International Journal of Computer Science Trends and Technology (IJCST) – Volume 10 Issue 5, Sep-Oct 2022

RESEARCH ARTICLE OPEN ACCESS

An Image-Based Approach for Detection of Fake Coins

Dr K Sailaja, MCA, M.Tech, M.Phil, Ph.D [1], U Mani Varma [2]

[1] Professor & HOD, Department of Computer Application
[2] Student, Department of Computer Application
[1], [2] Chadalawada Ramanamma Engineering College (Autonomous)

ABSTRACT
In this study, we offer a novel method for spotting counterfeit coins in photographs. The dissimilarity space is a vector space built by comparing a coin picture to a collection of prototypes. Dissimilarity between the target picture and a reference one is quantified in many dimensions. The local keypoints on each picture are recognised and explained to calculate the dissimilarity between the two coin images. In accordance with the coin's details, it is possible to quickly find the corresponding landmarks in the two photos. Furthermore, we offer a post-processing approach to get rid of duplicate keypoints. One-class learning is used for fake coin identification because there are so few fake coins in circulation that only actual coins are required to train the classifier. Many experiments have been run to test the suggested method with a variety of datasets. Those are some very outstanding outcomes, proving the legitimacy and usefulness of the approach.
Keywords: - Fake coins, fake coin detection, coin image representation, dissimilarity space, one-class learning.

I. INTRODUCTION

Money in the form of coins is employed in a broad variety of equipment and services throughout our everyday lives. With their superior durability against wear and tear, coins outlast paper money by many years. Coins aren't only useful for exchanging hands; they're also interesting collectibles because of the aesthetic worth they often have and the vivid glimpse they provide into the social life of the past. However, in recent years, several illicit counterfeiting groups have produced and sold phoney coins, resulting in substantial financial loss and social disruption. So, the ability to spot counterfeit money is crucial. In numismatics, this is a similar major issue. Though it's theoretically possible to have forensic professionals analyse the coins in question, the sheer number of coins involved makes this approach unfeasible. Because of this, there is a need for a system that can identify phoney coins automatically. Coin diameter, thickness, weight or shape may be used to distinguish between genuine and fake coins as presented in the patents [1, 2]. Although these measurements are easy to make, they are rather limited in the discriminative power. The fake coins made nowadays are of fairly high quality, so they often bear great resemblance to their genuine counterparts, which renders the detection of fake coins extremely challenging. Fake coins were detected by electronic means as proposed in the patent [3]. To this end, a primary coil that was excited by a signal with a particular frequency was imposed on one side of a coin passage. For the other side of the coin passage, it was associated with a secondary coil that was electromagnetically coupled with the primary coil. When a coin passed through, the attenuating voltage signal coming from the secondary coil could be used to determine whether the coin was genuine or fake. In addition to the electronic means, the magnetic properties of the coin were employed for fake coin detection in the patent [4].

II. RELATEDWORKS

In [5, 6], Hida et al. proposed to use X-ray fluorescence and X-ray di_raction to detect fake coins, and the raw materials used to make the coins were differentiated between genuine and fake coins.

There are a few attempts in the literature that exploit images for fake coin detection. They can be used stand alone or in conjunction with the methods mentioned above. Employing images to detect fake coins usually benefits from low cost and ease of use. With the growing popularity of smartphones, it is highly desired if one can determine the authenticity of a coin by simply taking a picture of it. More specifically, given the image captured from a coin, some pattern recognition techniques can then be applied to automatically decide whether it is genuine or fake. For example, Tresanchez et al. [7] proposed to detect two-Euro fake coins based on the coin images captured by an optical mouse sensor, with each image corresponding to a small area, viz. 1=14, of the coin. Several reference images from the two- Euro genuine coins were selected. Afterwards, the detection of fake coins was carried out by template matching. Yet, it was vulnerable to distortions resulting from coin rotation, wear and so on. Sun et al. [8] detected fake Danish coins based on their image characteristics. Although the experimental results were inspiring, the dataset used was extremely small which consisted of only 16 coins. The images were also employed for fake banknote detection as proposed in the papers [9, 10]. Several studies employed coin images to address the issue of coin recognition.

