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On ancient coin classification†

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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. The first step of a computer aided system is the segmentation of the coin in the image. Next, a feature extraction process measures the coin in order to describe the coin unambiguously. In this paper, we focus on the segmentation task, followed by a comparison of features relevant for coin classification. Results of the algorithms implemented are presented for an image database of ancient coins.

Categories and Subject Descriptors (according to ACM CCS): I.3.6 [Computer Graphics]: Methodology and Techniques I.3.8 [Computer Graphics]: Applications

1. Introduction

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 raises rapidly. 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 to a minor extend. To date, no automatic coin recognition system for ancient coins has been researched – and thus – applied successfully.

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 [FOTK92] [BBSC05] to eigenspaces [HRM*05], decision trees [Dav96], edge detection and gradient directions [NPR*03] [RRB06], and contour and texture features [vdMP06b].

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 [vdMP06b]. Ancient and modern coins bear fundamental differences that influence the choice and applicability of existing classification algorithms. Ancient coins have limited rotational symmetry and thus their diameter in uncertain. Furthermore, due to their nature, ancient coins exhibit a larger variation in size and texture independently of their actual conservation. In this paper we outline some of the limitations of existing coin classification algorithms and present recognition methods that show promising results with the classification of ancient coins.

The remainder of the paper is organized as follows: Section 2 presents recent approaches for coin recognition al-

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gorithms and addresses their limitations with respect to the classification of ancient coins. Section 3 gives an overview over the dataset used for the performed evaluation. The segmentation process is described in Section 4. Section 5 presents different approaches for the classification of ancient coins. Preliminary results are presented in Section 6. At the end of the paper in Section 7 conclusions and outlook for further research are drawn.

2. Related Work

In this section we present recent approaches for coin recognition techniques, namely algorithms based on the eigenspace approach, gradient features, contour and texture features. Finally, we discuss the limitations of the proposed algorithms in respect to the classification of ancient coins.

2.1. Eigenspace approach

Huber et al. present in [HRM*05] a multistage classifier based on eigenspaces that is able to discriminate between hundreds of coin classes. The first step is the preprocessing performed to obtain translationally and rotationally invariant description. The data was recorded in an controlled environment which eased the task of segmentation. Rotational invariance is obtained by estimation of the rotational angle. This involves cross-correlation of the coin presented to the system with reference images. Each reference image is associated with a coin class depending on thickness (estimated from additional thickness sensor measurement) and diameter. In the second stage an appropriate eigenspace is selected. Again, based on the diameter and thickness measurements multiple eigenspaces are constructed. Thus, each eigenspace spans only a portion of the thickness/diameter plane and a moderate number of coin classes. In the last stage Bayesian fusion is applied to reach the final decision. Bayesian fusion incorporates probabilities for both obverse and reverse sides of the coin and knowledge about its orientation coherence. They report correct classification for 92.23% of all 11,949 coins in the sample set.

2.2. Contour based algorithms

In [vdMP06a] Maaten et al. present a coin classification system based on edge-based statistical features, called COIN-O-MATIC. It was developed for the MUSCLE CIS Coin Competition 2006 [NRH06] focusing on reliability and speed (for example images see Figure 1). The system is subdivided into five stages: in the segmentation step (1) the coin is separated from the coin image. Next a feature extraction process measures edge-based statistical distributions (2). In order to give a good description of the distribution of edge pixels over a coin, they combine angular and distance information: edge distance measures the distance of edge pixels from the center of the coin and angular distance measures distribution of edge pixels in a coarsely discretized polar space. In the third step (3) – preselection – area and thickness measurement are used in order to obtain a reliable decision on the class of a coin. A 3-nearest neighbor approach on the two sides of the coin is applied (4). The last step (5) – verification – is only performed for coins for which the two coin sides were classified differently. It is based on mutual information of a test sample and an average coin image that corresponds to the classification assigned to the test sample. At the MUSCLE CIS Coin Competition the method achieved a recognition rate of 67.31% on a benchmark set of 10,000 coins.

Figure 1: *Example images from MUSCLE CIS dataset.*

The Dagobert coin recognition system presented by Nölle et al. [NPR*03] aims at the fast classification of a large number of modern coins from more than 30 different currencies. In their system coin classification is accomplished by correlating the edge image of the coin with a preselected subset of master coins and finding the master coin with lowest distance. For the preselection of possible master coins three rotation-invariant visual features, besides sensor information of coin diameter and thickness, are used: edge-angle and edge-distance distributions similar to [NRH06] and a third feature counting the occurrences of different rotation-invariant patterns on circles centered at edge pixels. In their experiments they achieved a recognition rate of 99.24% on a test set of 12,949 coins.

