From Manual to Automated Optical Recognition of Ancient Coins

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Abstract. Illegal trade and theft of coins appears to be a major part of the illegal antiques market. Image based recognition of coins could substantially contribute to fight against it. Central component in the permanent identification and traceability of coins is the underlying classification and identification technology. However, currently available algorithms focus basically on the recognition of modern coins. To date, no optical recognition system for ancient coins has been researched successfully. In this paper, we give an overview over the challenges faced by optical recognition algorithms. Furthermore, we show that image based recognition can assist the manual process of coin classification and identification by restricting the range of possible coins of interest.

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. However, these methods only prevent the illicit trade of ancient coins in a rather partial way. To date, no automatic coin recognition system for ancient coins has been researched – and thus – applied successfully. From optical coin recognition point of view we distinguish between two approaches: coin identification and coin classification. A coin classification process assigns a coin to a predefined category or type, whereas a coin identification process assigns a unique identifier to a specific coin.

Recent research approaches for coin classification algorithms focus mainly on the recognition of modern coins. Applied pattern recognition algorithms are manifold ranging from neural networks [1][2] to eigenspaces [3], decision trees [4], edge detection and gradient directions [5][6], and contour and texture features [7]. Huber et al. present in [3] a multistage classifier based on eigenspaces that is able to discriminate between hundreds of coin classes. Due to the controlled setup of the system presented coin detection becomes a trivial task. They report correct classification for 92.23% of all 11,949 coins in a sample set. In [7] Maaten et al. present a coin classification system based on edge-based statistical features. The coin

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classification method proposed by Reisert et al. [6] is based on gradient information. Similar to the work of Nölle et al. [5] coins are classified by registering and comparing the coin with a pre-selected subset of all reference coins (for example coins from the MUSCLE CIS 06 database[1] see Figure 1).

Fig. 1. Example images of modern coins

Tests performed on image collections both of medieval and modern coins show that algorithms performing well on modern coins do not necessarily meet the requirements for classification of medieval ones [8]. In this paper we present challenges faced by optical recognition techniques, especially we differentiate between classification and identification of coins. Section 2 describes the process of coin classification from both a numismatic and an image processing point of view. Section 3 continues with a description of coin identification again from a numismatic and image processing point of view. Results on experiments performed on both classification and identification of ancient coins are presented in Section 4. We conclude and give an outlook for future research in Section 5.

2 Classification Workflow

2.1 Manual Classification

Numismatics deals with various aspects of the phenomenon Money[2]. That can be a historical approach, the systematic research of the minting plan, the distribution of coin finds or economic background. Fundamental work is the classification of coins according to standard reference books since they provide additional information such as accurate dating, political background or minting places.

The process of manual classification can be very short, nonetheless a number of steps are to be taken. To assign a coin to the correct time period or to determine which side is the obverse and which the reverse usually does not take more time than to grab the object but involves a great deal of knowledge. Reading the legends, if there are any, and identifying the pictures correctly is depending on the experience of the

[1] MUSCLE CIS Benchmark Competition 2006, http://muscle.prip.tuwien.ac.at (last visited: 2007-06-15)

[2] The Institute for Numismatics and Monetary History of the University of Vienna is the only one of its kind worldwide that is dedicated only to the Historic Studies of Money.

numismatist and his or her fields of specialization. The classification process is accomplished when the coin is identified according to a standard reference book so that by its reference number a full description or even a photograph of a similar piece is available to everyone. Usually classification also includes documentation of the object, covering taking pictures, making a description and taking certain measurements.

