Image-Based Measurement of Ancient Coins

Michael Herrmann, [1] Sebastian Zambanini,[1] and Martin Kampel[1]

[1] Institute of Computer Aided Automation, PRIP, Vienna University of Technology, Vienna. Austria.

Abstract

Museums catalogue their ancient coins using top view photographs in which a ruler is placed next to the coin. We present an automatic method that allows numismatists to process such images faster and more accurately. The method consists of two parts. The first part uses a novel algorithm to calculate the images' scale by a Fourier analysis of the characteristic pattern produced by the ruler. Distances can thus be measured in terms of the units on the ruler. The second part uses a shape-adaptive thresholding method to isolate the coin from the background. This makes it possible to determine the real-world size of the coin. Experimental results on 30 images show the high accuracy and robustness of the two algorithms with respect to different coins and rulers as well as the ruler's orientation, position, and size.

Keywords: *computer vision, scale detection, segmentation*

1 INTRODUCTION

Important characteristics of an ancient coin include its physical dimensions.[1] However, obtaining this information is difficult and time consuming and has therefore not been done for large parts of most numismatic databases. Since many historic coins are catalogued by top view images in which a ruler is placed next to the coin, an automatic, image-based way of extracting this data could be of great value to numismatists.

This paper presents an automatic method for taking measurements on coins by means of a ruler placed next to the coin. The method consists of two steps:

1. Determination of the image scale, i.e. the pixels' real-world size, from the ruler visible in the image.
2. Segmentation of the coin.

Generally, the output of the two steps allows for the measurement of various spatial features of a coin, such as area, perimeter, or the size of certain symbols. However, only the maximum diameter (i.e. the largest distance between any two points on the coin's border) is usually recorded by numismatists, and therefore experiments were only conducted for this measurement.

An important feature of the proposed solution is that it imposes only minimal requirements on the image acquisition process. The scale detection is not restricted to a specific type of ruler and is robust with respect to the placement and orientation of the ruler. Similarly, the coin segmentation works for a wide range of coins and backgrounds and is independent of the position of the coin. Usually, a camera mounted on a camera stand providing parallelism between the coin and the camera's image plane is sufficient.

The contribution of this paper is twofold. On the theoretical side, it proposes a novel algorithm for detecting the scale of an image that, unlike existing approaches, is designed to be invariant with respect to the placement and orientation of the ruler. On the practical side, it gives an automatic method that can be used by non-computer scientists and evaluates its accuracy and use in practice.

The remainder of the paper is composed as follows. Section 2 gives an overview of related work in automatic scale interval detection and coin image segmentation. A detailed description of the proposed method for computing the scale of the images is given in Section 3 and the coin segmentation is addressed in Section 4. Experiments on a set of 30 images are reported in Section 5. A conclusion is given in Section 6.

2 RELATED WORK

The computation of the image scale by means of a ruler can be defined as the task of finding equidistant parallel lines in an image. Several approaches have been proposed for solving the line detection problem, including the Hough transform,[2] eigenvalue analysis,[3] or

[1]Philip Grierson, *Numismatics* (Oxford: Oxford University Press, 1975).

[2]J. Illingworth and J. Kittler, "A Survey of the Hough Transform," *Computer Vision, Graphics, and Image Processing* 44 (1988): 87–116.

[3]D. S. Guru et al., "A Simple and Robust Line Detection Algorithm Based on Small Eigenvalue Analysis," *Pattern Recognition Letters* 25 (1) (2004): 1–13.

image gradient analysis.[1] A line detection method gives the orientation and length of each line found in the image and such information can be easily used to detect equidistant parallel lines. However, line detection appeared to be unstable for the ruler marks shown in our image database, since line detection and the correct determination of the line orientation suffers from noisy lines due to cracks or irregular borders of the ruler marks. Therefore, in order to make the method more robust, we decided to base the determination of the ruler interval on the Fourier transform.[2] Our method is inspired by an approach which detects regular patterns shown in the Fourier transform for determining the ruler interval.[3] However, the method is only able to process horizontally placed rulers, a limitation which is overcome by our method.

