IJCTA, 9(20), 2016, pp. 347-355

Novel Method for Ancient Indian Coins Classification

N. Jayanthi[1], Prateek Tripathi[2], Snigdhaa Hasija[3] and S. Indu[4]

ABSTRACT

Image-based classification of ancient coins is of great importance to the field of Numismatics. An automated classification system is required for achieving greater efficiency than the manual cataloging of coins. Several classification systems have been put in place for the recognition and categorization of modern coins but little or no work has been done to classify the ancient Indian coins. Less work in this domain is a result of the uniqueness of the ancient coins. Modern day coins are largely symmetric, uniform and identical as they are machine-made whereas the ancient coins were made manually. The algorithm proposed delves into the solution for classification of coins of the ancient periods in India by a two stage material- based classification which is robust and helps to achieve the highest recorded accuracy for any method of ancient coin classification. The method proposed has been experimented on an extensive dataset of 166 coins and has provided positive results in the classification.

Keywords: HSV plane, coins, Ancient periods, India, two step classification,

1. INTRODUCTION

The fields of computer vision and numismatics provide for each other. Computer vision facilitates numismatics by the classification of the coins according to their currency, denomination or period of use and numismatics provide an extensive dataset to computer vision augmenting the research prospects. An automated system for classification is any-day better than a tedious manual system. The benefits of an automated system for the classification of ancient coins are manifold [4]. These ancient coins have been subject to varying environmental conditions and have signs of wear and tear due to extensive use. Due to the way they were manufactured, as well as wear from use and exposure to chemicals in the soil, the same ancient coin type can exhibit great variability in appearance [20]. Hence, their classification has indeed been a challenge. Moreover, as large amounts of coins are daily traded over the Internet, it becomes necessary to develop automatic coin recognition systems to prevent illegal trades [21]. Although algorithms for the classification of ancient Roman Republican and European coins have been explored and work efficiently [1,2,3,4], no such methodology exists for the automatic classification of the various ancient Indian coins. Moreover, the methods used in all of these papers are based on feature matching using SIFT or SURF algorithms and hence need a similar coin to be present in the dataset which is a big disadvantage. SIFT imposes a large computation burden especially on real-time systems. SURF is an improvement over it but many key point detectors include an orientation operator (SIFT and SURF are two prominent examples). There are various ways to describe the orientation of a key point; many of these involve histograms of gradient computations, for example in SIFT [14] and the approximation by block patterns in SURF [15]. These methods are either computationally demanding, or in the case of SURF, yield poor approximations.

[1] Department of Electronics and Communication Engineering Delhi Technological University, Delhi, India, *Email: njayanthi@dce.ac.in*

[2] Department of Electronics and Communication Engineering Delhi Technological University, Delhi, India, *Email: prattrip@gmail.com*

[3] Department of Electronics and Communication Engineering Delhi Technological University, Delhi, India, *Email: snigdhaahasija@gmail.com*

[4] Department of Electronics and Communication Engineering Delhi Technological University, Delhi, India, *Email: s.indu@dce.ac.in*

Although the SURF algorithm improves on speed and is faster than SIFT, SURF also has a poor performance on rotational invariance as compared to the local feature operator [16]. In this paper, we present a novel method catering to the classification of Ancient Indian coins and removal of the disadvantages of the methods used previously. The method is designed to be effective irrespective of the shape and symmetry of the coin. We have targeted the classification of the coinage of the colonial powers and the ancient city state of Ujjain. The colonial powers included the Dutch, the Danish and the British. In the British coinage, we have included coins from all the three major presidencies: Bengal, Madras and Bombay and those of the imperial series as well.