The classification process is like putting the objects through various sieves, from coarse to fine [9, 10]. Classifying one coin as Roman-Imperial and another one as Medieval is still a result. The numismatic requirement is basically to give the correct number in a reference book. For every period or every fraction of the monetary history there are different books, some covering several centuries[3] and others only a few years of a single minting place. A reference book does not cite single specimens of coins but coin types, which is a combination of picture and legend [10]. While some older books list all coin types known to the author(s) in chronological order sorted by metal or even in the alphabetical order of their reverse legends, other books present the coins by mint[4]. During the Roman period groups of coin types can often be identified as being minted in the same production issue. For example, when Marcus Aurelius (161-180) won his first victory in the Marcomannic wars, a distinct group of coins was issued with a limited number of reverse types but covering all denominations (coin values) from gold to brass-metal. However, in the coin production of the Celts, no such intricate organization and administration ever existed so that a Celtic ”issue” needs to be defined differently. Thus, not only the arrangement of coin types differs in books but they also display the state of research on a certain subject. Consequently, the quality of information gained varies considerably.

The classification process is also depending on both the time period and the reference literature itself. In any case, one has to gain as much information as possible even before consulting any books. *Hard* information is metal, weight, die-axe, and diameter. The reading of the legends and the interpretation of the pictures are to be considered as *soft* data. Additional information on the find spot or archaeological contexts is of no relevance to the classification process. Providing the original specimens is still the usual way of classifying coins. A good picture can show both legends and pictures clearly, and can also give away the metal and size. When information like weight and die-axe are provided, it is possible to work only on pictures (given the coin itself is in a good condition). When a specimen is badly worn, it is necessary to keep changing the angle of light to be able to retrieve a clearer view.

The actual process of classification is not to describe a coin but to figure out what it is or what is depicted. The job is only half done when reading the legend. Titles are abbreviated but iterated so that COS VI means Consul for the 6th time and the 6th ascension of Consulship narrows down the dating of a coin to a very short time span. A female figure with wings, for example, would be the Roman goddess Victory or the Greek Nike. Her favorite attributes are a palm-leaf or a crescent. Sometimes she is

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[3] E.g. the series of "Roman Imperial Coinage" (RIC, London 1923–1994) covers the time from 31 BC to AD 498 in ten volumes. Although there are literally thousand of more detailed studies on this period it is still considered as a standard reference.

[4] The series "Moneta Imperii Romani" (MIR, Vienna 1984–2007) is to replace the often alphabetical layout of the RIC by the actual minting rhythm.

without attributes accompanying or crowning the emperor. This concept makes it often possible to recognize certain coin types from only few visible features. Usually, an experienced numismatist can also deal with coins that are corroded or badly worn[5] as it can be often observed in coin-hoards.

The single steps of the classification process do not always follow the same patterns. If the legends are readable and apt to narrow down the number of possible coin types, one will possibly not have to bother with the pictures to retrieve a proper reference number. Although databases are commonly used nowadays, no big systematic approach has been successfully launched so far that has both a standardized description scheme and a complete basis of numismatic material. Even though computers make it much easier to provide and obtain pictures of coins, the classification process did not change basically in the last centuries – its speed and accuracy is depending on both knowledge and experience of the numismatist in charge.

2.2 Automated Classification

From image processing point of view coin classification process passes well-defined stages as shown in Figure 2.

In the *segmentation* stage an image is partitioned into its parts or objects. The segmentation process is one of the most difficult tasks in the image processing. A robust segmentation is essential for imaging problems that require objects to be classified or identified individually. A weak segmentation algorithm causes the eventual failure of the whole classification process. In general, image segmentation algorithms follow three approaches. The first group partition an image based on abrupt changes in the intensity (e.g. edges in an image [11]). The second category identifies the image regions that are similar to a set of predefined criteria (e.g. threshold, color information [12, 13]). The third group of segmentation techniques is based on finding regions directly (e.g. region splitting and merging [14]). In the next step – *object detection* – the perceptually salient regions or objects are identified. In general, this process is based on predefined criteria ranging from simple measurements such as area dimensions or circularity to complex shape descriptors [15]. As output single or multiple objects that fit the criteria are identified for further processing. The goal of the *feature extraction* stage is to find those features that describe the object in a robust and compact way and provide optimal discriminative information.

