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AN EXTENSIVE STUDY ON CURRENCY RECOGNITION SYSTEM USING IMAGE PROCESSING

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ABSTRACT

We propose a new approach to detect fake currency using their images in this paper. A currency image is represented in the dissimilarity space, which is a vector space constructed by comparing the image with a set of prototypes. Each dimension measures the dissimilarity between the image under consideration and a prototype.

In order to obtain the dissimilarity between two currency images, the local key points on each image are detected and described. Based on the characteristics of the currency, the matched key points between the two image can be identified in an efficient manner. A post processing procedure is further proposed to remove mismatched key points.

Due to the limited number of fake currencies in real life, one-class learning is conducted for fake currency detection, so only genuine currency is needed to train the classifier. Extensive experiments have been carried out to evaluate the proposed approach on different datasets. The impressive results have demonstrated its validity and effectiveness.

INTRODUCTION

Currency recognition systems have become a vital part of our life. They are used in banks, supermarkets, grocery stores, vending machines etc. There is a basic need of highly accurate and efficient automatic currency recognition systems in our daily life. In -spite of daily uses currency yore cognition systems can also be used for the research purpose by the institutes or organizations that deal with the ancient currency. There are three types of currency recognition systems based on different methods used by them available in the market:

- Mechanical method-based systems
- Electromagnetic method-based systems
- Image processing-based systems

Mechanical method-based systems: The mechanical method-based systems use parameters like diameter or radius, thickness, weight and magnetism of the currency to differentiate between the currency. But these parameters cannot be used to differentiate between the different materials of the currency. It means if we provide two currency one original and other fake having same diameter, thickness, weight and magnetism but with different materials to mechanical method based currency recognition system then it will treat both the currency as original currency so these systems can be fooled easily.

Electromagnetic method-based systems: The electromagnetic method-based systems can differentiate between different materials because in these systems the currency is passed through an oscillating coil at a certain frequency and different materials bring different changes in the amplitude and direction of frequency. So, these changes and the other parameters like diameter, thickness, weight a magnetism can be used to differentiate between currency. The electromagnetic based currency recognition systems improve the accuracy of recognition but still they can be fooled by some game currency.

Image processing-based systems: In the recent years currency recognition systems based on images have also come into picture. In these systems first of all the image of the currency to be recognized is taken either by camera or by some scanning. Then these images are processed by using various techniques of image processing like FFT, DCT, edge detection, segmentation etc. and further various features are extracted from the images. Based on these features different currency is recognized.

LITERATURE SURVEY

Rotational Invariant Neural Pattern Recognition System: They have used 500 yen currency and 500 won currency to perform the experiment. In this work they have created a multilayered neural network and a preprocessor consists of many slabs of neurons. This preprocessor was used to get a rotational invariant input for the multilayered neural network. For the weights of neurons in preprocessor, concept of circular array was used instead of square array. The results show that 25 slabs with 72 neurons in each slab give the best recognition. They have used 500 yen currency and 500 won currency.

Characteristic Decision Trees: Decision trees constructed by ID3-like algorithms were unable to detect instances of categories not present in the set of training examples. Instead of being rejected, such instances get assigned to one of the classes actually present in the training set. To solve this problem the algorithm with learning characteristic, rather than discriminative, category descriptions was proposed. In addition, the ability to control the degree of generalization was identified as an essential property of such algorithms.

Dagobert: the ARC Seibers Dorf research center in 2003 developed a currency recognition and sorting system called Dagobert. This system was designed for fast classification of large number of modern currency from 30 different countries. Currency classification was accomplished by correlating the edge image of the currency with a pre-selected subset of master currency and finding the master currency with lowest distance. Pre-selection of master currency was done based on three rotation-invariant features (edge angle distribution, edge distance distribution, occurrences of different rotation-invariant patterns on circles centered at edge pixels), currency diameter and thickness. Experiments on 12,949 currency were performed and 99.24% recognition rate was achieved.

Vector Quantization and Histogram Modeling: A currency recognition system to recognize US currency using vector quantization and histogram modeling. The system mainly focuses on the texture of various images imprinted on the currency tail. Based on different image texture the system differentiate between Bald eagle on the quarter, the Torch of liberty on the dime, Thomas Jefferson's house on the nickel, and the Lincoln Memorial on the penny. Experiments show that out of 200 currency images 188 were correctly classified. Thus,94% recognition accuracy rate was achieved.

