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Optical Recognition of Modern and Roman Coins

Abstract: The recently granted EU project COINS aims to contribute substantially to the fight against illegal trade and theft of coins that appears to be a major part of the illegal antiques market. A central component of the permanent identification and traceability of coins is the underlying image recognition technology. However, currently available algorithms focus basically on the recognition of modern coins. To date, no optical recognition system for ancient coins has been successfully researched. It is a challenging task to work with medieval coins since they are – unlike modern coins – not mass manufactured. In this project, the recognition of coins will be based on new algorithms of pattern recognition and image processing, in a field – classification and identification of medieval coins – as yet unexplored. Since the project recently started, preliminary results and work already performed in this field are presented and discussed.

Introduction

Nowadays, ancient coins are subject to a very large illicit trade. Thus, interest in reliable automatic coin recognition systems within cultural heritage and law enforcement institutions is quickly raised. Traditional methods to fight the illicit traffic of ancient coins comprise manual, periodical searches in auction catalogues, field searches by authority forces, periodical controls at specialist dealers, and a cumbersome and unrewarding internet search, followed by human investigation. However, these methods only partially prevent the illicit trade of ancient coins. To date, no automatic coin recognition system for ancient coins has been researched and applied successfully.

Recent research approaches for coin classification algorithms focus solely on the recognition of modern coins. Applied pattern recognition algorithms are manifold ranging from neural networks (Fukumi et al. 1992; Bremananth et al. 2005) to eigenspaces (Huber et al. 2005), decision trees (Davidsson 1996), edge detection and gradient directions (Nölle et al. 2003; Reisert / Ronneberger / Burkhardt 2006), and contour and texture features (van der Maaten / Postma 2006). 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 (van der Maaten / Postma 2006).

In this paper, we present preliminary results on tests performed on three different data sets of coin images. The results achieved reflect the essential differences between ancient and modern coins.

The remainder of the paper is organized as follows: The following section presents state of the art techniques for coin classification. The third section gives an overview over the datasets used for the performed evaluation. The classification process is described in detail in the fourth section. Experiments and results are presented in the fifth section. At the end of the paper, conclusions and an outlook for further research are drawn.

Coin Recognition Algorithms

In this section we present recent approaches for coin recognition techniques, namely algorithms based on the eigenspace approach, gradient features, contour and texture features.

Eigenspace Approach

Huber et al. (2005) present a multistage classifier based on eigenspaces that is able to discriminate between hundreds of coin classes. The first step consists of preprocessing performed to obtain translationally and rotationally invariant description. Due to the controlled setup of the system presented, coin detection becomes a trivial task. 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.

Contour Based Algorithms

Van der Maaten / Poon (2006) 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 (Nölle / Rubik / Hanbury 2006), focusing on reliability and speed. The system is subdivided into five stages: in the segmentation step (1) the coin is separated from the coin photograph. 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, preselection (3), area and thickness measurement are used in order to obtain a reliable decision on the class of a coin. A three-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.

The Dagobert coin recognition system (Nölle et al. 2003) 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 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.

Gradient Based Algorithm

The coin classification method proposed by Reisert / Ronneberger / Burkhardt (2006) and presented at the MUSCLE CIS Coin Competition 2006 is based on gradient information. Similar to the work of Nölle et al. (2006), 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.

Datasets

For our tests we used three different data sets addressing different application scenarios and thus different challenges for coin recognition and classification techniques. The first two datasets – MUSCLE CIS 06 and MUSCLE CIS 07 – contain images of modern coins of European countries before the introduction of the Euro currency. The images are taken under very controlled situations – constant background (conveyer belt) and light conditions. Furthermore, all images are grey level of the same dimensions (640 × 576 px). The MUSCLE training set contains more than 9100 images unequally distributed over around 100 classes. The test sets consist of 1000 test images (corresponding to 500 coins) respectively. The MUSCLE CIS 07 test set differs from the MUSCLE CIS 06 by addressing the recognition and classification of coins in the presence of occlusion. The following figures demonstrate the difference: *Fig. 1* shows images of coins as collected by monetary authorities and in *Fig. 2* randomly selected parts of the coins are cut to simulate the presence of occlusion.