Choosing an appropriate set of features is critical for the classification process. Using a large number of features may better represent the object. However, the risk of overfitting arises since collecting a large amount of information can overfit the available training data and will not generalize well enough to it. On the other side, the selection of too few features decreases the separability of the object description. As a result, an object can be assigned to multiple classes. Ideally, for classification purposes, only those features are considered that are class-specific, i.e. with high separability and globalization power. Finally, in the *classification* step the extracted features are compared with the available training data. Current classification

[5] In the Roman Empire a single coin could circulate for more than 200 years.

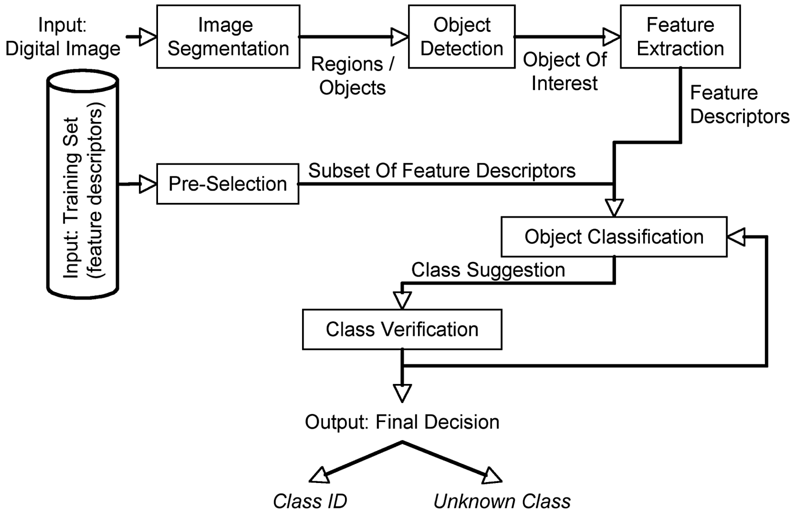

Fig. 2. Coin classification process

algorithms are manifold ranging from simple similarity measurements (e.g. Euclidean or Mahalanobis distances, etc.) to various statistical classifiers (Bayes, k-Nearest Neighbour, etc.) [16], and approaches based on neural networks [17]. As result, a class membership is identified. Eventually, an additional *verification* step can assure the final decision of the classification process.

Current research approaches for coin classification algorithms possess mainly two limitations. On the one hand, the input digital image is well defined – there is always only one coin pictured and the image is taken under very controlled conditions (such as background, illumination, etc.). On the other hand, current coin classification algorithms focus mainly on the recognition of modern coins. Those assumptions facilitate the classification process substantially. In this case of controlled conditions and the well-known circular shape of modern coins, the process of coin detection and segmentation becomes an easier task. The almost arbitrary shape of an ancient coin narrows the amount of appropriate segmentation algorithms. A case in point is the segmentation approach based on the Generalized Hough Transform as proposed by Reisert et al.[6]. By definition, this method is only applicable for completely round coins. In contrast, edge-based segmentation algorithms in a combination with morphological operations can work even in the case of an unknown coin shape [18]. However, varying conditions of image acquisition – e.g. illumination changes, multiple objects, multiple coins, varying background, etc. – remain the most challenging part of the segmentation process.

The differences between ancient and modern coins do not only influence the segmentation process but also the selection of appropriate feature set. Ancient coins differ strongly from modern ones. Crucial influence have both the nature of the ancient coins – less details, no rotational symmetry – and the poor conditions due to wear or fouling. Fundamental differences between ancient and modern coins originate from the manufacturing process. Ancient coins were hammered or casted whereas modern coins are minted. Thus, ancient coins exhibit a larger amount of size and texture variations independently of their actual condition. The features must cope with a list of problems, some of them are particular to historical coins, e.g. coin design is not centered or completed, excessive wear, irregular shape and/or edges, die deterioration, and so on. Edge-based statistical features as the one proposed by Maaten et al. [8, 7] for the classification of modern coins fail with the classification of ancient ones [18]. These features represent a combined angular and distance information about the edge pixels in the coin image. Since the design of an ancient coin is usually not centered edge-based feature tend to provide insufficient coin description. Similar problem arises by the use of gradient-based techniques [6, 5] since they are also based on features extracted from polar grid images. Figure 3 illustrates the problem. Since modern coins are the product of an automated manufacturing process, they are always circular and their design perfectly centered. Thus, the position of the polar grid with respect to the coin design will not change for coins of the same type (see Figure 3(a) and 3(d)). In contrast, the design positioning of ancient coins differ even among representatives of the same coin type. For example, the coin represented in Figure 3(b) is of the same type as the one shown in Figure 3(c)). However, their stamps have completely different positions[6]. The task to find the center of a coin design is an open research issue.