2.3. Gradient based algorithm

The coin classification method proposed by Reisert et al. [RRB06] and presented at the MUSCLE CIS Coin competition 2006 [NRH06] is based on gradient information. Similar to the work of Nölle et. al [NPR*03] coins are classified by registering and comparing the coin with a preselected subset of all reference coins. In the preselection step the radius of the segmented coin is determined and only coins with a similar radius are taken for comparison. The registration and similarity computation of coin images is done by means of a Fast Fourier Transformation on binary images of discretized gradient directions. The final classification of a coin image is accomplished by a nearest neighbor scheme. The proposed method won the MUSCLE CIS Coin Competition 2006 with a recognition rate of 97.24% on a benchmark set of 10,000 coins.

2.4. Discussion

Current research approaches for coin classification algorithms possess mainly two limitations. On one hand, the input digital image is well defined – there is always at most one coin presented and the image is taken under controlled conditions (such as background, illumination, etc.). That part that could not be controlled (e.g. the dirt on the conveyor belt) makes correct segmentation a difficult task. On the other hand, current coin classification algorithms focus mainly on the recognition of modern coins. Those assumptions facilitate the classification process substantially. Given 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. [RRB06]. 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 [ZKZ07]. 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(s). 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 and tear or staining. 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. [vdMP06b] [vdMP06a] for the classification of modern coins fail with the classification of ancient ones [ZKZ07]. 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 features tend to provide an insufficient coin description. Similar problems arise by the use of gradient-based techniques [RRB06] [NPR*03] since they are also based on features extracted from polar grid images. Since modern coins are the product of an automated manufacturing process, they are always circular and their design is perfectly centered. Thus, the position of the polar grid with respect to the coin design will not change for coins of the same type. In contrast, the design positioning of ancient coins differ even among representatives of the same coin type. The task to find the center of the design of an ancient coin is an open research issue.

3. Image Database

For our experiments we used a dataset of images we acquired at the Fitzwilliam Museum in Cambridge, UK. We used varying technical setups – scan as well as fixed and free hand cameras, and varying lighting conditions. The dataset consists of 350 images of three different coin types (10 to 16 coins à coin type, 3 to 5 pictures à coin side). An example of different pictures of the same coin from the dataset is shown in Figure 2. Figure 3 presents example pictures of different coins of the same coin type.

Figure 2: *Different images of the same coin.*

Figure 3: *Different coins of the same coin type.*

4. Segmentation

Prior to identification or classification the location of the coin contained in the image is required. The separation of an object of interest from the background is commonly termed segmentation. Due to inhomogeneous or poor illumination and low contrast straightforward methods based on global image intensity thresholding tend to fail. Thresholding using adaptive threshold surfaces is able to work under the mentioned situations [TT95]. The employed adaptive method was suggested by Yanowitz and Bruckstein and derives a threshold surface which is interpolated using tie points placed at positions obtained from thinned and thresholded gradient values [YB89]. Instead of using the gradient values we used zero crossings of the second derivative to indicate edge positions [MH80]. Figure 4 shows segmented images of the obverse side of Denarius silver coins minted during the rule of Caesar, circa $47-46$ BC, obtained under different conditions.

Figure 4: *Segmentations of a Denarius coin.*

5. Feature description and matching

Ancient coins are in general not of a perfect circular shape. From a numismatic point of view, the shape is a very specific feature for individual coins. Therefore, the shape serves as a first clue in coin identification and discrimination. Additionally, it is possible to infer the orientation of the coin from the shape in many cases. Concerning coins we are interested in the shape described by the perimeter of the coin. A possible representation of the coin perimeter is given by the set of pixel positions sampled along the perimeter. The comparison of objects characterized by their shape description is termed shape matching [Vel01].

Invariance against geometrical transformations, e.g. rotation, translation and scaling, is major goal in matching. Invariance with respect to perspective distortions, which is also commonly studied in computer vision, is of less importance for coin images, as they are usually depicted from a frontal view. As the coins are segmented, translation is no problem for shape matching.

In this work we use different approaches to gain robustness against variations in scale and rotation. First, we apply the shape context description [BMP02], in a rotational-invariant version. Second, we deploy a registration technique that allows us to match two shape descriptions via a robust correlation algorithm. A similar approach was successfully used in [NPR*03] to recognize modern coins and in curvature based rail data localization [Öme06]. Finally, we evaluated the performance of SIFT features which are invariant to image scaling, rotation and translation and proved to be highly discriminative for matching.

5.1. Shape contexts matching

Invariance with respect to scaling and rotation can be solved using a shape contexts representation [BMP02]. The shape context description, in a rotational-invariant version, was used in this work.