Methods proposed for the segmentation of coins in images mainly focus on present day coins. All of them make special assumptions that cannot be expected to be satisfied on all coin image data. Reisert et al.[4] apply the Hough transformation for circle detection. By definition, this approach is not applicable to historical coins, which are unlikely to show perfect circularity due to abrasions and to the non-industrial manufacturing procedure. The global thresholding methods presented in van der Maaten and Poon[5] and Nölle et al.[6] are applied to images acquired under controlled conditions and are therefore not appropriate to segment images from many different sources. In Zaharieva et al.,[7] segmentation of historical coins was achieved using an adaptive thresholding method originally suggested in Yanowitz and Bruckstein.[8] However, experiments[9] showed that this method fails if the coin images show a high variability. Because of the problems mentioned above, we use our recently pro-posed method, which was able to segment images robustly from many different sources.[10] It is described in Section 4.

3 SCALE DETECTION

An overview of our method for scale detection is shown in figure 1. As Ueda et al.,[11] we observe that the marks on the ruler form a regular pattern that produces ridges in the frequency domain of the picture. We therefore first calculate the image's power spectrum using the fast Fourier transform. Then we locate the ridges that correspond to the marks on the ruler, which allows us to calculate the frequency of the dashes and thus the scale of the image. As a final step, we apply the inverse Fourier transform to the ridges found in the previous step. This makes it possible to determine the location of the ruler and thus give visual feedback to the user. The following sections explain the last two steps in more detail.

3.1 RIDGE DETECTION

Because the frequency of the marks of the ruler can reasonably be assumed to lie within certain bounds, we only need to scan a comparatively small window around the center of the power spectrum for the ridges. In addition, we observe that the ridges are much brighter than the rest of the power spectrum and therefore do not consider points whose intensity lies below the window's average.

To determine the location of the ridges in the window, we look at each point in turn and walk along its tangent to the left and right (fig. 2). As long as the intensity decreases, we continue walking while always keeping track of the lowest intensity we have encountered so far. If the intensity starts to increase, the remembered lowest intensity is used to calculate a threshold that determines how far we can go back "uphill". This way, we walk longer on ridges which have a constant, high intensity around their defining points than on tangents with fluctuating, low intensity. For each point, the result of

[1] R. C. Nelson, "Finding Line Segments by Stick Growing," *IEEE Transactions on Pattern Analysis and Machine Intelligence* 16 (5) (1994): 519–523.

[2] J. C. Russ, *The Image Processing Handbook*, 5th edition (Boca Raton: CRC Press, 2006).

[3] K. Ueda et al., "Detection of Scale Intervals in Digital Images," *Proceedings of the 21st International Conference on Data Engineering, Tokyo, Japan, 5–8 April 2005*: 1232.

[4] M. Reisert et al., "An Efficient Gradient Based Registration Technique for Coin Recognition," *Proceedings of the Muscle CIS Coin Competition*, 2006: 19–31.

[5] L. J. van der Maaten and P. J. Poon, "Coin-o-matic: A Fast System for Reliable Coin Classification," *Proceedings of the Muscle CIS Coin Competition*, 2006: 7–18.

[6] M. Nölle et al., "Dagobert–A New Coin Recognition and Sorting System," *Proceedings of Digital Image Computing: Techniques and Applications'03*, 2003: 329–338.

[7] M. Zaharieva et al., "On Ancient Coin Classification," *Proceedings of the International Symposium on Virtual Reality, Archaeology and Cultural Heritage* (VAST'07), 2007: 55–62.

[8] S. D. Yanowitz and A. M. Bruckstein, "A New Method for Image Segmentation," *Computer Vision, Graphics and Image Processing* 46 (1) (1989): 82–95.

[9] S. Zambanini and M. Kampel, "Robust Automatic Segmentation of Ancient Coins," *Proceedings of the 4th International Conference on Computer Vision Theory and Applications* 2 (VISAPP'09), 2009: 273–276.

[10] Ibid.

[11] K. Ueda et al., "Detection of Scale Intervals in Digital Images," *Proceedings of the 21st International Conference on Data Engineering*, 2005: 1232.

this analysis is the length we were able to walk on its tangent. We call this the *score* of the point (fig. 3).