From the brief description of the ancient coinage [5], we can see that the material used in the manufacture of coins differed for the different rulers. The Danish used copper to fabricate coins. The Dutch mainly used silver and gold except for the one in Pondicherry, which were made of copper. The British coinage was also fabricated using gold and silver. The coinage of Ujjain was made using copper and silver. The coins have been identified and classified with a two-step classification procedure in which we first process the images of coins by thresholding using the value matrix of the HSV plane and then find the aggregate hue value of the coin. This step helps us differentiate the coins based on the material that was employed in their manufacture. Hence, the first step classification partly distinguishes between the coins of these different rulers. Due to their exposure to different conditions, some coins are dull and some are bright. Therefore, in the second step, further processing was done on the images using the saturation component allowing the classification to be dependent on the conditions to which these coins were subjected to due to the difference in the locations of their existence

The remainder of this paper is organized as follows: Section II analyses the related works and why they do not provide a complete solution to the above-mentioned problems. Section III highlights the goal of this paper and the contribution that this paper makes. Section IV explains the proposed methodology. Section V mentions the experimental results. Finally, Section VI provides the conclusion based on the experimental proofs obtained.

2. RELATED WORKS

There are a few approaches proposed by various researchers for image based ancient coin recognition and the work can be termed as very little:

G Das et al. [8] attempt to classify some ancient coins on the basis of histogram processing and training by artificial neural networks but they have just worked on 20 coins and their algorithm gives a 75% accuracy only which is lower compared to what most other algorithms in this very field propose.

Kaiping Wei et al. [10] in 2007 presented a novel approach for the classification of ancient coins based on textual information of the images. For extracting textual information, it uses Tree-Structured Wavelet Transform (TWT) and Ant Colony Optimization (ACO) algorithm [10]. The multi-resolution character of texture is extracted with the use of TWT, and this information is accessible in various scales rather than low frequency [10]. The limitation to this proposed method is that it is dependent on the text on coins and as noticed the dataset does not necessarily always contain distinction in the form of text.

In 2006 Laurens J.P. van der Maaten et al. [2] present algorithms for automatic coin classification. The algorithms take digital images of coins as the input and generates output as a class. The method uses two stages of automatic classification, feature extraction stage followed by classification stage [2]. The accuracy achieved by this feature is 76% and the presence of a similar coin is required for positive results which significantly reduces the robustness of the algorithm.

Abdolah Chalechale [11] presented a novel approach for coin image recognition using image abstraction and spiral decomposition in 2007. SDAI (Spiral Decomposition of Abstract Image) enables measuring similarities between the full colour multi- component coin images and requires no cost intensive image segmentation [11]. The abstract image is derived from the original image based on strong edges of the coin. This is followed by the spiral distribution of pixels in the abstract image which is employed as a key concept for feature extraction. The ancient coins however are not symmetric and thus the centre detected can vary in each coin, thus the theory used to make the method rotation invariant can produce errors as all the coins of this paper's dataset are symmetric.

In 2007 Martin Kampel et al. [12, 13] gives the overview and the preliminary results of EU project COINS (COmbatting Illicit Numismatic Sales). They used edge based statistical distribution for extracting the features and then compared these features to recognize the coin by using the K-nearest Neighbor algorithm. The accuracy achieved is 76% and here as well, feature extraction requires the presence of similar coins.

The above literature survey highlights the dearth of research conducted in the field of ancient coins. This observation is supported [9] which concludes that there is very little work done in the field of classification of ancient coins. This problem is attributed to the lack of symmetry in the boundaries of these coins as they were made by simple hammering and casting processes. They were also subjected to different poor conditions due to wear and fouling [9]. These two factors have made classification unsuccessful. On one hand, methods of the classification of modern coins have 90%+ classification accuracy; on the other, the methods for ancient coins struggle to cross the 80% accuracy mark.

3. GOAL AND CONTRIBUTIONS

Goal: To classify ancient Indian coins into different categories based on their ancient rulers.

Contributions: The following is the contribution that this paper has made to improve classification of these ancient coins.

- Ancient coins are largely asymmetric, to resolve this issue, we extract the points that only lie on the surface of a coin by first using the thresholding method. This makes possible the proper processing of coins of any shape.
- For material based distinction we perform hue feature extraction. Hue is popular as a noiseless factor and is a unique property for the different alloys. We calculate the average value of hue over the entire coin surface. This makes the process rotation invariant. This is the first step of classification.
- Despite belonging to different eras, some coins used similar alloys in their manufacture. They were classified on the basis of the effects of the conditions to which they were exposed. The fouling and wear of the coins are bound to affect the colour factor of saturation in the HSV plane of the image and thus we use this to our advantage to differentiate between coins made of similar materials. This is the second step of classification.
- The method thus obtained does not depend on the orientation, features or text present on the coins, and is therefore able to achieve maximum robustness.

