The 9th International Symposium on Virtual Reality, Archaeology and Cultural Heritage
VAST (2008)
M. Ashley, S. Hermon, A. Proenca, and K. Rodriguez-Echavarria (Editors)

On the Use of Computer Vision for Numismatic Research

S. Zambanini[1], M.Kampel[1] and M. Schlapke[2]

[1]Pattern Recognition and Image Processing Group, Vienna University of Technology, Favoritenstr. 9-183/2, A-1040 Austria
[2]Thüringisches Landesamt für Denkmalpflege und Archäologie, Weimar, Germany

Abstract

This paper gives a survey about numismatic research fields where computer vision methods have the potential to improve the effectiveness and impact of research work. In total, five different parts of numismatic research areas are identified: the classification of coins into given types, the identification of concrete coin specimens, the identification of coins struck by the same die, the reassembling of broken coin fragments and the segmentation and surveying of coins. For each application a problem description is given and the use of computer vision methods is discussed in detail. Additionally, for the image-based classification, identification and segmentation of coins results achieved so far are presented. Since computer vision methods are applied on photographs of coins, their acquisition (both in 2D and 3D) is covered as well.

Categories and Subject Descriptors (according to ACM CCS): I.4.9 [Image Processing and Computer Vision]: Applications

1. Introduction

Numismatics deals with various historical aspects of the phenomenon Money. Computer vision explores the theory and technology to obtain and interpret information from images. Nowadays, numismatics is at a point where it can benefit greatly from the application of computer vision methods, and in turn provides a large number of new, challenging and interesting conceptual problems and data for computer vision.

In the past a number of computer vision applications have been developed for the recognition of present day coins (e.g. [NPR*03] [RRB06] [vdMP06a]). However, tests performed on image collections both of ancient and modern coins show that algorithms performing well on present day coins do not necessarily meet the requirements for classification of ancient ones [ZKZ07a]. As a first attempt to use computer vision for numismatic needs, the EU funded COINS project [ZKZ07b] started on February 2007 and comprises the development of technologies for the image-based identification and classification of ancient coins.

This paper identifies parts of numismatic research where computer vision can provide a significant contribution. Besides coin identification and classification, which are part of the COINS project and are discussed in Section 3.1 and 3.2, computer vision is believed to increase the effectiveness of coin analysis regarding die identification (Section 3.3), the assembly of coin fragments (Section 3.4) and the measurement of coin size (Section 3.5). Since computer vision methods are applied on photographs of coins, their acquisition (both in 2D and 3D) is initially covered in Section 2.

2. Image Capture

The data on which computer vision methods are applied are images, and the way that they were captured is crucial for any image-based analysis. The performance that can be achieved by computer vision is highly related to the quality of the respective images. For example, a method for the automatic classification of ancient coins has to extract details out of the image which could become lost if an inadequate illumination or a too low resolution is chosen.

In general, coins can be captured in two and in three dimensions. The advantage of 3D coin data is that it allows a more detailed and reliable analysis due to an exact description of the coins' surface. However, 3D acquisitions are more laborious and expensive and, to our knowledge, 3D databases of coins do not exist at the moment. Therefore, and because of the fact that analyses have to be possible on existing inventories of 2D coin images as well, from our point of view computer vision for numismatic research has to focus initially on 2D images.

2.1. 2D

A detailed treatment of coin photography from a numismatists' point of view is given in [Hob82]. A guide for numismatic photography using digital cameras was also recently published [Goo08]. A guide explaining the basics and needs of coin image acquisition for an automatic image analysis is given in [ZKed].

A fixed setup using a copy stand is mandatory to rapidly produce images of adequate quality. This provides a constant distance and parallelism between the coin and the camera's image plane.

A major issue of coin photography is illumination. To capture the fine reliefs of the highly reflective coin surface the appearance of shadows and highlights is unavoidable. Therefore, for the illumination setup it has to be compromised between accenting the surface structure and preventing data loss from shadows and highlights. Of especial importance for an automatic image-based analysis is avoidance of shadows at the coin border since here a shadow cast impedes the segmentation of the coin, a necessary prerequisite for any further processing. In the literature the use of one or more light sources placed near the camera is suggested. This yields to slightly obliquely angled illumination directions which help to capture the surface structure of the coin. To mitigate the shadows diffusion filters or reflectors can be used.