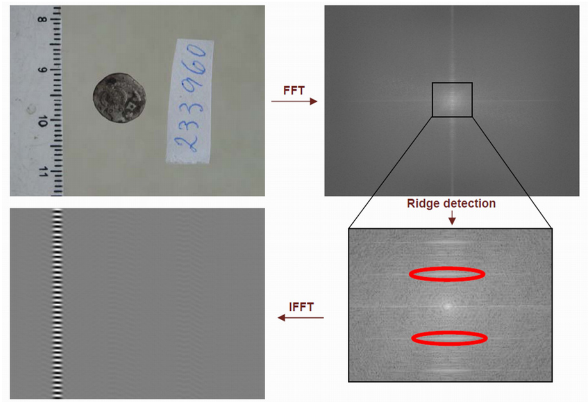

Figure 1. *Overview of the method for scale detection.*

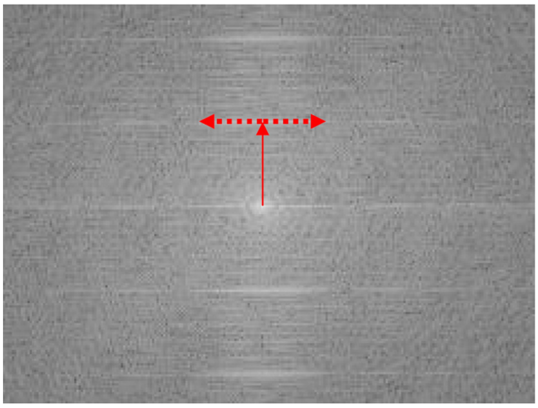

Figure 2. *Walking along a point's tangent.*

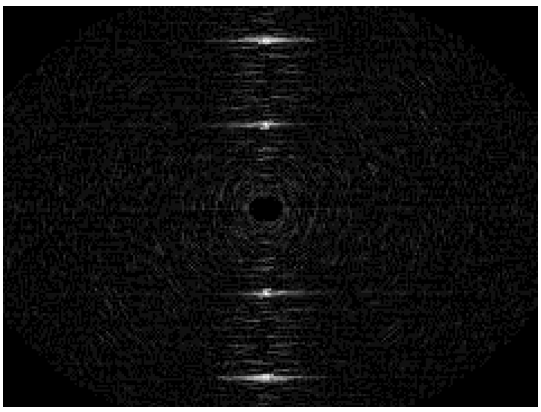

Figure 3. *The* scores *for the points as obtained in fig. 2.*

We can clearly see that the image of the scores contains peaks at the mid-points of the ridges in the original sub-region. We detect these peaks by finding the local maxima in the image.

In order to identify the peak that corresponds to the marks on the ruler while eliminating false peaks, we exploit the following fact. According to the theory of the Fourier transform, the marks on the ruler form a regular pattern that results in two opposite ridges in the power spectrum of the original image (these are marked by an ellipse in fig. 1). However, this also applies to the regular patterns of every second mark on the ruler, every third mark and so on. Since these patterns have a frequency that is 1/2, 1/3... of the original frequency, the distances of their ridges from the origin are 2, 3... times the corresponding distance of each of the two ridges that are produced by all marks on the ruler. The peak we are interested in is therefore the one whose distance is a low integer fraction (i.e. 1, 1/2, 1/3…) of the most other peaks' distances.

The position *(m,n)* of the detected peak relative to the center can be used to calculate the distance *d* in the original image between two marks on the ruler by the following formula:

$$d(m,n) = \left(\left(\frac{m}{M} \right)^2 + \left(\frac{n}{N} \right)^2 \right)^{-\frac{1}{2}}$$

Here, *M* and *N* are the width and height of the original image, respectively.

3.2 VISUAL FEEDBACK

In order to be able to give visual feedback to the user, we have to calculate the location and orientation of the ruler in the original picture. The location is found by applying the inverse Fourier Transform to just the ridges detected in the previous steps and searching the resulting image (see fig. 1) for its minimum intensity. The effective orientation ψ is calculated using the position *(m,n)* of the detected peak relative to the origin of the frequency spectrum by

$$\psi(m,n) = \tan^{-1} \frac{nM}{mN}.$$

4 COIN SEGMENTATION

Coin segmentation is based on the assumption that the coin itself possesses more local information content and details than the rest of the image, i.e. the background. Therefore two filters are applied to the image to highlight regions with high information content: the local entropy and the local range of gray values. Local entropy derives the measure of local information content from local gray value histograms,[1] whereas 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 a thresholding is applied. To obtain a robust segmentation accounting for the high variability of coin image

[1] J. N. Kapur et al., "A New Method for Gray-level Picture Thresholding Using the Entropy of the Histogram," *Computer Vision, Graphics, and Image Processing* 29 (1985): 273–285.