PROPOSED SYSTEM

The dissimilarity space is a vector space where an image is compared against a set of K prototype images, forming a K-dimensional vector based on dissimilarity measures. The effectiveness depends on the dissimilarity function and prototype selection.

For currency image comparison, preprocessing separates the currency from the background. Since most currencies are circular but may appear elliptical due to perspective distortion, an ellipse detection via Hough transform normalizes them into circles.

Key points are detected using the DOG (Difference of Gaussian) detector, and described using SIFT descriptors. The dissimilarity between two images is based on the number of matched keypoints, determined using Lowe's nearest neighbour ratio test.

To reduce computational complexity, key points are represented in polar coordinates (radius r and angle θ). Instead of searching all key points, only those with a similar normalized radius ($r \pm 0.05$) are considered, ensuring robustness to scale variations. This approach improves efficiency while maintaining accuracy in currency comparison.

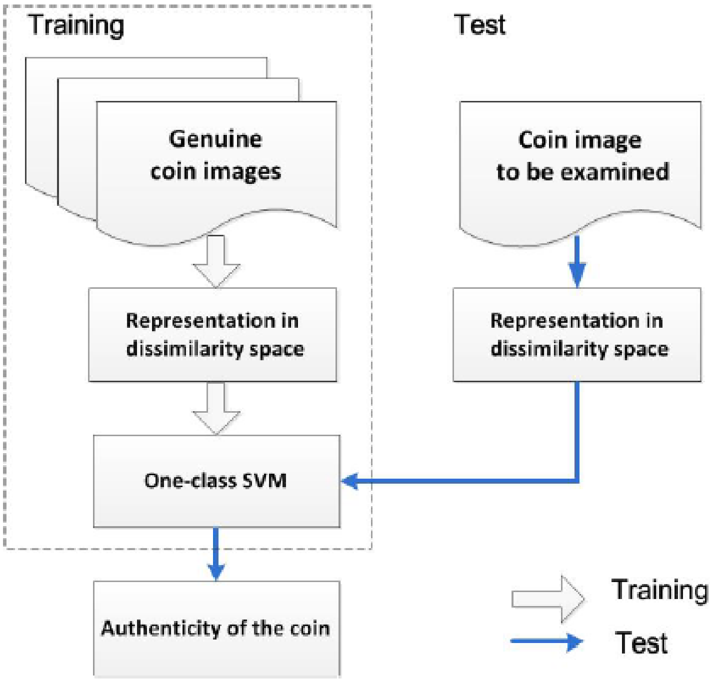


Figure.1 Block Diagram

Currency Representation in Dissimilarity Space

- A currency image is represented as a K-dimensional vector, where each dimension measures dissimilarity with K pre-selected prototype images.
- Prototype selection methods:
- Random selection: Selecting K genuine currency images randomly.

- Clustering-based selection: Using K-medoids clustering to select representative prototypes.
- Genuine currency is used as prototypes, as comparisons are made against real notes rather than fake ones.

2. Fake Currency Detection Using One-Class Learning

- Imbalance issue: Fake currencies are fewer and vary greatly, making traditional two-class classification ineffective.
- One-Class SVM Approach:
- Decision Rule: If a currency sample closely matches genuine samples, it is classified as real; otherwise, it is considered fake.