Another important issue for the digital capturing of coin data is the actual image resolution used. Here the *Shannon Sampling Theorem* [Sha49], known from signal processing theory, has to be adopted for image sampling: the sampling interval has to be in size such that it is at least half of the smallest interesting detail in the image (see [ZKed] for further explanations and an example).

2.2. 3D

Besides automated coin recognition on 2D images, 3D acquisition has to be investigated as well because the shapes of ancient coins might not be as regular or flat as their present day counterparts or the surface of the coin is *coarse* enough to allow 3D measurements by a 3D scanning device. This would lead to new perspectives of studying ancient coins as well as new strategies for representing them.

There have not been many attempts to develop a reliable method for the 3D documentation of coins. Difficulties are caused by the reflectance of the metallic surface which makes it difficult for light projection or the insufficient accuracy of state-of-the-art scanning devices. Recent advances in rangefinder technology, together with algorithms for combining and processing 3D data, allow us to propose new strategies for numismatics. Hossfeld et. al [HCEA07] present the so called Three-Color Selective Stereo Gradient method: the objective is to classify EURO coins based on a comparison of specially measured and processed 3D surface information with characteristic topographical data stored in a database. They report that analyzing only the measured characteristic 3D surface topography leads to a distinction between 2-Euro, 1-Euro and 50-Cent coins and, within each sort, to a classification in 13 reference classes belonging to a coin's country of origin.

The acquisition method proposed for estimating the 3D shape of a coin is shape from structured light, which is based on active triangulation. A very simple technique to achieve depth information with the help of structured light is to scan a scene with a laser plane and to detect the location of the reflected stripe. The depth information can be computed out of the distortion along the detected profile. For 3D coin acquisition synchronous acquisition of 3D data and texture/color information is needed. This allows the subsequent combination of 2D and 3D image analysis. Furthermore texture mapping of high quality 2D images leads to a realistic representation of a coin and fulfills numismatists' needs.

Realistic representation of coins can also be achieved by photometric stereo or Polynomial Texture Mapping (PTM), as proposed by Mudge et al. [MVSL05]. They used a setup able to photograph a coin 24 times with different illumination directions to obtain the according PTMs. With interactive viewing software the assembled PTMs are used to obtain a photo-realistic visualization of the coin. PTM imaging can also be combined with shape from structured light to acquire more accurate 3D coin models.

Generally, portability of the equipment is essential since coin acquisition has to take place at the museum where the coins are kept. A 3D scanning device developed for applications in arts and cultural heritage is the so called BREUCKMAN 3D Scanner, a 3D scanner scanner [BHKK97] based on fringe projection techniques. It offers the features mentioned and is used for 3D data acquisition of coins.

3. Selected Applications

In this Section the five numismatic research fields outlined in the introduction are discussed. Each problem is described from a numismatists' point of view and proper technical solutions derived from computer visions are presented and argued.

3.1. Coin Classification

Problem Description: A main but not simple task of numismatic research is to *classify* coins (i.e. determine the coin type). There are millions of coin types from all over the world and the times since 700 BC. Classification means to find out the correct reference number(s) of the coin in reference numismatic literature (for instance RIC [HM94] for ancient coins or Krause-Mishler [KMB04] for modern coins) but there is no definition of a "unique" reference literature. Often there are more than one reference book and year by year new relevant books where published.

The workflow of a manual classification was described by Zaharieva et al. [ZKZ07a]. First of all a numismatist has to

Figure 1: *Obverse side of different coin specimens from the Roman period. Coins in the same row denote coins of the same class.*

find the correct time slot and origin of the concrete coin before he can use the right reference literature in the library. Then he must find out a common view of the coin and separate common features of the coin (the features of the coin types) from individual features of the concrete coin (for instance varieties in mint marks). There are also differences in the "depth" of the reference books. Some describe only the main types, other lists also subtypes (or varieties).

Modern technologies allow new ways for coin classification. Database-based search engines help to find out the coin type by partial inscription search. There are also databases using descriptions of image patterns, e.g. "figure male standing right with spear", for searching (see, for instance, the ISEGRIM project [ISE]). This helps in the process of classification but nevertheless numismatic knowledge is essential.