"styles," seven thresholds T_i ($T_i = 0.3, 0.35, ..., 0.6$) are applied to the normalized intensity image and for each resulting segmentation a score that represents the confidence level of the given segmentation is computed. Since the shape of a coin is close to a circle, we use the form factor[1] of the binary segmentation mask as the confidence measure. The form factor of a binary mask is computed as follows:

$$formfactor = \frac{4\pi A}{P^2}$$

where A is the area and P the perimeter of the binary mask. The form factor is sensitive to both the elongation of a region and the jaggedness of its border. The higher the jaggedness of the border is, the less the form factor is. The form factor 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 a circle with a regular border, the form factor provides a convenient measure for the confidence of the segmentation.

Because of the assumption that the coin possesses more local information content than the rest of the image, the proposed method for coin segmentation works best when the image background is as homogeneous as possible. This and further issues regarding the image acquisition process are discussed in Kampel and Zambanini.[2]

5 IMPLEMENTATION AND EXPERIMENTS

The two methods presented in Section 3 and Section 4 were implemented as plugins for the freely available *ImageJ* software. *ImageJ* is a public domain, Java-based image processing program that is mainly used for analyzing medical images.[3] The reason we chose to base our implementation on *ImageJ* is that it offers good tools for taking and managing measurements in images and has an extensible architecture that makes it comparatively easy to write custom plugins. Additionally, the methods were also implemented as plugins for Adobe *Photoshop*®. This image editing software is not freely available but is well known and widely used in the numismatic community.
The method was evaluated on a set of thirty images gathered from the Romanian National History Museum. For each image the ground truth was obtained by manually segmenting the coin and measuring the distance between ruler marks using a commercial image editing program. Since the final output is the maximum diameter of the coin, this is determined by computing the maximum distance between border points of the manual and automatic segmentation. The results are listed in Table 1. The table shows the minimum, maximum and average values for both the absolute and relative errors. For an individual evaluation of the segmentation, the first row shows the errors for the diameter computation in pixels. The second row purely reports the errors on the computation of the ruler marks distance (i.e. the determination of the image scale), and the third rows lists the errors for the final output, which is the maximal coin diameter in real world size.

	Absolute errors			Relative errors		
	Min.	Max.	Avg.	Min.	Max	Avg.
Diameter (px)	0.04	15.02	3.67	.01%	1.85%	0.49%
Ruler marks distance (px)	0.08	1.40	0.34	.17%	6.67%	1.00%
Diameter (real size)	.00mm	1.07mm	.20mm	.02%	6.64%	1.19%

Table 1. *Absolute and relative errors of the proposed method.*

With an average error of 0.49% for the segmentation and 1.00% for the scale detection, it can be concluded that both methods give accurate results for the given dataset. This also leads to an accurate measurement of the real coin diameter, with an average error of 0.20 mm or 1.19%. Furthermore, the maximum error of 6.64% emphasizes the robustness of the proposed method. Figure 4 shows the results on two particular coin images. To give appropriate user feedback the distance between 20 units is marked by a yellow line and the maximum diameter by a red line.

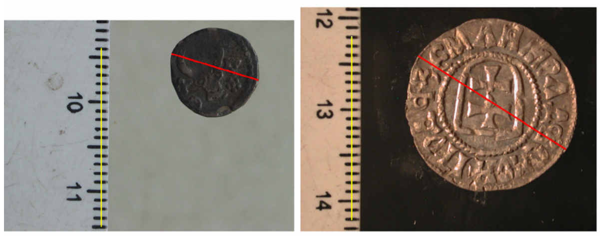

Figure 4. *Two results for determining the ruler marks distance and maximum diameter.*

The robustness of the scale detection is also indicated by a maximum error of 6.67%. However, on the given dataset all rulers were placed vertically in the image. Therefore, to verify the robustness of the method for arbitrarily rotated rulers, 10 randomly selected images were rotated in 20 degree steps. In this way we obtain 18 individual measurements for each image; the error is evaluated by means of the coefficient of variation, i.e. the standard deviation of the samples divided by their mean. As a result of the experiment, the average coefficient of variation for all 10 images lies at 0.52%,

[1] J. C. Russ, *The Image Processing Handbook*, 5th edition (Boca Raton: CRC Press, 2006).