4. PROPOSED METHODOLOGY

Here we describe in detail the proposed approach for classification of coins of the ancient periods in India. The process involves a two-step material- based classification using the concepts of hue and saturation. This thus requires the mapping of the image to the HSV (Hue Saturation Value) plane. The HSV plane has certain advantages over the RGB plane such as the hue is invariant to highlights, shading and shadows [18, 19].

4.1. Transformation of Plane

The mapping of the RGB plane to the HSV plane is done as depicted below.

The mapping process [6] is For R, G, B $\in$ [0, 255], H $\in$ [0, 1], S, V $\in$ [0, 1], let Max = max (R, G, B) and Min = min (R, G, B).

When Max $\neq$ Min, define

$$R' = (Max - R)/(Max - Min) \tag{1}$$

$$G' = (Max - G)/(Max - Min) \tag{2}$$

$$B' = (Max - B)/(Max - Min) \tag{3}$$

Thus,

$$H = H/6 \tag{4}$$

$$S = (Max - Min)/Max \tag{5}$$

$$V = Max/255 \tag{6}$$

Where,

$$H = \begin{cases} (5 + B'), R = Max, G = Min \\ (1 - G'), R = Max, G \neq Min \\ (1 + R'), G = Max, B = Min \\ (3 - B'), G = Max, B \neq Min \\ (3 + G'), B = Max, R = Min \\ 5 - B'), others \end{cases} \tag{7}$$

When Max = Min or R = G = B, H = S = 0 and V = Max/255.

4.2. Foreground Extraction

The value matrix is then used for separating the coin from the background data using the thresholding algorithm[7] delineated below. This helps recognize the points for hue and saturation feature extraction.

Thresholding Algorithm [7]:

- Mapping from RGB plane to HSV plane.
- Extraction of value matrix from HSV color map.
- Creation of a local window for foreground – background separation.
- Filtration based either on mean or median: Mean- based: Using an averaging filter based on border replication; Median- based: Using median filtering for a given window size.
- Subtraction of the original value matrix from the filtration matrix and shifting of values for threshold-control.
- Binarization of the image.
- Complementation of the image.

Now, we compute the two features of hue and saturation for the classification in the following sections.

4.3. Hue Feature Extraction

The extraction of the coin from the background allows the comparison of the hue value with the original mapped image by recording the hue at the points where the value matrix depicts black color. The average hue value is then calculated at these points. The calculation of the average value of hue renders the process rotation invariant. The variation in the plane of rotation by any degree would provide the exact same hue value.

The different hue values help in the first step classification wherein the material used in the manufacture of the coin is identified based on the average hue value calculated.

4.4. Saturation Feature Extraction

The classification based on hue features however has certain common intersections in the dataset due to the reason that many ancient powers used almost identical materials for the manufacture of coins. This issue is resolved with the second step of classification wherein we take into account the noisy factor of saturation, which shows different values for the coins of the exact same material due to the difference of the location, and the various local environmental factors to which the coins were exposed. The saturation value is also calculated as an average over the entire surface of the coin and this helps us in the second step of classification by taking advantage of the deviation in texture due to the wear and fowling that the coin underwent. An illustration of the overall process is shown in Fig. 1.

5. EXPERIMENTAL RESULTS

The proposed two-step classification has been tested in MATLAB on the dataset [5]. The range of values of hue and saturation obtained of the coins of the different ancient powers is as depicted by the plots in Fig. 2 and Fig. 3. Fig. 2 depicts the first step classification range.