Coins may be recognized in terms of their issuing countries, denominations and so on. For example, two types of coins, namely, 500 Wons and 500 Yens, were recognized based on their image characteristics in [11]. Kim and Pavlovic [12] aimed at recognizing ancient Roman coins according to the engraved empires on the coin image. Huber et al. [13] proposed to recognize coin images in terms of their denominations and countries of origin. However, the problem of coin recognition significantly differs from fake coin detection investigated in this study. For coin recognition, one important concern is to reduce the sensitivity to the variations among the coins from the same class. So it is highly probable that the fake coins, especially those of high quality, are classified as belonging to the same class as their genuine counterparts under the coin recognition framework. However, these particular variations may be a very useful signal indicating the authenticity of the coin, and therefore need to be highlighted for fake coin detection. Moreover, detecting fake coins is considered more tricky due to the possibility that the aforementioned variations may arise from coin wear or contamination caused by daily use. In this case, the variations should be ignored like in the coin recognition problem. In order to exploit images for fake coin detection, the very first step is image representation. An informative as well as compact image representation is of paramount importance. Compared with using raw pixels for image representation, a preferable way is to extract features characterizing several different aspects of the image such as its texture or shape. The common practice is to put these features into a vector to represent the image. Using vectorial representation does not only benefit from its compactness but also facilitate the access to a rich repository of machine learning tools such as SVM [14, 15] and neural networks [16, 17] which work in the vector space. However, representing an image by a single vector usually lacks suffcient descriptive power. Moreover, the dimension of the vector has to be decided a priori and fixed for all the images regardless of their characteristics. Besides vectors, researchers came up with different ways of image representation. For example, trees [18, 19] and graphs [20, 21] were employed to represent images, while a variable length image signature was proposed in [22]. Although these representations are more flexible and powerful compared with the vectors, they are limited in the real world due to the high computational overhead.

In recent years, the local keypoint detectors and descriptors have been widely employed to describe an image [23–26]. The common pipeline is to first detect some keypoints in the image using detectors like Di_erence-of-Gaussian (DOG) [27], Harris-Laplace, Harris-A_ne, Hessian-Laplace or Hessian- A_ne [28]. Subsequently, the image region within a certain radius around the keypoint is described using descriptors such as Scale Invariant Feature Transform (SIFT) [27], PCA-SIFT [29], gradient location and orientation histogram (GLOH) [24] and shape context (SC) [30]. The local keypoint detectors and descriptors are distinguished by their great discriminative power and robustness to image distortions such as illumination, resolution and viewpoint transformations. Besides, the number of keypoints varies across images according to their characteristics. However, representing an image in terms of a set of keypoints cannot fit in the vector-based machine learning tools. To deal with this problem, the Bag-Of-Visual- Words (BOVW) model proposed by Sivic and Zisserman [31] may be employed. Analogous to the Bag-Of-Words (BOW) model in the text domain [32], a visual word vocabulary is built through clustering the local descriptors obtained from a training set. Hence an arbitrary descriptor can be represented by its nearest visual word in the vocabulary. Consequently, an image is represented by a vector, the dimension being equal to the size of the vocabulary. Each dimension of the vector denotes the occurrence statistics of the corresponding visual word in the image. Thanks to the vectorial representation, the machine learning tools are applicable. In spite of the popularity of the BOVW model, the discriminative power of the local descriptors is substantially diminished due to the involved clustering process. In this study, we also employ the local descriptors to generate image representations because of their superb discriminative power. However, instead of resorting to the BOVW model for generation of vectorial representations, we represent a coin image in the dissimilarity space [33–35]. A block diagram of the proposed approach. The dissimilarity space is constructed based on a very basic operation, viz. comparison. It benefits from mimicking human perceptions well. When presented a suspected coin, we humans tend to compare it with its genuine counterparts to see whether they are different or not. Likewise, to construct the dissimilarity space, each coin image to be detected will be compared with some prototype coins that are genuine and selected beforehand, based on which the image can be represented as a vector. The dimension of the vector is determined by the number of prototypes and each dimension measures the dissimilarity between the coin image under consideration and one of the prototypes. In order to compute the dissimilarity between the two coin images, the keypoints on each image are detected by the DOG detector and then described using the SIFT descriptor. The matched keypoints between the two images can be identified effciently by taking into account the characteristics of the coins. Furthermore, we propose a postprocessing procedure to remove mismatched keypoints. The dissimilarity between the two images is then derived from the number of matched keypoints. In this study, we compare two different prototype selection methods: random selection and clustering-based selection.

