 1154×866 image on the same machine.

	Average	Median
Adaptive Thresholding	0.517	0.720
Mean Shift	0.983	0.988
Our method on original gray values	0.923	0.980
Our method	0.983	0.993

Table 1: Average and median MO achieved on the 92 test images.

Figure 3 shows results on selected images where the obtained coin border is outlined by a black or white line. Figure 3a-c belong to the best segmentation results with a MO of 0.9973, 0.9981 and 0.9970, respectively. Figure 3d-e belong to the worst results with a MO of 0.9441 and 0.9500, respectively. You see that shadows pose a problem to the method since they produce a strong edge not belonging to the actual coin border. However, on the image of Figure 3f the method correctly excludes the shadow from the segmentation, producing a MO of 0.9904.

4 CONCLUSIONS

The method shows convincing results with a median MO of 0.9928 and proves that local entropy and gray value range give a convenient estimate of the actual coin region. However, although the method's robustness is indicated by a minimum MO of 0.9048 on a set of 92 test images, shadows still pose a problem. Nevertheless, the method outperforms the state-of-the-art mean shift segmentation method both in segmentation accuracy and speed. Furthermore, our method needs no parameter adjustment and is therefore able to deal with a large variety of coin image styles. To sum up, the results achieved satisfy the needs of automatic coin identification for a large variety of coin image styles, nevertheless future research focuses on the segmentation accuracy in the occurrence of shadows.

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