The plot depicts the range of hue values in which the coins of the Dutch, Danish, Ujjain and British fall in. The range of hue values for the Danish is 0.06 to 0.08 and 0.09 to 0.1061. The range of hue values for the

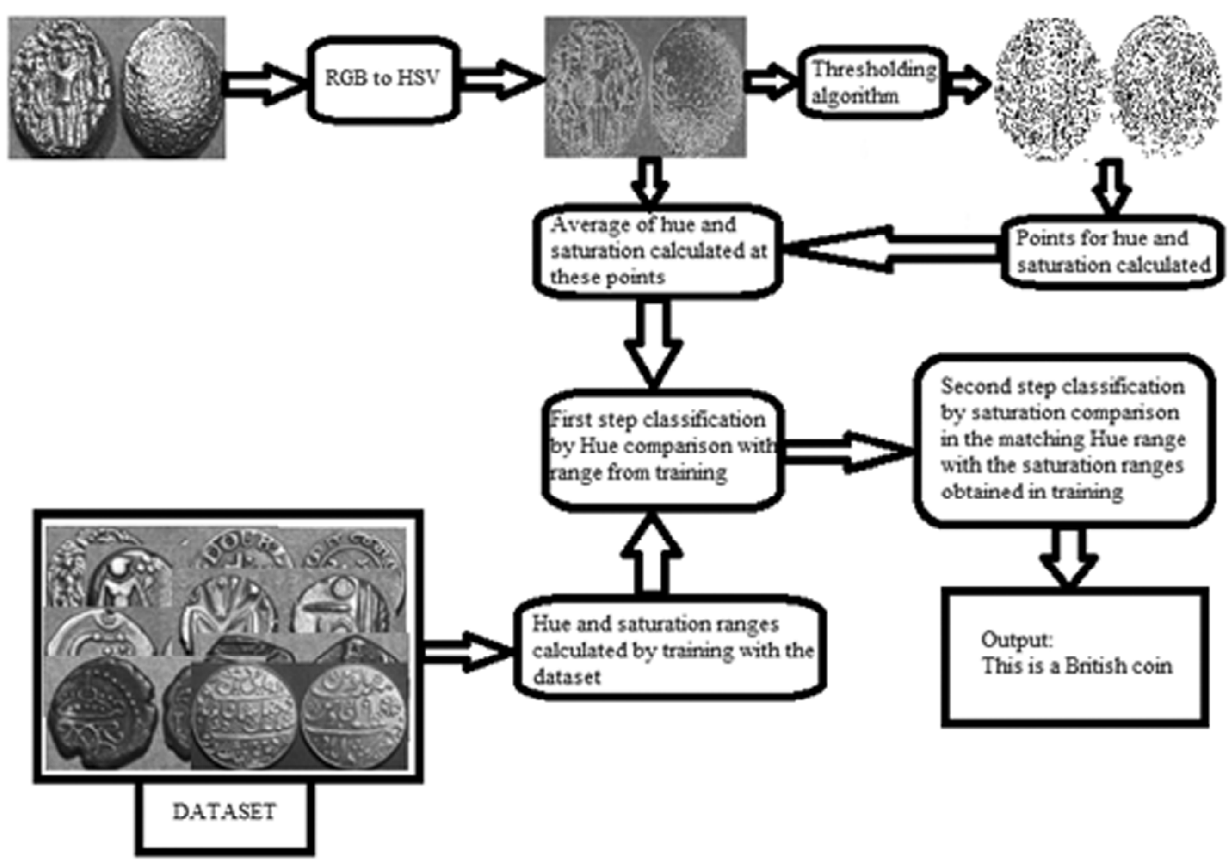


Figure 1: Illustration with British coin

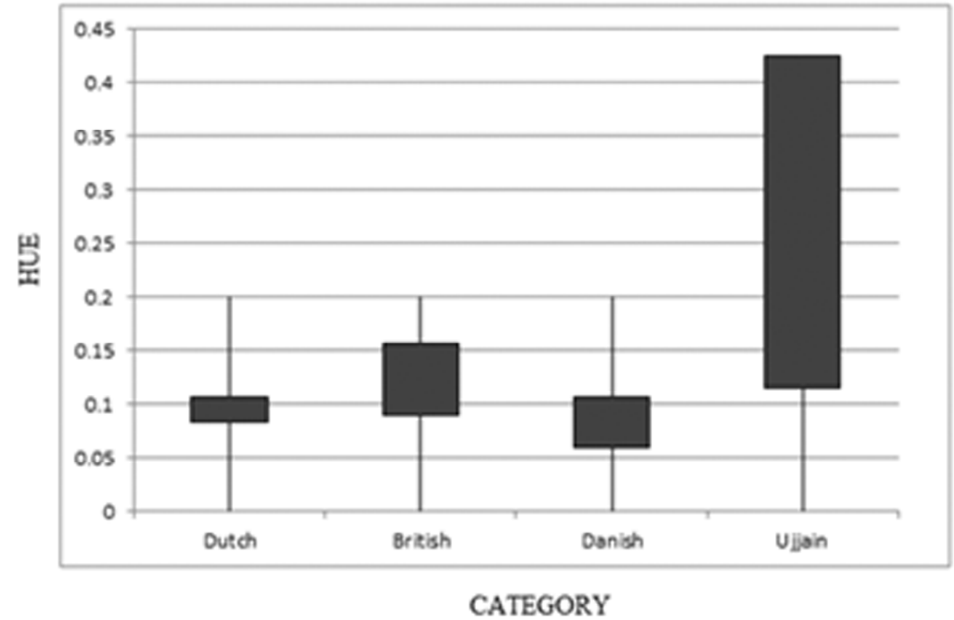


Figure 2: First step classification range

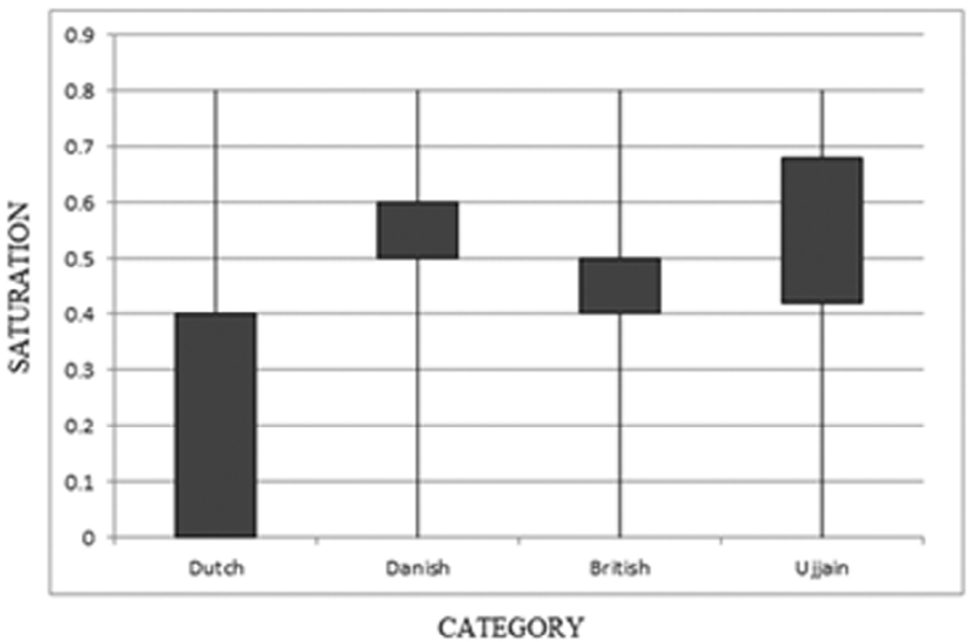


Figure 3: Second step classification range

Dutch is 0.083 to 0.1061. The range for the British is 0.09 to 0.1560. The range for Ujjain is 0.1164 to 0.4251. The classification based on hue features allows any coin in the 0.06 to 0.08 to be classified into the Danish category, the coins in the 0.083 to 0.09 to be classified into the Dutch, 0.1061 to 0.1560 to be classified into the British category, and 0.1560 to 0.4251 to be classified into the Ujjain category. The classification based on saturation feature is for the coins whose values are in the hue range 0.09 to 0.1061 and 0.1164 to 0.1560 because of the similar material used in the manufacture of these coins as mentioned in the introduction. We thus now see the second step of classification in terms of the saturation where if the value of saturation is less than 0.4 it is a Dutch coin. If the value is 0.5 to 0.6, it is Danish. If the saturation range is between 0.4 to 0.5 or 0.6 to 0.8, the coin is of British origin. Similarly, in differentiating in 0.1164 to 0.1560 among the British and Ujjain coins, if the saturation is between 0.3254 to 0.4183, the coin is British and if the range is 0.4183 to 0.6800, the coin is Ujjain. The above used second step classification range is depicted in Fig. 3.