The random selection approach, as its name suggests, selects a set of prototypes randomly, while the K-medoids clustering [36] is employed for prototype selection in the clustering-based selection approach. Since no clustering is applied to the local descriptors like in the BOVW model, we are able to achieve the best of both worlds: the great discriminative power of the local keypoint descriptors and the availability of the machine learning tools. The superiority of using dissimilarity space over the BOVW model in generating image vectorial representations is evident from the experiments presented in Section IV-C. Considering the fact that the number of fake coins is usually very limited in the real world, one-class learning is conducted for fake coin detection. We employ one-class SVM [37, 38], which adapts the SVM methodology proposed by Vapnik to the one-class scenario, so only genuine coins are needed to train the classifier. The proposed approach is evaluated extensively on four different datasets, containing coins that are of different denominations and from different countries. Besides, the impact of the parameters involved in the proposed approach is thoroughly investigated. We also compare it with the fake coin detection method in the literature. The promising results have confirmed the potential of the proposed approach.

III. PROPOSED SYSTEM ARCHITECTURE

At first, a coin image is preprocessed to separate the coin from the background. Almost all the coins are circular except the ancient ones which are beyond the scope of this study. However, the coin may appear as an ellipse instead of a circle when it is not captured well. To address this issue, the Hough transform [39] aiming at ellipse detection is first employed. Afterwards, the obtained ellipse is normalized as a circle. Because of the great descriptive power of local descriptors, they are employed to measure coin image dissimilarity. More specifically, we first detect keypoints on the coin image based on the DOG detector. Afterwards, the SIFT descriptor is chosen for keypoint description. The combination of DOG detector and SIFT descriptor has been shown to outperform other detector & descriptor combinations in many applications [40, 41]. Given two coin images, their dissimilarity can be derived from the number of matched keypoints. Generally speaking, the smaller the number of matched keypoints, the more dissimilar the two coin images are. To find matched keypoints between two images, Lowe's methodology [27] is adopted. So the descriptor associated with the keypoint on one coin is compared with the descriptors of all the keypoints on the other coin in terms of Euclidean distance, from which its closest and second-closest neighbors can be identified. Based on the distance ratio of closest to second-closest neighbors, a decision with respect to whether the keypoint under consideration and its closest neighbor keypoint on the other coin are matched or not can be made by comparing the ratio with a threshold. Since there are usually hundreds or even thousands of keypoints on a coin image, searching the closest neighbor for each keypoint is computationally expensive. However, this problem can be alleviated by taking into consideration the characteristics of the coins.

Because the coins are circular, polar coordinates are preferred to the Cartesian coordinates when referring to the keypoints on the image. In real life, there is usually an imbalance with respect to the number of genuine and fake coins. It is much easier to obtain genuine coins compared with the fake ones. The issue of imbalance hampers the generalization ability of the commonly used two-class classifiers which need both positive and negative samples for training. To address this issue, we conduct one-class learning, so that the classifier can be built from genuine coins only. Adopting one-class rather than the two-class learning is also justified by the fact that it is not reasonable to classify the fake coins into one single class. Since most of the existing anti-counterfeiting techniques aim at one particular type of counterfeiting, the malicious counterfeiters usually make fake coins that are different from each other, and thus can fool the anti-counterfeiting techniques. So the fake coins may belong to multiple classes. Yet, all the genuine coins can roughly be assumed to be alike. Thanks to one-class learning, we are able to focus on the genuine coins, and will not get distracted by the diversities of fake coins. Given a coin to be examined, if it bears great resemblance to its genuine counterparts, it will be classified as genuine; otherwise, it will be considered as fake. We employ

one-class SVM for fake coin detection in this study. One-class SVM was proposed by Scholkopf et al. and was considered a natural extension of the support vector algorithm to the case of unlabelled data [37]. In general, the objects belonging to the class are termed as targets, while those outside the class are called outliers. With a set of training samples from the same class, the basic idea of one-class SVM is to learn a hypersphere which can enclose most of the training samples while minimizing the volume of the sphere at
the same time. As with SVM, the kernel trick is employed to map the input data to some feature space in which they can be linearly separable. In the mapped feature space, the origin is considered as the only sample from the second class. Then a maximum margin hyperplane separating the training samples from the origin will be learned.