Contribution of Computer Vision: An automatic classification system for coins based on images could provide a significant speed-up of numismatic research. Such a system has to find general image features of a coin class which discern it from other classes. On the other side it has to ignore unique features of specimens, like border shape and use-wear traces. For ancient coins the task is challenging since specimens within a single class show large degree of diversity and on the other side diversity between coin classes can be low. This is exemplified in Figure 1 where the upper and lower row show coin specimens of the same class, respectively.

Although methods useful for ancient coin classification can be manifold depending on the era and origin of the coin, two techniques show high potential for ancient coin classification: local image features [KZ08] and the coin legend provided by optical character recognition (OCR).

Local image features provide a mathematical description of the image pattern in a window surrounding specific interest points and offer thereby a set of distinctive features for an image. By matching corresponding features among coin image pairs similarities can be detected and used for classification. The features have to described invariant in terms of translation, rotation and scale transformations. Key issue in dealing with local points is that there may be large numbers of keypoints in each image which makes image matching more complicated. Typically, interest points are detected at multiple scales and are expected to capture essential features. If a given coin class is represented by more than one image sample or a model, essential features which are discriminative for the class can be identified through the matching process. An important advantage of using local features is that they may be used to recognize an object despite significant clutter and occlusion. To summarize, the detection, description and matching of local descriptors is a powerful scheme which can be used to identify class-specific features and ignore the coin-specific ones (resulting from striking variations and abrasion).

Widely used descriptors are, for instance, the Scale Invariant Feature Transform (SIFT) [Low04] and Speeded Up Robust Features (SURF) [BTG06].

Optical character recognition (OCR) is defined as the translation of written characters contained in images into an internal computer-usable representation. It has been extensively studied over the last decades [MNY99]. In general, there are five major stages in the OCR problem: (1) preprocessing, (2) segmentation, (3) representation, (4) training and recognition and (5) post-processing. It must be noticed that a complete reliable recognition of the coin legends can not be assumed in many images due to abrasions on the coin and low contrast of the coin legend. However, even single characters or legend fragments can limit the number of possible reference coins.

By applying OCR to the classification problem, the overall process can be pointed in another direction where no matching against pre-indexed coin specimens is needed. For instance, specific models and/or a decision tree can be created to exploit the well-known characterization for a given group of coins.

Recent research approaches for coin classification focused mainly on the classification of present day ones [NPR*03] [RRB06] [vdMP06a]. However, the differences between present day and ancient coins exposed to be too large to effectively apply such methods on ancient coins [vdMP06b]. Due to abrasions over the centuries and the non-industrial manufacturing of ancient coins, they naturally exhibit a larger variation in their appearance.

First promising results on the classification of ancient coins were presented in context of the COINS project in [ZHMNK07]. Here the SIFT local descriptor was used to classify coin images against a dataset of 350 images of three different coin types with an average classification rate of 84.24 %. The reported results show high potential. However, they have to be qualified since the dataset used was a small one. This is due to the fact that museums in general are not interested in collecting multiple specimens of the same coin type.

Despite of being a challenging problem for computer vision, work on image-based classification of ancient coins can also provide directions for the definition of a coin's class digital signature, considered as a set of digital parameters characterizing them in a unique way. Such a machine-readable fingerprint would help to unify reference databases as well.

3.2. Coin Identification

Problem Description: Often for numismatists there is the problem to identify a given coin, i.e. the question "is the coin in an old auction catalogue the same coin which I have in my collection?". Another scenario is to identify stolen coins to give it back to the owner.
Identical coins are of course from the same type and they have the same weight. To check this, if possible, is the first step, then a numismatist has to compare the shape of the "two" coins. Afterwards, a comparison of the both sides' pictures has to be made. A main feature to identify same coins is to search for individual structures, for instance scratches (see Figure 2) or marks on the coin. However, a reliable coin identification is difficult because an image is compared to a real object. The quality of the images can vary, thus often details are not visible in the images.