The above procedure was tested on the dataset of 166 coins and the accuracy has been calculated using (8) and the result is presented in Table 2. Table 1 presents the process above for one correct classification of each category. Table 3 presents the comparison of the proposed methodology with the existing methods.

$$Accuracy = \frac{TP}{TP + FP} \times 100\% \tag{8}$$

TP = No. of true classifications

FP = No. of false classifications

Table 1
Intermediate Processing Results

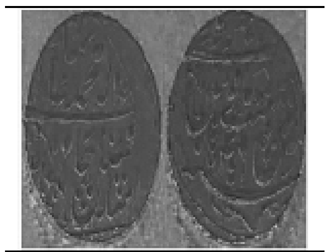
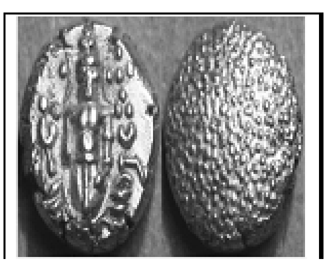
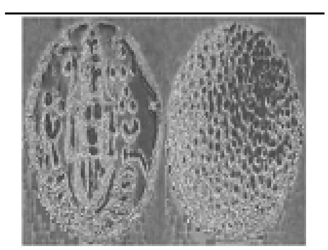
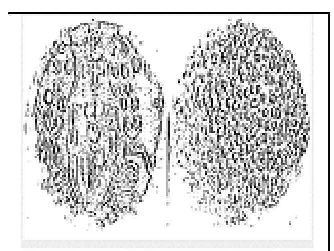
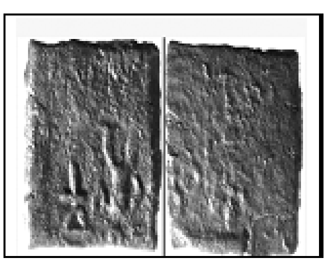
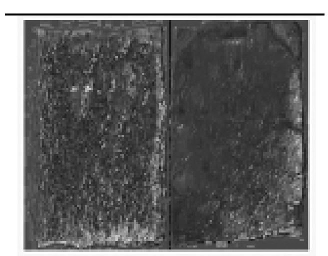
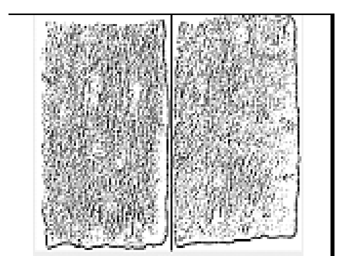
Input Coin	Plane transformation	ThresholdedImage	Hue Value	Saturation Value
			0.1100	0.3516
			0.0779	0.5509
			0.0896	0.6547
			0.2395	0.259

Table 2
Results

Total No. of Input Images	166
Correct classifications	149
Incorrect classifications	17
Overall Accuracy	89.75%

Table 3
Comparison of Different Classification algorithms

Algorithm	*Dataset*	*Accuracy*
Zambanini, S et al [1]	180 coins	83.3%
vander Maaten, L.J et al [2]	MUSCLE CIS dataset and Merovingen coin	76%
Quraishi et al [8]	20 coins	75%
Zaharieva, M et al and Kampel, M [12, 13]	MUSCLE CIS	76%
Arandjelovic, O. [17]	250 coins	57%
Proposed Method	166 coins [5]	89.75%

6. CONCLUSION

This paper proposes an algorithm to classify Ancient Indian coins based on the materials used for their manufacture. The novel method thus proposed has shown an 89.75% accuracy in the classification of coins based on the hue and saturation calculated from the images of the coins. The method although attains a very high accuracy is not able to provide a 100% accuracy due to the reason that some coins have similar material used by the ancient rulers and were produced and used in similar regions. The method thus proves its advantage over the existing methods by eliminating the need for the existence of a similar coin in the dataset and is invariant with respect to orientation. The proposed method is thus a novel approach that helps achieve a robust and complete solution for classification of ancient coins.