A shape context for a contour point is expressed by a 2-dimensional histogram containing the measured distances to all other points on the contour along with the difference in tangent orientation for pairs of points. Normalization of the distances provides scale invariance, whereas the tangent orientation difference provides rotational invariance. Figure 5 shows how a typical entry in the shape context histogram for a pair of contour points (p_i, p_j) is derived. The histogram entry at position $(r_{ij}, \theta_i - \theta_j)$ is obtained from the distance between points p_i and p_j and the difference of the tangent angles θ_i, θ_j orientations with respect to the x-axis. Details of shape matching are given in the original paper [BMP02]. Shape matching actually involves the solution of an assignment problem using either the so called Hungarian algorithm [Kuh55] or more efficient improvements thereof. As coins are rigid objects, we do not consider a transformation model and the suggested iteration scheme.

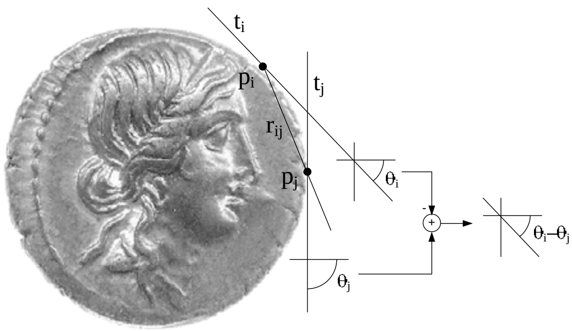

Figure 5: *Rotational invariant description of a coins shape.*

5.2. Robust shape matching

Given a segmentation, i.e. a set of points, $(x_i, y_i), i = 1, \ldots, n$, represented by their coordinates in the image, we may calculate the corresponding center of mass $(x_m, y_m) = 1/n(\sum_i x_i, \sum_i y_i)$. From the moment of inertia we gain $r^2 = 2/n\sum_i (x_i - x_m)^2 + (y_i - y_m)^2)$ the radius of an equivalent solid disk rotating around the center of mass. By renormalizing the radius (and coordinates) of all segmentations to one and we become independent against variations in scale. The points on the perimeter of the segmentation read in clockwise direction define a cyclic list $s = (p_1, \ldots, p_k)$ which we resample via a spline interpolation at equidistant intervals resulting in $S = (s_1, \ldots, s_l)$, l fixed, for all shapes. The distance of each s_i to the unit circle gives a cyclic list $D = (d_1, \ldots, d_l)$ which is our final description of the shape. Distances inside the circle are taken negative, outside they are marked as positive. Note that the parametrization of perimeter according to the length might be problematic as this can vary for different image resolutions when more details of the object become visible. Other parameterizations might be more effective and will be analyzed in the future.

As a second step we have to define a distance measure between two shapes which is invariant against cyclic translations of their shape descriptions. Here we use a technique developed elsewhere ([NÖ06]) which uses a distance measure for probability distributions together with a fast correlation approach. The algorithm requires to have an estimate of the maximal absolute distance of possible shapes which, as the ancient coins do not diverge too much from a circle, can be either fixed by the maximal absolute distance or a meaningful constant d_{max}.

Let $D_a = (d_1, \ldots, d_l)$ be a shape description as given above and define two sequences

$$a_i^{\mp} = \sqrt{\frac{d_{max} \mp d_i}{2d_{max}}}, i = 1 \ldots, l. \tag{1}$$

Please note that $(a_i^+)^2 + (a_i^-)^2 = 1$ and may be interpreted as a Bernoulli distribution of a probability variable $P(X_i = +) = (a_i^+)^2$ and $P(X_i = -) = (a_i^-)^2$. Therefore, we may deploy a distance measure for probability distributions to separate two shapes. From our experiments we conclude that a metric measure based on Bhattacharyya coefficients [ATR97, Nöl03] is most suitable for the given task.[†] Other measures like the relative entropy [NC00] or Kullback Leiber divergence or those analyzed in [Nöl03] might be used as well.

For two shape descriptions D_a, D_b the distance is given by

$$f(D_a, D_b) = \sqrt{1 - \frac{1}{l^2}\left(\sum_{i=1}^{l} a_i^+ b_i^+ + a_i^- b_i^-\right)^2}. \tag{2}$$

As the cyclic translation between the two shape descriptions is unknown Eq.2 has to be evaluated for all possible translations and the final distance is given by

$$F(D_a, D_b) = \min_j \sqrt{1 - \frac{1}{l^2}\left(\sum_{i=1}^{l} a_i^+ b_{j\oplus i}^+ + a_i^- b_{j\oplus i}^-\right)^2}, \tag{3}$$

j=1,..., l, where $\oplus$ denotes the addition modulo l. Eq.3 may be evaluated using the fast Fourier transform and gives a very efficient implementation. Given a shape description D_a we calculate Eq.3 for all known coin shapes and classify it according to the minimal distance.