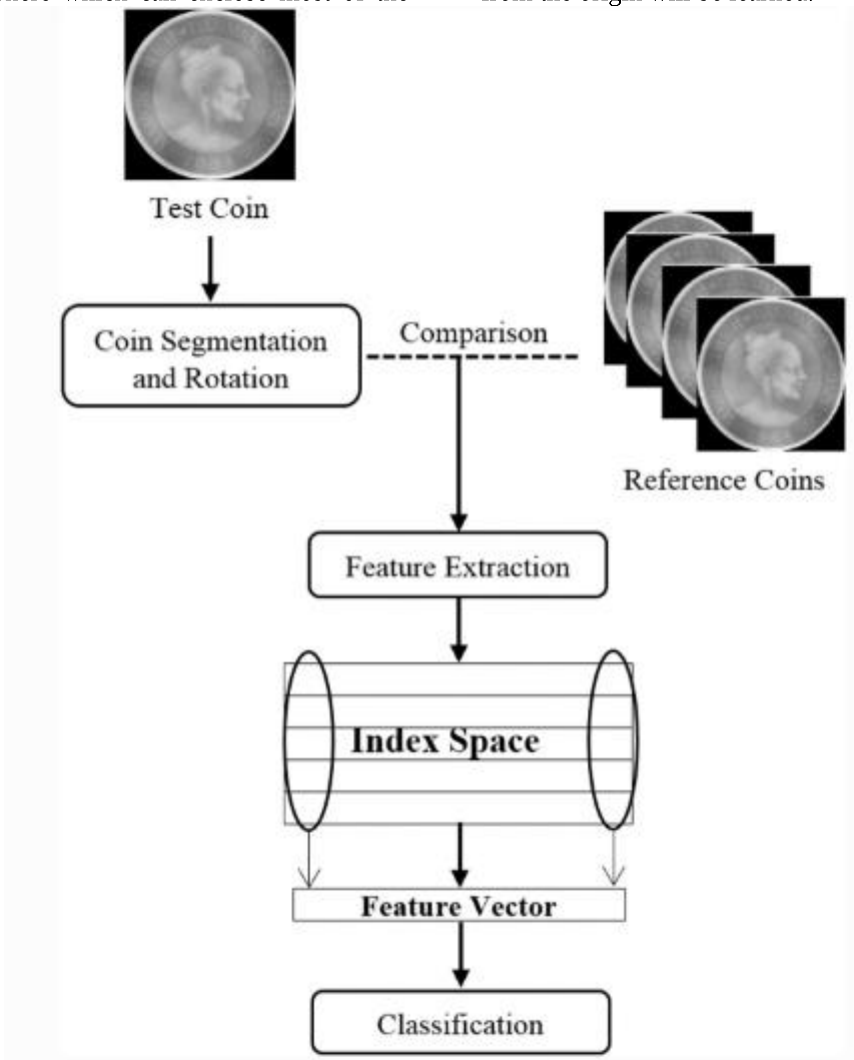


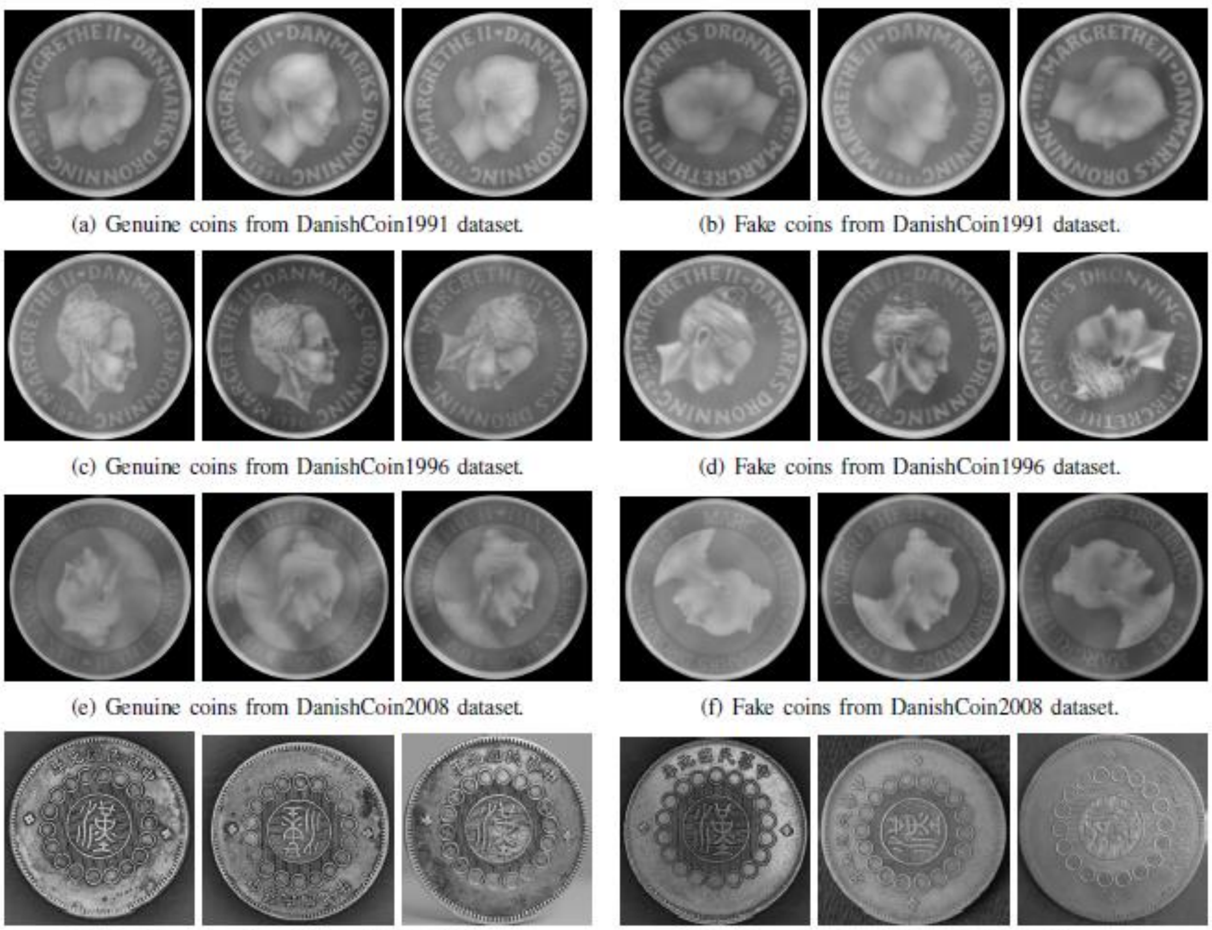
Fig.1 Proposed System Architecture

IV. RESULTS AND DISCUSSION

To validate the proposed approach, we evaluate it on different coin datasets. In addition, the impact of the parameters involved in the proposed approach is thoroughly investigated. In order to demonstrate the effectiveness of the proposed coin image representation in the dissimilarity space, we compare it with the representation generated from the commonly used BOVW model [31]. We further compare the proposed approach with Sun et al.'s method presented in [8]. Four datasets, namely, DanishCoin1991, DanishCoin1996, DanishCoin2008 and ChineseCoin1912, are employed in this study. The former three datasets are composed of the images captured from the obverse side of Denmark 20 Kroner of different years, while the ChineseCoin1912 dataset consists of images captured from the obverse side of one-yuan coins issued in the first year of the Republic of China. All the images are grayscale in JPEG format. The images in the same dataset are subject to different distortions. They are varied in several aspects involving resolution, orientation and illumination, etc. The number of genuine as well as fake coins in each dataset is specified in Table I. We show several genuine and fake coin samples in Fig. 2. Moreover, each dataset is randomly split into an independent training set, validation set and test set as shown in Table I. A classifier is learned based on the training set and then evaluated on the test set. Regarding the validation set, it is used to select the parameters involved in the proposed approach as detailed in Section IV-B. Note that the training set is composed of genuine coin images only. To evaluate the performance of the proposed approach, we employ the Receiver Operating Characteristics (ROC) curve [46]. It is obtained by applying different thresholds to the output of the decision function. Besides, to summarize the performance in terms of a single-figure measure, the Equal Error Rate (EER) is used. Ten different splits were made to construct the training, validation and test sets on each dataset, and the performance is reported in terms of the average ROC curve and average EER.