REFERENCES

[1] Zambanini S and Kampel M, “Coarse-to-fine correspondence search for classifying ancient coins”, ACCV Workshops. Heidelberg: Springer, vol. 7729, pp. 25-36, 2013.

[2] Maaten LJ and Postma EO, “Towards automatic coin classification”, Proceedings Of The EVA Vienna, pp.19-26, 2006.

[3] Zambanini S, Kavelar A and Kampel M, “Improving ancient roman coin classification by fusing exemplar-based classification and legend recognition”, ICIAP Heidelberg: Springer, vol. 8158, pp.149-158, 2013.

[4] Kavelar A, Zambanini S, Kampel M, Vondrevec K and Siegl K, “The ILAC-project: supporting ancient coin classification by means of image analysis”, XXIV International CIPA Symposium, 2013.

[5] COIN INDIA: The Virtual Museum of Indian Coins, coinindia.com, 2016.

[6] Hongru L, Xiaochen H and Yubin Z, “Research on case representation method based on image information”, Sixth International Symposium On Computational Intelligence And Design, pp.1, 2013.

[7] Jayanthi N, Indu S, Tripathi P and Gola P, “Novel method for manuscript and inscription text extraction”, IEEE International Conference On Signal Processing And Integrated Networks, 2016.

[8] Quraishi DG and Dhal DP, “Classification of ancient coin using artificial neural network”, International Journal of Computer Applications, vol. 62, pp. 0975-8887, 2013.

[9] Modi S and Bawa S, “Image processing based systems and techniques for the recognition of ancient and modern coins”, International Journal Of Computer Applications, vol. 47, pp. 1-5, 2012.

[10] Kaiping W, Bin H, Fang W, Tao Z and Quanjun D, “A novel method for ancient coins based on image textures”, Second Workshop On Digital Media And Its Application In Museum And Heritage, pp. 63-66, 2007.

[11] Chalechale A, “Coin recognition using image abstraction and spiral decomposition”, 9th International Symposium On Signal Processing And Its Applications, 2007.

[12] Zaharieva M, Kampel M and Zambanini S, “Image based recognition of coins- an overview of the COINS project”, 31st AAPR/OAGM Workshop, 2007.

[13] Kampel M and Zambanini S, “Optical recognition of modern and roman coins”, Layers Of Perception- CAA, 2007.

[14] Lowe DG, “Distinctive image features from scale-invariant keypoints”, International Journal Of Computer Vision, vol. 60, pp. 91-110, 2004.

[15] Bay H, Tuytelaars T and Gool LV, “SURF: Speeded up robust features” Computer Vision And Image Understanding, vol. 10, pp. 346-359, 2008.

[16] Li L and Zic J, “Image matching algorithm based on feature point and DAISY descriptor”, Journal Of Multimedia, vol. 9, pp. 6, 2014

[17] Arandjelovic O, “Automatic attribution of ancient roman imperial coin”, Conference On Computer Vision And Pattern Recognition, pp.1728-1734, 2010.

[18] Cheng H, Jiang X, Sun Y and Wang J, “Color image segmentation: advances and prospects”, Pattren Recognition, vol. 34, pp. 2259-2281, 2001.

[19] Cheng HD and Sun Y, “A hierarchial approach to color image segmentation using homogeneity”, IEEE Transactions On Image Processing, vol. 9, pp. 2071-2082, 2009.

[20] Arandjelovic O, “Automatic attribution of ancient Roman imperial coins”, Proc. IEEE Int. Conf. Computer Vision and Pattern Recognition, pp. 1728–1734, 2010.

[21] Kim J and Pavlovic V, “Ancient Coin Recognition based on Spatial Coding”, 22nd International Conference on Pattern Recognition, pp. 321-326, 2014.