The third dataset consists of 3000 high-resolution images of ancient coins on constant, white background. The coins picture Roman emperors from approx. 30 B.C. to approx. 300 A.D. who form the

Fig. 1. Example of cropped images of MUSCLE CIS 06 dataset.

Fig. 2. Example of cropped images of MUSCLE CIS 07 dataset.

106 classes of the dataset. Furthermore, the coins are in different conditions and exhibit different level of wear and fouling. An example of a coin from the dataset is shown in *Fig. 3*.

Classification Workflow

In this section we describe in detail the steps of the classification process we performed on all three data sets of coin images.

Segmentation

The first step of the classification process involves the segmentation of the coin from the background of an image. Recent research in coin classification proposes two different segmentation approaches – edge-based segmentation (van der Maaten / Postma 2006; van der Maaten / Poon 2006) and segmentation based on Hough transformation (Reisert / Ronneberger / Burkhardt 2006). Our edge-based segmentation process consists of the following steps: (1) contrast enhancement and filtering operation, (2) edge detection, (3) application of morphological operations, and (4) segmentation verification. Increasing the contrast in the first step can enhance image details and facilitate the coin detection in the presence of partial occlusion and various light conditions. For the edge detection, we use the Canny method since the Sobel approach used by Maaten (van der Maaten / Postma 2006; van der Maaten / Poon 2006) tends to provide inaccurate edge information in the presence of noise. In the third step, we apply morphological and fill operations to close the border of the coin and create a mask of its shape. The additional verification step scans the roundness (Russ 1995) and area information of the coin shape using fixed thresholds. In case of segmentation error the Canny operator is reapplied using increasing thresholds until no segmentation error is detected.

Fig. 3. Example images of the ancient data set.

The second segmentation method follows the approach proposed by Reisert / Ronneberger / Burkhardt (2006) based on the Generalized Hough Transform (GHT) (Ballard 1981). It uses three-di-

Fig. 4. Examples of coin segmentation.

mensional voting space whereas each image gradient votes for coin's centers and radii along its direction. For performance reasons, a hierarchical voting scheme with stepwise parameter estimations is applied. By definition, this method is only applicable for completely round coins. Examples of segmentations obtained using both the edge-based and the GHT method on the three different data sets are shown in *Fig. 4*.

Feature Extraction

A crucial step in any classification algorithm is feature extraction. For our tests we applied the algorithm provided by Maaten et al. (van der Maaten / Postma 2006; van der Maaten / Poon 2006) based on edge-based statistical distributions. The first step of the feature extraction is the extraction of an edge image using the Sobel operator. In the next step, edge-based statistical features are computed – multi-scale edge angle-distance distribution. These features represent combined angular and distance information about the edge pixels in the coin image. Details on the algorithm can be found elsewhere (van der Maaten / Poon 2006; van der Maaten / Postma 2006). For the classification of coins, van der Maaten et al. propose to remove the outer border of the coins since it does not substantially contribute to the classification process. However, segmentation based on the Hough transformation already tends to cut the coin border as already described in the previous section. Furthermore, ancient coins often bear essential details on the border due to possible misalignment of the stamp. Thus, in these two cases we process the whole coin image for feature extraction.

Classification

For coin classification we apply a simple k-Nearest Neighbor algorithm with $k = 5$. Since a coin is represented by two images – obverse and reverse side – coin classification can be performed either processing a single side or both sides of the coin. Due to their nature, the two sides of an ancient coin are often in very different conditions. If one side is fully destroyed (either by wear or fouling), classification based on a single image becomes relevant. Furthermore, both modern and ancient coins bear a certain level of diversity within a single coin type – coins change their appearance over time. An example is coins of a special edition to mark a specific occasion (modern coins) or the aging of the coin picture of an emperor with the person itself (ancient coins). Tests show that classification based solely on the obverse side of a coin outperform classification based on its reverse side, due to the higher level of detail incorporated into the obverse side of an ancient coin. For classification based on images of both sides of a coin, each side is first classified separately. If the respective classifications are identical, the coin is classified adequately. If the individual classifications differ, the coin is classified as the most represented class in the top ten hit list, which is an union of the five nearest neighbor classes of each coin side.