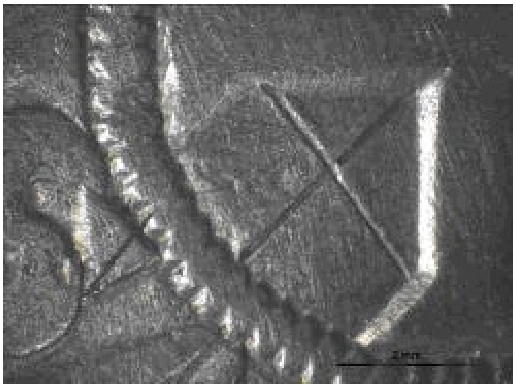

Figure 2: *Scratches on a coin that can be used to identify it.*

Contribution of Computer Vision: In an image-based identification, two images of coins are compared to decide if the show the same coin specimen. In contrast to coin classification, the variable appearance of ancient coins facilitates an automatic image-based identification process (note that this is contrary to present day coins which can be more easily be classified than identified due to the lack of use-wear signs). In general, information to be extracted from 2D images for identification can be the shape of the coin border as well as the appearance of the die. From a numismatic point of view, the shape of the coin border is a very discriminative feature and therefore provides a first clue in the process of coin identification. The comparison of objects described by their shape is referred to as shape matching [Vel01].

Similar to coin classification, die information can be captured using local descriptors. For illustration, an example of matching interest points between two images showing the same coin using the SIFT descriptor is shown in Figure 3.

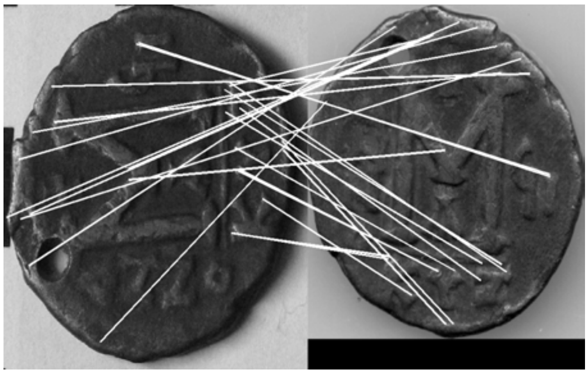

Figure 3: *Example matches by SIFT descriptor matching on two images showing the same coin.*

As a conclusion, the best way is to combine shape and die information for the identification process. This identification scheme is illustrated in Figure 4. The first step is to separate the coin region from the background, commonly termed image segmentation. The segmented coin border serves as input for the shape matching to preselect a small subset of possible coin matches from the database. After the local descriptors have been extracted from the segmented input image, they have to be only matched against the preselected candidates. Ideally, the output of identification is an ordered list of matchings with a similarity grade attached automatically. Similarity measurement can be derived, for instance, from the number of matched interest points.
In the COINS project this workflow was used in the final image recognition tool to match coin images against a

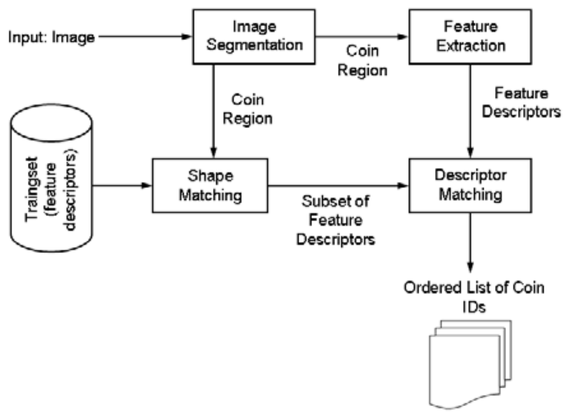

Figure 4: *Identification workflow for ancient coins.*

pre-created database. For shape matching a modified version of Fourier descriptors [ZL02] was developed and SIFT and SURF were taken for the final matching. The tool was tested on a set of 240 coins, each one represented by 5 images per side acquired using a flat-bed scanner and a fixed camera at the *Fitzwilliam Museum, Cambridge, UK*. The average identification rate achieved was about 95 %. Keeping in mind that all images are from the same coin class (which naturally handicaps the discrimination of different coin specimens), this result shows that an automatic identification of ancient coins is a feasible task for computer vision.