5.3. Scale Invariant Feature Transform (SIFT) Features

SIFT features were introduced by Lowe [Low99] [Low04] as a method for extracting local image descriptors that are highly discriminative for object recognition. SIFT features are invariant to changes in image translation, scaling, and rotation and partially invariant to changes in illumination and affine distortion. Furthermore, they outperform further interest point descriptors such as steerable filters, differential invariants, complex filters, moment invariants, and cross-correlation [MS05].

The extraction of SIFT features passes four stages [Low04]. First, stable keypoint locations are identified at peaks of Gaussian function applied in scale space. All keypoints with low contrast or keypoints that are localized at edges are eliminated using a Laplacian function. At each feature location, an orientation is selected by determining the peak of the histogram of local image gradient orientations. Finally, subpixel image location, scale and orientation are associated with each SIFT feature vector. Figure 6 visualizes selected descriptors (a set of 16 histograms aligned in a 4×4 grid, each with 8 orientation bins) on the obverse and reverse side of an ancient coin.

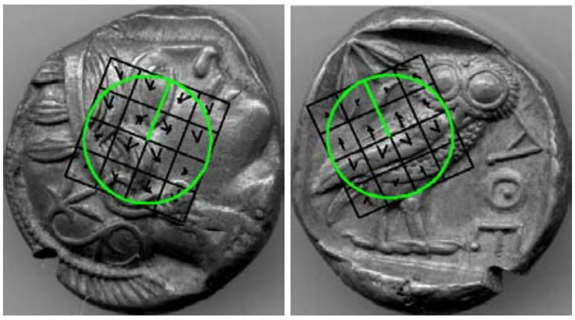

Figure 6: *SIFT descriptors.*

SIFT descriptors are matched by identifying the first two nearest neighbors in terms of Euclidean distances. A descriptor D_1 is accepted only if the distance ratio of the nearest $(1.NN)$ to the second nearest $(2.NN)$ neighbors is less then or equal to 0.5:

$$2d(D_1, D_{1.NN}) <= d(D_1, D_{2.NN}). \tag{4}$$

In [Low04] Lowe suggests a distance ratio of 0.8. However, our experiments showed that for the case of lower interclass differences (all classes are coins), a lower distance ratio tends to keep more distinctive descriptors while eliminating

[†] For those interested there is a nice link to measures based on the so called fidelity in quantum information theory [NC00].

a great part of the false matches. The value of 0.5 was determined experimentally and used through the tests described in the following section. Figure 7 visualizes the matching keypoints of two different images of the same ancient coin. Despite the different image quality, lighting conditions or scale, the two images were matched successfully in a pool of 350 images of ancient coins.

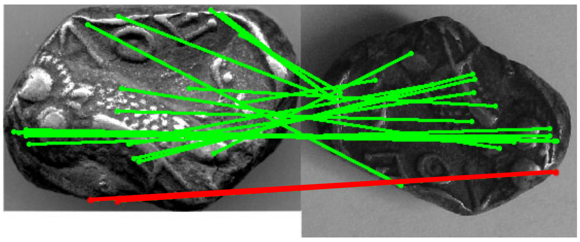

Figure 7: *SIFT descriptors matches (the two matches on the bottom are the only two incorrect matches).*

6. Results

Results for matching different images, taken with different acquisition devices (scanners, cameras), and under different illumination conditions, are presented.

Using shape contexts, the contour points are obtained from segmentation and sampling the contour border at 600 points. Shape context histograms contained five distance and twelve orientation bins. For 10 out of 12 the most similar coin image was the same coin imaged by a different acquisition device. Figure 8 shows twelve images, where 4 images of each coin exist, of three considered Denarius coins. For each coin, the solid arrow indicates the closest coin found by shape matching. The only confusion occurred with a scanned image (Scan 2) of the second coin.

On the given very limited data set the evaluation of Eq.3 matched all the coins into their correct class as is visualized in Figure 8. We used 512 contour points for each shape descriptor. More tests need to be done on much bigger data sets in order to quantify the performance of the described method.

Evaluation tests on the performance of SIFT features also show promising results. We have performed classification tests on the whole set of 350 images of ancient coins. Table 1 summarizes the results broken down by coin type. The Byzantine coins outperformed all other coin types and achieved a classification rate of 93.93%. The identification rate for ancient coins, which is significant for the traceability of stolen cultural heritage, achieved 76.41%, i.e. 76.41% of all coins were correctly matched against an image of the same coin pictured by different acquisition device and using different lighting conditions.