3 Identification Workflow

3.1 Manual Identification

The act of identifying a certain coin on a picture to be the specimen in question is not always successful. Therefore, we summarize the process briefly.

The first coins were struck in Asia Minor in the late 7th century BC and since then coins are a mass product. In the Antiquity coins were hammer-struck from manually engraved coin-dies, so that those coins from the same production batch will have very much the same picture and also the same quality of its relief. The die was not struck with the same force on every coin and was not centered with the same accuracy on the flan.

The flans were handcrafted and differ in size, shape and – most important – in weight. Furthermore the coin-die itself began to wear off by the time[7]. If a coin-die did not break in this process it was usually re-cut, so that either the old pictures and legends became clearer again or new features were applied.

Depending on the series of coins in question, the only varying details can be either part of the picture or legend or there can be a difference in a prominent detail such as the face of figure but there can also be just a different number of dots in the circle that usually frames the coin-die. This kind of work is very time-consuming but in the first place depending on providing the original specimens, excellent photos or plaster casts. From a numismatic point of view it is necessary to separate the traces due to the

[6] The images of ancient coins were made available by Dr. Mark Blackburn, Fitzwilliam Museum, Cambridge, UK.

[7] It is estimated that the number of coins possibly struck from the same die can range up to between 5.000 or 10.000 [19].

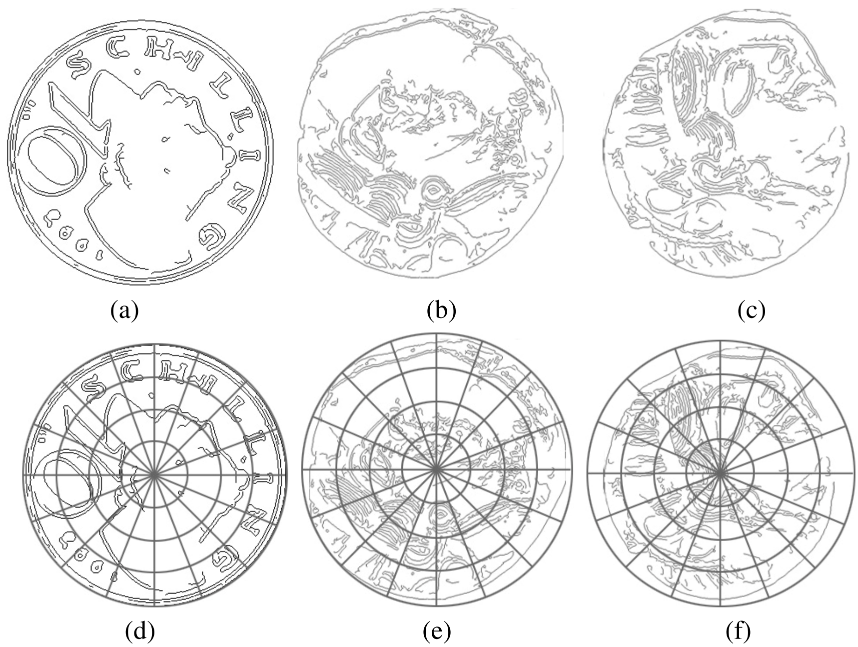

Fig. 3. Example of polar grid and edge coin images

production from those of intentional design of coin-dies. For the identification of coins a greater number of individual features facilitates the process even if they were applied after the minting.