3.3. Die Identification

Problem Description: "Between" classification and identification there is die identification [Est90]. Ancient coins were made by striking (see Figure 5 for an illustration). For striking two dies (upper and lower) were used. In the Middle Ages about 10.000 coins were struck by one hand-made die-couple, but often upper and lower dies were changed in the mint. Often the die-cutter made dies with individual attributes, for instance small differences in the letters of the inscription (see Figure 6). Numismatists try to determine if coins were struck by the same dies (separately for both sides of the coin). Generally, this process is very difficult since all image features have to be compared. Older coins are often in bad conditions and partly damaged. There are a lot of technical aspects of striking which make the comparison to hand-made coins demanding, for instance: the position of the images of flan varies, double strikings (the flan was struck twice) or damaged dies (so-called die breaks). Another problem is the so-called overstriking: this occurs when existing coins were used as flans instead of new plain flans in the mint. As a result, structures (parts of the images and the legends) of the "old" coins can be found on the "new" ones. See [How05] for a more detailed overview about the difficulties of die identification.

Die-identification is a main research part of coin hoards processing. In hoards often a lot of coins are from the same type and the same date. The scientific potential of die studies is very high: groups of coins which were struck and used in the same time and in the same mint (or part of the mint) can be identified. Of great interest are combinations of different upper and lower dies because they show the developing of the minting sequence of a concrete coin type in the mint. In this way a diagram of existing die links like the one shown in Figure 7 can be created.

By knowing the number of different dies a numismatist can estimate the volume of minted coins. These numbers are very valuable to reconstruct the economical structures of ancient countries and states because often there are no other historical sources for these questions.

Contribution of Computer Vision: From a technical point of view, die identification can be seen as a classification problem with a finer subdivision of classes (every coin class

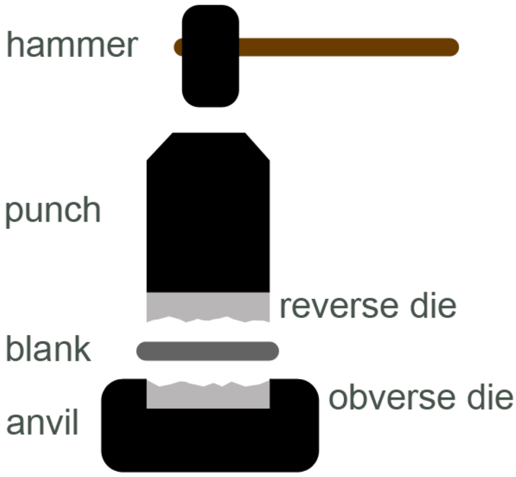

Figure 5: *The striking of an ancient coin.*

Figure 6: *Variations of the letter "H" made by the die-cutter.*

consists of several different dies used for striking). However, the general process may differ if no specimens for different dies are identified beforehand (which is usually the case for hoard finds). Problems arise both from distortions at time of striking (see above) as well as subsequent distortions (holes, cuts, surface dis-colorization and wear). Anyhow, despite of these problems Howgego emphasizes the possibility to use computer vision techniques for die studies [How05].

Generally, an automatic die analysis has to compare every coin with each other and compute some measurement of "die similarity" which can then be used to cluster the coin series into different die groups. The most promising way for comparison would be to use techniques from image registration [ZF03]. Image registration is the process of geometrically aligning two images showing the same or similar objects. In the image registration process one image is kept unchanged and the other one is transformed to be aligned with