In Table 2 the classification rate is further broken down by

Coin type	Classification	Identification
Byzantine	93.93%	79.80%
Greek	79.78%	77.53%
Roman	79.01%	71.91%
	84.24%	76.41%

Table 1: *SIFT classification and identification rates.*

acquisition device. Again, 98.31% of the Byzantine coins that were pictured using a fixed camera setup were correct classified. In general, pictures originating from professional setup (e.g. scan or fixed camera setup) tend to achieve better classification rate due to (partly) controlled conditions and high quality. The drop in the classification rate of Roman coins is due to an error occurred in the acquisition process. Figure 9 shows an example of incorrect classified images.

Coin type	Scan	Fixed camera	Free hand camera
Byzantine	95.00%	98.31%	80.00%
Greek	80.00%	84.00%	78.95%
Roman	43.75%	90.43%	80.56%
	72.92%	90.91%	79.84%

Table 2: *SIFT classification rate (by image acquisition device).*

Figure 9: *Example of incorrect classified images from Roman coins.*

The evaluation results are very promising and show high research potential. However, they have to be qualified since the dataset we 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. Nevertheless, the results can be further improved by e.g. combining two of the methods.

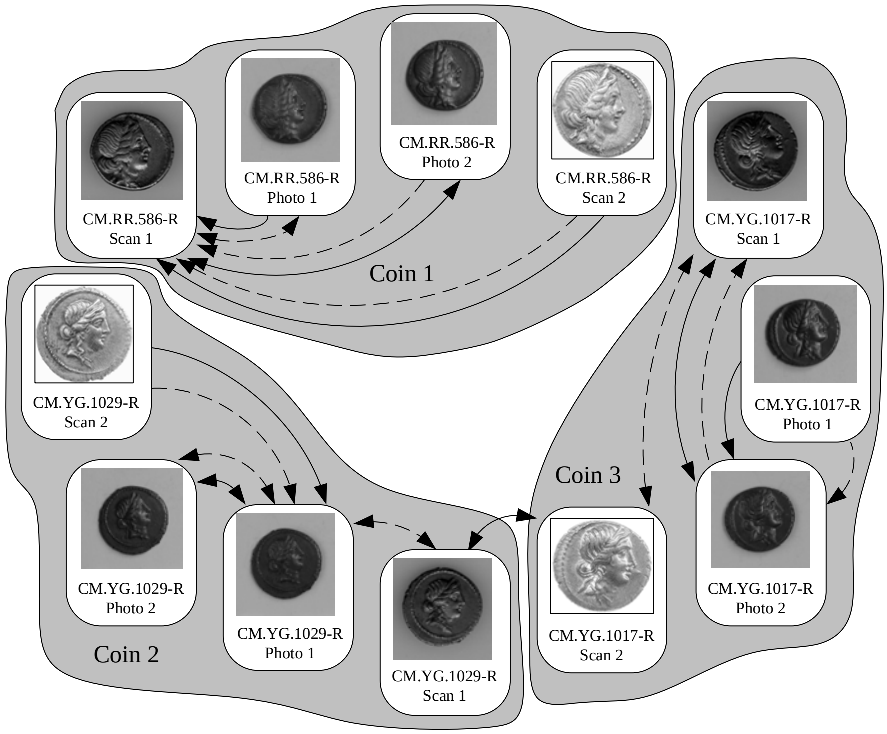

Figure 8: *Shape matching of coins: solid arrow indicates the most similar coin found by shape context matching and a dashed arrow indicates the most similar coin found by the robust shape matching algorithm.*

For example, a preselection stage based on shape matching can be used to reduce the amount of comparisons in the SIFT matching process. This will improve the performance of the process for coins in worse condition since wear and tear mostly affects the design of a coin. Further tests are required to find the set of parameters and feature descriptions that most influence the visual representation of ancient coins. Moreover, image quality (e.g. acquisition process) as well as coin quality (e.g. level of details) have an essential impact on an automated classification process and need to be further specified.

7. Conclusion

In this paper we addressed recent research in the field of automatic coin classification algorithms and discussed the challenges faced by a computer aided classification of ancient coins. Further research is required to find those features (or set of features) that most influence the quality of ancient coin representations. 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. We presented new approaches for the optical representation and matching of ancient coins based on shape description and SIFT features. In a next step, it is intended to acquire larger collections of images of ancient coins in order to verify and improve the achieved results.

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