In the 16th century minting machines were introduced that facilitate both speed and quality of the coin production. Furthermore, the flans started to be produced on industrial level and differ in size and weight only beyond possible measuring. In the 18th century a kind of reducing-machine was invented. With that, a big model of a coin-die could be reduced to its required size, so that from that time there is no difference between coin-dies anymore. Thus, only alterations applied to single specimens can be used to identify coins from this time period individually, like small scratches, graffiti, etc. In contrast, throughout the entire Antiquity and Middle Ages all the required preconditions for a successful identification are given by the minting process. Also the state of wear or corrosion interferes with both classification and identification since the damage to the coins is permanent.

A good picture is to be considered sufficient even for die-studies if several preconditions are provided. For digital images a minimum of 1000dpi resolution is required. Furthermore, the actual size of the coin has to be displayed correctly. While grave mistakes can be easily identified, a deviation of only a few percent is almost impossible to detect and can spoil the results. In the days of handcrafted coin dies, coins of the same denomination can differ in size by several millimeters. So if a Sesterius is 27mm in diameter and is displayed at 29mm it will be considered as a bigger specimen. Furthermore, an image in color gives more information than one in black and white since it displays more grades of the relief or its shadows. The lighting of the coin has great influence on the identification process. If the light comes from very different angles it will be almost impossible to identify the same coin on such pictures.

3.2 Automated Identification

The workflow of an automated identification process (see Figure 4) differs from the one of classification (as described in Section 2.2) in its feature extraction step.

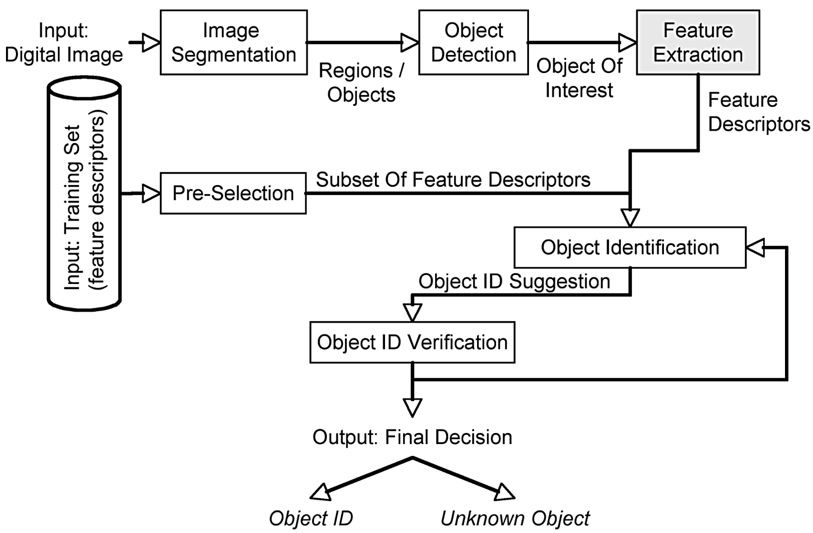

Fig. 4. Coin identification process

Classification ignores the individual features and focuses on the general ones to assign an individual object to a general category. In contrast, identification relies on individual, unique features that make given object different from all other individuals in the same class, and ignores general features that are common to many individuals. In the field of image processing, identification algorithms can be mostly found in image based quality control or surveillance scenarios (e.g. biometric recognition). To date, no identification system for ancient coins has been proposed or researched successfully.

Due to their nature ancient coins provide a set of identifying features. The unique shape of each coin originates in the manufacturing process (hammering procedure, specific mint marks, coin brockage, die deterioration, etc.). Furthermore, the time leaves its individual mark on each coin (fractures, excessive abrasion, damage, corrosion, etc). Eventually, from image processing point of view, identification of ancient coins turns out to be "easier" compared to classification. For example, Figure 5 shows ten different coins of the same coin type. A classification algorithm should ideally classify them all of the same class. However, technically spoken, they all provide complete different characteristics (see shape, die position, mint marks or level of details). At the same time, exactly those features enable the identification process.