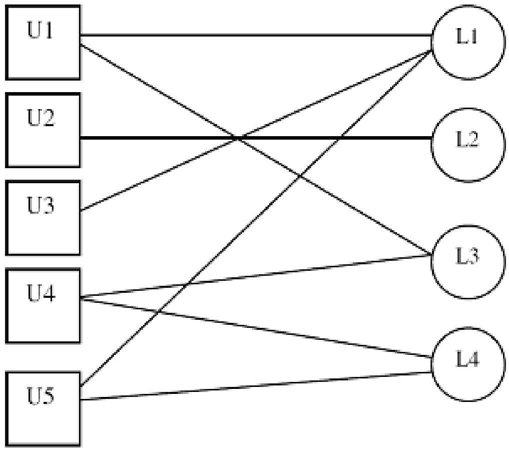

Figure 7: *A diagram showing existing links between 5 upper and 4 lower dies.*

the reference image. One major concept are feature-based registration methods. They identify corresponding control points in both images and use this points to estimate a transformation from one image to the other.
This basic principle bears high potential for an image-based comparison of coins for die studies. For instance, control points can be detected and matched using local descriptors, similar to coin classification and identification. A special constraint here has to be that the spatial arrangement of matched control points have to be nearly the same to decide that two coins are struck from the same die. In other words, matched control points have to be aligned after transformation. Since coins are usually photographed from an orthogonal view, transformation between images is a simple 2D scaling, translation and rotation.
As a side note, this concept can also be used semi-automatically, e.g. control points can be placed or refined manually if the automatic method fails. The automatic registration can also be used to overlay one image with another to visualize the differences.
As a conclusion, an image-based die study would yield a twofold benefit for the numismatist. Firstly, it could be used to identify groups of coins struck from the same die in a series of coin images. And secondly, automated die studies could provide a control and verification of those solely based on human judgement. In the long run, it could help to standardize the general procedure and make results more reproducible. Naturally, the accuracy and significance of automated die identification hardly depends on the data, i.e. the constitution of the coins as well as the quality of acquired images. Especially the automatic grouping is only feasible if the various coin dies show a certain amount of divergence.

3.4. Assembly of Coin Fragments

Problem Description: In the middle ages Hacksilver emerged in northern Europe around the northern sea and the Baltic sea. The vikings and slaves often used silver-fragments of coins, jewellery or ingots as money. The value of this Hacksilver was defined by the weight of the silver and not by counting the coins.
For this reason in hoards a high amount of small and very small coin fragments can occur, often of Arabic coins. To identify the coins numismatists have to identify the fragments itself or to puzzle the fragments to greater coin parts. It is very difficult and time-consuming to find out if and which fragments belong to a concrete coin or to the same coin type.
There also exist finds where some coins are broken. A set of such broken fragments is shown in Figure 8. To find out which fragment belongs to which coin all fragments and all incomplete coins have to be compared manually.

Figure 8: *Broken coin fragments.*

Contribution of Computer Vision: Computer-aided reassembly of objects from 2D or 3D fragments is subject of several disciplines like archaeology [KS04], art restoration, and medicine [BS97]. The problem is related to shape matching [Vel01] since the goal is to find corresponding contour parts along the fragments. However, if a large set of fragments has to be reassembled exhaustive matching is not computationally feasible and more sophisticated strategies have to be found. A suitable method has been proposed by Leitão and Stolfi in [dGLS02]. They present a multi-scale approach using dynamic programming to automatically reassemble thousands of fragments. To apply such a method to reassemble broken coin fragments stands to reason. Evidently, besides the 2D shape information, motives shown on the fragments can be included in the process as well [PSM03]

3.5. Coin Segmentation and Surveying

Problem Description: Numismatists describe coins not only by the coin type. A significant part of the coin description are the technical values of the concrete coin. Usually, the weight, the diameter, the height and the die-orientation are described. However, to determine the diameter and area of the coin, it is difficult and inaccurate to directly measure the coin with a calliper. A more accurate way would be to use image-based measure tools.
Another issue is that for the publication of coin images they have to be prepared for the layout process. Thus, there is a need for an automatic coin segmentation to rapidly create coin tables with white background for publishing. Furthermore, the scale of the coins has to correspond to their real world size to print the coins for instance in a 1:1 scale.
Figure 9 shows a a coin image where a ruler was placed next to the coin. Please note that the ruler can be used to determine the actual size and diameter of the coin as well as to transform the image to the correct scale.