Table I Statistics of coins in the four datasets.

Datasets	No. of genuine coins	No. of fake coins	Total
DanishCoin1991	8, 210	2, 408	10, 618
DanishCoin1996	8, 236	2, 126	10, 362
DanishCoin2008	8, 160	2, 308	10, 468
ChineseCoin1912	6, 200	1, 300	7, 500



(a) Genuine coins from DanishCoin1991 dataset. (b) Fake coins from DanishCoin1991 dataset.

(c) Genuine coins from DanishCoin1996 dataset. (d) Fake coins from DanishCoin1996 dataset.

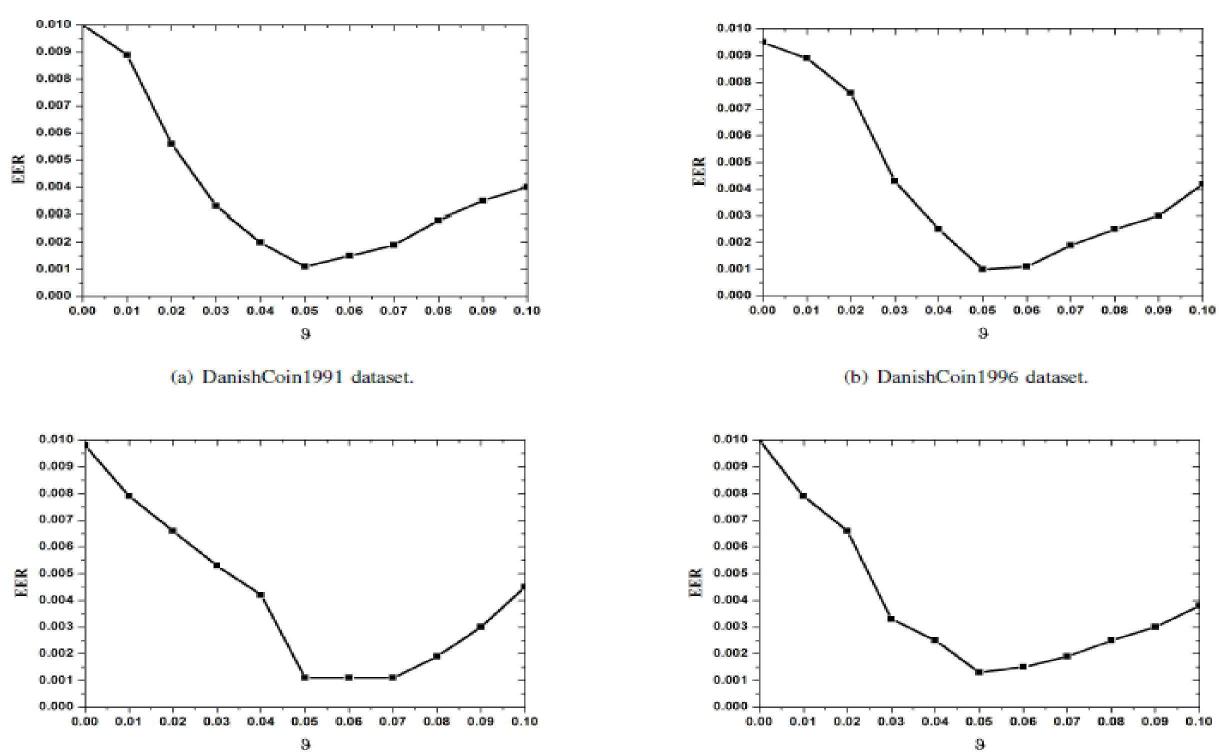
(e) Genuine coins from DanishCoin2008 dataset. (f) Fake coins from DanishCoin2008 dataset.

(g) Genuine coins from ChineseCoin1912 dataset. (h) Fake coins from ChineseCoin1912 dataset.

Fig. 2 Genuine and fake samples from the four datasets.