Evaluation

We evaluated the classification performance for multi-scale edge agle-distance distribution (MSEADD) for the three coin datasets. The algorithm was evaluated in combination with edge-based segmentation

	MUSCLE 06	MUSCLE 07	Ancient
Edge-based segmentation & MSEADD			
– single side classification	~61%	~30%	~6%
– single side classification + preselection	~64%	~33%	–
– both side classification	~48%	~34%	~4%
– both side classification + preselection	~76%	~40%	–
GHT & MSEADD			
– single side classification	~41%	~28%	~4%
– single side classification + preselection	~50%	~34%	–
– both side classification	~50%	~32%	~4%
– both side classification + preselection	~53%	~36%	–

Tab. 1. Percentage of correctly classified coins.

and segmentation based on the Generalized Hough Transformation (GHT). 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 a preselection stage based on area measurement. Only those coins that have a radius of ±2 mm 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. The following *Tab. 1* summarizes the results. The results show that classification based on images of both obverse and reverse coins side outperforms classification based on single image. Furthermore, tests using edge-based segmentation achieve a better classification rate than those using the Generalized Hough Transformation (GHT). The smaller segmentation error of GHT did not result in better classification since the misalignment of the coin centroid decreases the feature performance of edge angle distribution.

The main difference between ancient and modern coins is that the ancient coins have no rotational symmetry and consequently their diameter is unknown. Since ancient coins are all too often in very poor condition, common recognition algorithms can easily fail. The features that most influence the quality of the recognition process are as yet unexplored.

Both the nature of the ancient coins – less detail, no rotational symmetry – and the poor conditions due to wear or fouling are significant. Fundamental differences between ancient and modern coins originate from the manufacturing process *(Fig. 5)*.

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. Furthermore, current class partitioning is based solely on the portrait. This appears to be too broadly defined since the coins within a single class show a large degree of diversity – portraits are aging, details or marks

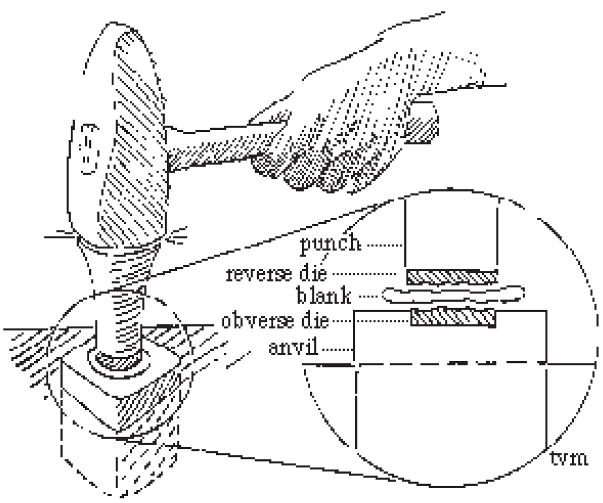

Fig. 5. Ancient coin striking process (http://www.lawrence.edu/dept/art/buerger/essays/production7.html [29 May 2007]).

Fig. 6. Sample images from DIVA FAVSTINA.

appear or disappear, the size, level of detail or even the whole reverse side can differ (see for example *Fig. 6*). Thus, edge-based features fail with classification of ancient coins.

Conclusion

In this paper, we presented evaluation results on state of the art coin classification algorithms applied on three different data sets of coin images. The results show that image features that achieve a good classification ratio with modern coins easily fail with the 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 particular to historical coins:

- design not centered
- design incomplete
- excessive abrasion
- irregular shape
- irregular edge
- cracks and fractures
- damage (manipulations)
- effects of corrosion (more serious than on modern coins)
- die deterioration (mainly a problem with medieval coins)
- less figural diversity in depiction compared to modern coins (especially in obverse).

Registration techniques can help to align images with respect to their size, orientation, and appearance. Another approach is to focus on particular patterns that help professionals to classify ancient coins. Preliminary tests with SIFT features also show promising results for both classification and identification of medieval coins. In the future, we intend to use the huge collection of medieval coins of the Fitzwilliam Museum in order to verify the practical applicability of the SIFT features for the recognition of ancient coins.

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