Figure 9: *A coin with a ruler placed next to it.*

Contribution of Computer Vision: Image Segmentation refers to the process of dividing an image into parts that have a strong correlation with objects or areas of the real world contained in the image [PP93]. In our context of image-based coin recognition an image segmentation algorithm has to robustly detect the image region showing the coin. Generally, segmentation of the coin region usually has to be done prior to an automatic analysis of a coin. Recently, a segmentation algorithm especially designed for ancient coins was proposed in [ZK08]. It was tested on a set of 92 images representing a wide variety of different coin images (e.g. resolution, illumination conditions, compression artifacts). The method proofed to be robust with a median mutual overlap to hand-drawn ground-truth data of 99.3 %. The conclusion of the experiments is that a proper segmentation can be achieved when no shadows occur at the coin border.
To use the region detected from image segmentation for a surveying of the coin the scale of image has to be determined. This can be achieved by placing a ruler next the to coin. For an automatic surveying the scale interval between ruler marks has to be estimated, e.g. by detecting parallel lines [ZLD05] and measuring the distance between them. Further methods to determine the scale are, for instance, line detection via the Hough Transform [Hou62] or 2D Fourier analysis [Bra00].

4. Conclusion

We have presented five different parts of numismatic work where computer vision methods can be usefully applied. The image-based classification and identification was addressed in the COINS project, and especially for coin identification convincing results have been achieved. Classification results are promising as well but there is great place for further research, e.g. by including OCR methods in the classification process.
From our point of view, the most significant contribution can be made towards die identification since this is an important research question and no standard technique or way for verification exists at the moment. The numismatic community would profit from an image-based die study by a greater impact of research work and a more efficient analysis of coins. However, also computer vision community could benefit through the development of new innovative algorithms on the basis of challenging conceptual problems and data.
The reassembling of broken coin fragments is also an interesting application from computer vision point of view since an automatic method has to deal with missing fragments. Segmentation of coins has already been covered and shows high accuracy when the images exhibit a certain degree of quality (primarily, no shadow casts at the border). The automatic measurement by means of a ruler shown in the image is considered to be less challenging, although it has not been addressed so far.

Acknowledgement

This work was partly supported by the European Union under grant FP6-SSP5-044450.

References

[BHKK97] BREUCKMANN B., HALDBAUER F., KLAAS E., KUBE M.: Topogrammetric 3d-metrology. In *Proc. of the 3rd International Workshop on Automatic Processing of Fringe Patterns* (1997).

[Bra00] BRACEWELL R. N.: *The Fourier Transform and Its Applications*. McGraw-Hill, 2000.

[BS97] BAREQUET G., SHARIR M.: Partial surface and volume matching in three dimensions. *IEEE Trans. Pattern Anal. Mach. Intell. 19*, 9 (1997), 929–948.

[BTG06] BAY H., TUYTELAARS T., GOOL L. J. V.: SURF: Speeded up robust features. In *Proc. of European Conference on Computer Vision* (2006), pp. I: 404–417.

[dGLS02] DA GAMA LEITÃO H. C., STOLFI J.: A multiscale method for the reassembly of two-dimensional fragmented objects. *IEEE Trans. Pattern Anal. Mach. Intell 24*, 9 (2002), 1239–1251.

[Est90] ESTY W.: The theory of linkage. *The Numismatic Chronicle 150* (1990), 205–221.

[Goo08] GOODMAN M.: *Numismatic Photography*. Zyrus Press, 2008.

[HCEA07] HOSSFELD M., CHU W., EICH M., ADAMECK M.: Fast 3D-vision system to classify metallic coins by their embossed topography. *Electronic Letters on Computer Vision and Image Analysis 5*, 4 (2007), 47–63.

[HM94] H. MATTINGLY E. A. S. E. A.: *Roman Imperial Coinage, vol. I–X*. 1923-1994.

[Hob82] HOBERMAN G.: *The Art of Coins and their Photography*. Lund Humphries, 1982.

[Hou62] HOUGH P. V. C.: *Methods and means for recognizing complex patterns*. US Patent 3,069,654, 1962.

[How05] HOWGEGO C. J.: The potential for image analysis in numismatics. In *Images and Artefacts of the Ancient World* (2005), pp. 109–113.

[ISE] The isegrim project. http://hist3-10.phil-fak.uni-duesseldorf.de/isegrim/anleitung_d.html, last visited July 26th, 2008.

[KMB04] KRAUSE C. L., MISHLER C., BRUCE C. R.: *Standard Catalog of World Coins: 1901 - Present*. Krause Publications, 2004.