Various configurations of the proposed approach have been tried and compared on the validation set. The configuration which achieves the lowest EER on the validation set is then selected and applied to the test set. We compare the performance of the proposed approach using different keypoint detectors and descriptors as stated in Section I-A. According to the comparisons shown in Table I, the best performance is obtained when the combination of DOG detector and SIFT descriptor is applied. It is evident from the table that the EER is greatly reduced through removing mismatched keypoints. Number of prototypes & prototype selection methods & kernel functions. As mentioned in Section II, a set of K prototype images is needed to represent a coin image in the dissimilarity space. In Table I, we demonstrate the performance of the proposed approach with respect to di_erent values of K. One can observe from the table that the clustering-based prototype selection outperforms the random selection method. Thus we employ the clustering-based prototype selection approach in this study. Moreover, the RBF kernel performs better than the linear kernel regardless of the number of prototypes selected. As the number of prototypes is equal to the dimension of image representation, 100 prototypes are selected, viz. K = 100, which is able to strike a balance between performance and computational cost.

With the selected parameters, the performance of the proposed approach is evaluated on the test set. We first demonstrate the effectiveness of the proposed coin image representation in dissimilarity space by comparing it with the representation generated from the well-known BOVW model. To represent a coin image in terms of the BOVW model, the keypoints on the image are detected and described in the same manner as the proposed approach. Then a visual vocabulary is built, based on which the local descriptor from an arbitrary coin image can be assigned to its nearest neighbor in the vocabulary. The image is thus represented by a histogram, whose dimension is equal to the size of the vocabulary. Each dimension denotes the occurrence statistics of the corresponding visual word in the image. Since the spatial layout of the visual words is totally disregarded in the BOVW model, the discriminative power is rather limited. To address this issue, a coin is uniformly divided into R concentric circular sectors as illustrated in Fig. 3, where R = 5. Compared with the spatial pyramid proposed in [47], which divided an image into rectangular blocks, the circular division takes full advantage of the coin's characteristics and is robust to coin rotation. Subsequently, the histograms generated from all the sectors are concatenated to form the image representation. If the size of the visual vocabulary is S , the dimension of the representation will be S _ R. To ensure a fair comparison, we replace the proposed image representation in the dissimilarity space with the concatenated histogram as stated above, while leaving other steps as they are. We have compared different combinations of S and R, and the best performance is obtained when S = 500 and R = 5, which are employed in the following experiments. Besides, the linear kernel is adopted for the one-class SVM when the BOVW model is employed to generate image representation, as it yields better performance over the RBF kernel in our experiment.



(a) DanishCoin1991 dataset.

(b) DanishCoin1996 dataset.

(c) DanishCoin2008 dataset.

(d) ChineseCoin1912 dataset.

Fig.3 EER of the proposed approach w.r.t. different values on the four datasets.

The ROC comparisons of different image representation methods on all the four datasets are illustrated in Fig. 3. BOVW refers to its original formulation where no spatial information is taken into account corresponding to R = 1; CircularBOVW refers to considering the spatial layout of visual words by dividing the coin into circular sectors as stated above. Compared with the original BOVW model, CircularBOVW yields a better performance as can be seen from the figure 3, which confirms that the spatial information is of great importance and can boost the descriptive power. The proposed image representation outperforms all the other representations, demonstrating the potential of representing a coin image in the dissimilarity space. The EER comparisons are given in Table I, from which consistent conclusions can be drawn. In order to show the validity of the proposed approach, we further compare it with Sun et al.'s method [8], which also employed images to detect fake coins. In their method, the shape of the Queen's head on the Danish coin was described on one hand; on the other hand, the characters were extracted from the coin image and the properties of the characters such as the character stroke width and the relative distance between the adjacent characters were employed to distinguish between genuine and fake coins. Then a small dataset consisting of only 16 Danish coins was used for performance evaluation. The ROC comparisons between Sun et al.'s method and the proposed approach are shown in Fig. 3, and the EER comparisons are shown in Table I. Since the image features employed in Sun et al's method are specified for the Danish coins, they cannot be applied to the ChineseCoin1912 dataset. Because character segmentation is extremely sensitive to the quality of the coins, the performance of Sun et al.'s method is adversely hampered. It is clear from the comparisons that our proposed approach yields more promising results.