[2] M. Kampel and S. Zambanini, "Coin Data Acquisition for Image Recognition," *Proceedings of the 36th Conference on Computer Applications and Quantitative Methods in Archaeology* (CAA'08), Budapest, Hungary, 2008. In press.

[3] W. S. Rasband. *ImageJ*. U. S. National Institutes of Health, Bethesda, Maryland, USA, 1997–2009. http://rsb.info.nih.gov /ij/.

which shows the low sensitivity of the method to the ruler orientation.

6 CONCLUSION

In this paper an image-based method for the automatic measuring of historical coins was presented. Experiments have shown the advantages of the method for numismatists by improving both the accuracy and speed of coin processing. The method is fully automatic except for the one-time manual adjustment of the unit length between two ruler marks for a given ruler type. Since the proposed method for determining the scale of images is in theory applicable to any type of ruler, the method can be used to measure or scale other kinds of objects as well, such as initials and letters of ancient documents. Though the experiments proved the general robustness of the method, in the future a more comprehensive evaluation with images from several sources is planned in order to underline the usefulness of the method for the numismatic community.

ACKNOWLEDGEMENTS

We would like to thank Ernest Oberländer-Tarnoveanu from the Romanian National History Museum for providing the test images. Additionally, we would like to thank the European Union for funding the project under grant FP6-SSP5-044450.

BIBLIOGRAPHY

Grierson, Philip. *Numismatic*s. Oxford: Oxford University Press, 1975.

Guru, D. S., B. H. Shekar, and P. Nagabhushan. “A Simple and Robust Line Detection Algorithm Based on Small Eigenvalue Analysis.” *Pattern Recognition Letters* 25 (1) (2004): 1–13.

Illingworth, J., and J. Kittler. “A Survey of the Hough Transform.” *Computer Vision, Graphics and Image Processing* 44.1 (1988): 87–116.

Kapur, J. N., P. K. Sahoo, and A. K. C. Wong. “A New Method for Gray-level Picture Thresholding Using the Entropy of the Histogram.” *Computer Vision, Graphics and Image Processing* 29 (1985): 273–285.

Nelson, R.C. “Finding Line Segments by Stick Growing.” *IEEE Transactions on Pattern Analysis and Machine Intelligence* 16 (5) (1994): 519–523.

Nölle, M., H. Penz, M. Rubik, J. Mayer, I. Holländer, and R. Granec. “Dagobert–A New Coin Recognition and Sorting System.” *Proceedings of Digital Image Computing: Techniques and Applications’03*, 2003: 329–338.

Rasband, W.S. *ImageJ*. U. S. National Institutes of Health, Bethesda, Maryland, USA, 1997–2009. http://rsb.info.nih.gov/ij/.

Reisert, M., O. Ronneberger, and H. Burkhardt. “An Efficient Gradient Based Registration Technique for Coin Recognition.” *Proceedings of the Muscle CIS Coin Competition*, 2006: 19–31.

Russ, J. C. *The Image Processing Handbook*, 5th edition. Boca Raton: CRC Press, 2006.

Ueda, K., T. Baba, Y. Nakagawa, and K. Amano. “Detection of Scale Intervals in Digital Images.” *Proceedings of the 21st International Conference on Data Engineering*, 2005: 1232.

van der Maaten, L. J., and P. J. Poon. “Coin-o-matic: A Fast System for Reliable Coin Classification.” Proceedings of the Muscle CIS Coin Competition, 2006: 7–18.

Yanowitz, S. D. and A. M. Bruckstein. “A New Method for Image Segmentation.” *Computer Vision, Graphics and Image Processing* 46 (1) (1989): 82–95.

Zaharieva, M., R. Huber-Mörk, M. Nölle, and M. Kampel. “On Ancient Coin Classification.” *Proceedings of the International Symposium on Virtual Reality, Archaeology and Cultural Heritage* (VAST’07) (2007): 55–62.

Zambanini, S., and M. Kampel. “Robust Automatic Segmentation of Ancient Coins.” *Proceedings of the 4th International Conference on Computer Vision Theory and Applications* 2 (VISAPP’09) (2009): 273–276.