[KS04] KAMPEL M., SABLATNIG R.: On 3D mosaicing of rotationally symmetric ceramic fragments. In *Proc. of 17th International Conference on Pattern Recognition, Cambridge, UK* (2004), Kittler J., Petrou M., Nixon M., (Eds.), vol. 2, IEEE Computer Society, pp. 265–268.

[KZ08] KAMPEL M., ZAHARIEVA M.: Recognizing ancient coins based on local features. In *Advances in Visual Computing* (December 2008), Lecture Notes in Computer Science, Springer Berlin / Heidelberg. in press.

[Low04] LOWE D. G.: Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision 60*, 2 (2004), 91–110.

[MNY99] MORI S., NISHIDA H., YAMADA H.: *Optical character recognition*. Nueva York, EUA : Wiley, 1999.

[MVSL05] MUDGE M., VOUTAZ J.-P., SCHROER C., LUM M.: Reflection transformation imaging and virtual representations of coins from the hospice of the grand st. bernard. In *Proc. of VAST'05* (2005), pp. 29–39.

[NPR*03] NÖLLE M., PENZ H., RUBIK M., MAYER K. J., HOLLÄNDER I., GRANEC R.: Dagobert – a new coin recognition and sorting system. In *Proc. of DICTA'03* (2003), pp. 329–338.

[PP93] PAL N., PAL S.: A review on image segmentation techniques. *Pattern Recognition 26* (1993), 1277–1294.

[PSM03] PAL A., SHANMUGASUNDARAM K., MEMON N.: Automated reassembly of fragmented images. In *Proc. of the 2003 International Conference on Multimedia and Expo* (2003), pp. 625–628.

[RRB06] REISERT M., RONNEBERGER O., BURKHARDT H.: An efficient gradient based registration technique for coin recognition. In *Proc. of the Muscle CIS Coin Competition* (2006), pp. 19–31.

[Sha49] SHANNON C. E.: Communication in the presence of noise. *Proc. of the IRE 37* (1949), 10–21.

[vdMP06a] VAN DER MAATEN L. J., POON P.: Coin-o-matic: A fast system for reliable coin classification. In *Proc. of the Muscle CIS Coin Competition* (2006), pp. 07–18.

[vdMP06b] VAN DER MAATEN L. J., POSTMA E. O.: Towards automatic coin classification. In *Proc. of the EVA-Vienna 2006, Vienna, Austria* (2006), pp. 19–26.

[Vel01] VELTKAMP R. C.: Shape matching: similarity measures and algorithms. In *Proc. of the International Conference on Shape Modeling and Applications* (2001), pp. 188–199.

[ZF03] ZITOVA B., FLUSSER J.: Image registration methods: a survey. *Image and Vision Computing 21*, 11 (2003), 977–1000.

[ZHMNK07] ZAHARIEVA M., HUBER-MÖRK R., NÖLLE M., KAMPEL M.: On ancient coin classification. In *Proc. of VAST'07* (2007), pp. 55–62.

[ZK08] ZAMBANINI S., KAMPEL M.: Segmentation of ancient coins based on local entropy and gray value range. In *Proc. of the 13th Computer Vision Winter Workshop* (2008), pp. 9–16.

[ZKed] ZAMBANINI S., KAMPEL M.: Coin data acquisition for image recognition. In *Proc. of 36th Annual Conference on Computer Applications and Quantitative Methods in Archaeology* (to be published).

[ZKZ07a] ZAHARIEVA M., KAMPEL M., ZAMBANINI S.: Image based recognition of ancient coins. In *Proc. of the 12th International Conference on Computer Analysis of Images and Patterns* (2007), pp. 547–554.

[ZKZ07b] ZAHARIEVA M., KAMPEL M., ZAMBANINI S.: Image based recognition of coins – an overview of the coins project. In *Proc. of the 31st AAPR/OAGM Workshop* (2007), pp. 57–64.

[ZL02] ZHANG D. S., LU G. J.: A comparative study of curvature scale space and fourier descriptors for shape-based image retrieval. *Journal of Visual Communication and Image Representation 14*, 1 (2002), 39–57.

[ZLD05] ZHENG Y., LI H., DOERMANN D.: A parallel-line detection algorithm based on hmm decoding. *IEEE Trans. Pattern Anal. Mach. Intell. 27*, 5 (2005), 777–792.