V. FUTURE SCOPE AND CONCLUSION

A fake coin detection method exploiting the characteristics of coin image is proposed in this paper. The coin image is represented in the dissimilarity space, whose dimension is determined by the number of prototypes. Each dimension corresponds to the dissimilarity between the coin image under consideration and a prototype. In order to compute the dissimilarity between two coin images, the local keypoints on each image are detected using the DOG detector and then described by the SIFT descriptor. Afterwards, the matched keypoints between the two images can be identified effciently based on the characteristics of the coins. We also propose a postprocessing method to remove mismatched keypoints. Since the number of fake coins is very limited in real life, we conduct one-class learning. It is distinguished by the ability to train the classifier using genuine coin samples only. The proposed approach is evaluated on four different coin datasets and very encouraging results have been obtained. In spite of the promising results achieved, the proposed approach is not without shortcomings. As stated above, for each type of the coins, some genuine coin images are needed for training. Yet, for some rare coins, it may not be easy to obtain enough genuine images for training. How to address this issue deserves a closer look and will be the focus of our future work.

REFERENCES

[1] B.M. Dobbins and J.E. Vaks. Method and apparatus for improved coin, bill and other currency acceptance and slug or counterfeit rejection. U.S. Patent, No. 5,167,313, Dec. 1, 1992.

[2] T. Nara and T. Ueki. Coin discriminating apparatus. U.S. Patent, No. 5,263,566, Nov. 23, 1993.

[3] Y. Furuya, T. Ishida and I. Fukuda, et al. Method and apparatus for sorting coins utilizing coin-derived signals containing di_erent harmonic components. U.S. Patent, No. 4,971,187, Nov. 20, 1990.

[4] K. Okada. Method and apparatus for discriminating coins or bank notes. U.S. Patent, No. 4,556,140, Dec. 3, 1985.

[5] M. Hida, T. Mitsuia and Y. Minamib. Forensic investigation of counterfeit coins. Forensic Science International, 89(1): 21-26, 1997.

[6] M. Hida, H. Sato and H. Sugawara, et al. Classification of counterfeit coins using multivariate analysis with Xray di_raction and X-ray fluorescence methods. Forensic Science International, 115(1): 129-134, 2001.

[7] M. Tresanchez, T. Pallej and M. Teixid, et al. Using the optical mouse sensor as a two-Euro counterfeit coin detector. Sensors, 9(9): 7083-7096, 2009.

[8] K. Sun, B.Y. Feng and P. Atighechian, et al. Detection of counterfeit coins based on shape and lettering features. Proceedings of

International Conference on Computer Applications in Industry and Engineering, pp. 165-170, 2015.
[9] A. Roy, B. Halder and U. Garain, et al. Machine-assisted authentication of paper currency: an experiment on Indian banknotes. International Journal on Document Analysis and Recognition, 18(3): 271-285, 2015.
[10] K. Yoshida, M. Kamruzzaman and F.A. Jewel, et al. Design and implementation of a machine vision based but low cost standalone system for real time counterfeit Bangladeshi bank notes detection. Proceedings of International Conference on Computer and Information Technology, pp. 1-5, 2007.
[11] M. Fukumi, S. Omatu and F. Takeda, et al. Rotationinvariant neural pattern recognition system with application to coin recognition. IEEE Transactions on Neural Networks, 3(2): 272-279, 1992.

igence, 27(1): 23-35, 2005.

[12] J. Kim and V. Pavlovic. Ancient coin recognition based on spatial coding. Proceedings of International Conference on Pattern Recognition, pp. 321-326, 2014.
[13] R. Huber, H. Ramoser and K. Mayer, et al. Classification of coins using an eigenspace approach. Pattern Recognition Letters, 26(1): 61-75, 2005.
[14] V.N. Vapnik. The nature of statistical learning theory. Springer-Verlag, New York, 1995.
[15] J.A.K. Suykens and J. Vandewalle. Least squares support vector machine classifiers. Neural Processing Letters, 9(3): 293-300, 1999.
[16] K. Hornik, M. Stinchcombe and H. White. Multilayer feedforward networks are universal approximators. Neural Networks, 2(5): 359-366, 1989.
[17] S. Marinai, M. Gori and G. Soda. Artificial neural networks for document analysis and recognition. IEEE Transactions on Pattern Analysis and Machine Intell