Fig. 5. Different coins of the same coin type

In contrast, Figure 6 presents five pictures of one and the same coin. The pictures were taken using different technical setup –different digital cameras (fixed setup as well as free hand), different lighting conditions, and different image quality. The figure points out the challenges for an automated identification process as well as the importance of high quality images for the process itself. Different lighting conditions can hide or show details on the coin that are significant for a successful identification process (e.g. compare the first and the third image in Figure 6).

4 Experiments

We evaluated the classification performance of edge-based statistical features as proposed by Maaten et al. [8, 7] for two coin datasets. The first dataset – MUSCLE 06 – contain images of modern coins of European countries before the introduction of the euro currency. The images are taken under very controlled situation – constant background (conveyer belt) and light conditions. The MUSCLE training set contains over 9100 images unequally distributed over <100 classes. The test sets consist of 1000 test images (corresponding to 500 coins) respectively. The second dataset consists of 3000 high resolution images of ancient coins on constant, white background[8]. The coins picture Roman emperors and family members from approx. 30 B.C. to approx. 300 A.D. who form the 106 classes of the dataset. Furthermore, the coins are in different conditions and show different level of wear and fouling.

Fig. 6. Different image representations of the same coin

[8] Dr. Klaus Vondrovec, Department of coins and medals, Museum of Fine Arts, Vienna, Austria, made the data set available.

The tests performed address both classification based on single coin image (either obverse or reverse side) and classification based on images from both coin sides. Further tests integrate preselection stage based on area measurement. Only those coins that have a radius ±2mm of the radius of the provided test coin were considered for the next stage of the classification process. Since ancient coins of the same class show large variation of their size, preselection based on area measure was not evaluated on the Ancient dataset. Table 1 summarizes the results.

Table 1. Percentage of correct classified coins

	MUSCLE CIS 06	Ancient
single side classification	~ 61%	~ 6%
single side classification + preselection	~ 64%	–
both side classification	~ 48%	~ 4%
both side classification + preselection	~ 76%	–

The results show that classification based on images of both obverse and reverse coins side outperforms classification based on single image. However, state of the art algorithms for automatic classification of ancient coins clearly fail with the classification of ancient coins. Further research is required to find those features that most influence the quality of ancient coin representations. From numismatic point of view, restricting the range of possible classes an unknown ancient coin can be assign to, is already of advantage. To a certain degree it is feasible by an automated process. Still, further research is required to explore the boundaries of the optical recognition and define the prerequisites and minimum level of details a coin should have to enable reasonable automated classification. Coins such as the one represented in Figure 7(a) are out of the scope of optical recognition in contrast to Figure 7(b). Furthermore, specific tasks such as the identification of fakes lie outside of the boundaries of an automated process since they require not only an optical but also a physical inspection and moreover – expertise that is not learnable by a machine.

(a) (b)

Fig. 7. Coins of Antonius Pius I for his adopted son Marcus

Preliminary evaluation on automated identification of ancient coins was performed using SIFT features [20]. The dataset consists of 26 Roman and Greek coins, single coin type respectively, whereas each coin side is pictured three to five times using different conditions (e.g. scan, camera, varying lighting conditions, etc.). The total amount of 251 images was randomly divided into training and test set. All images were identified correctly. However, the results have to be qualified. On the one side, the dataset used is a small one. This is due to the fact, that museums in general are not interested in collecting multiple coins of the same coin type. On the other side, the results are still very promising and show high research potential.

5 Conclusion

In this paper, we gave an overview over the challenges faced by optical recognition algorithms. We described coin identification and classification from both a numismatic and image processing point of view. Furthermore, we showed results on the classification and identification of ancient coins. It was shown that state of art approaches for modern coins fail, when they are applied to ancient coins. As a consequence we will extent our research towards other approaches like shape descriptors or feature detectors in order to reliably describe ancient coins. It is also planed to test and evaluate the results on larger databases.

Acknowledgments

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