SIMULATION RESULTS

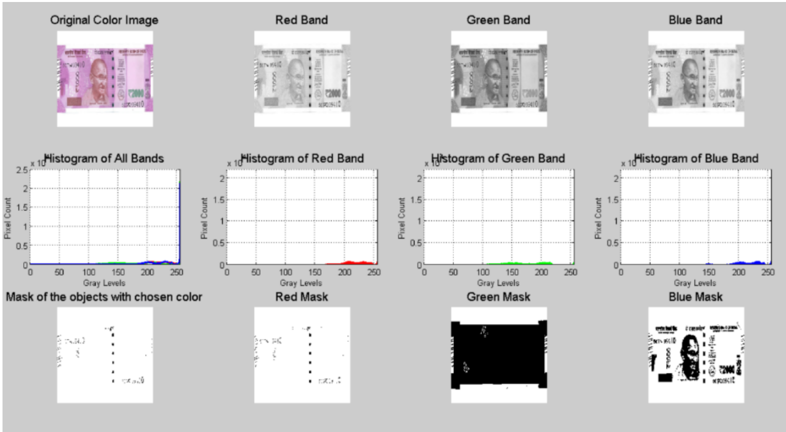
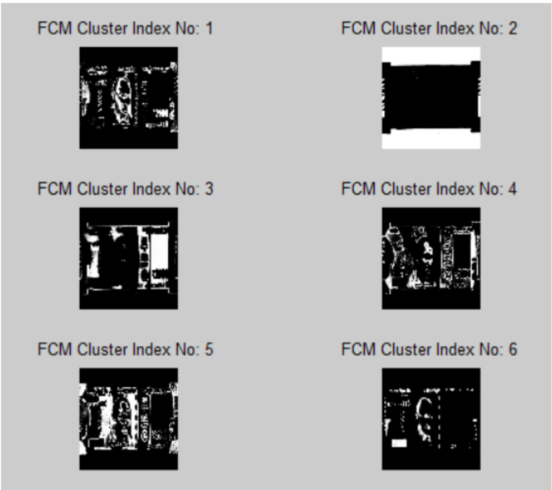


Figure.2 Simulation Result of Currency Note



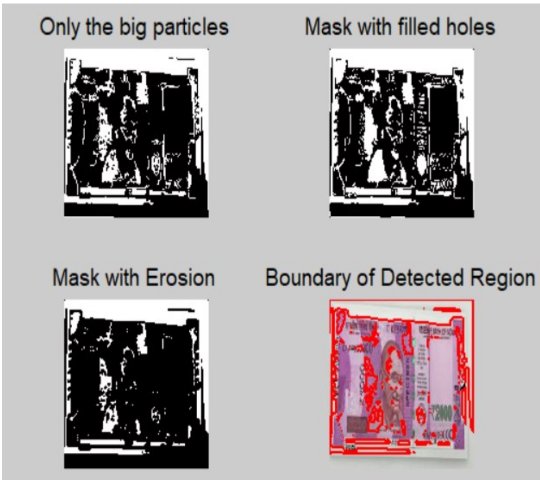


Figure.3 FCM Cluster Result

Figure.4 Boundary of Detected Region

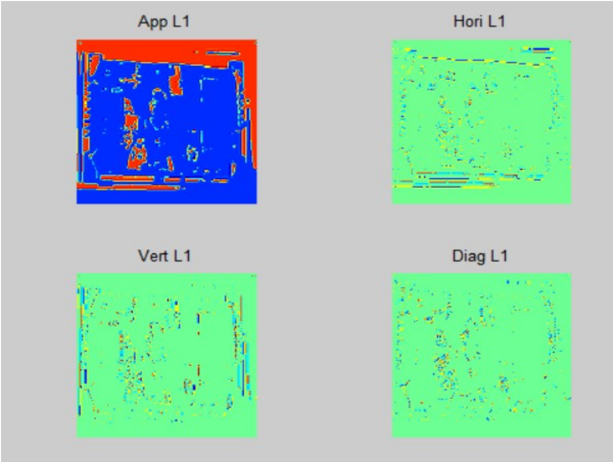


Figure.5 Line 1 Detection

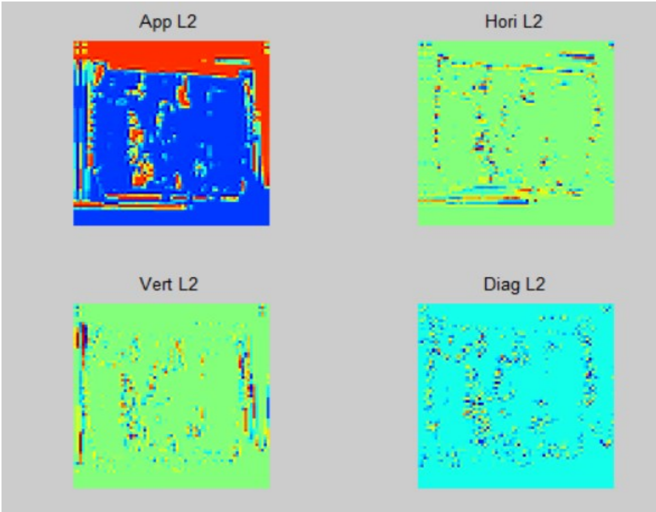


Figure.6 Line 2 Detection

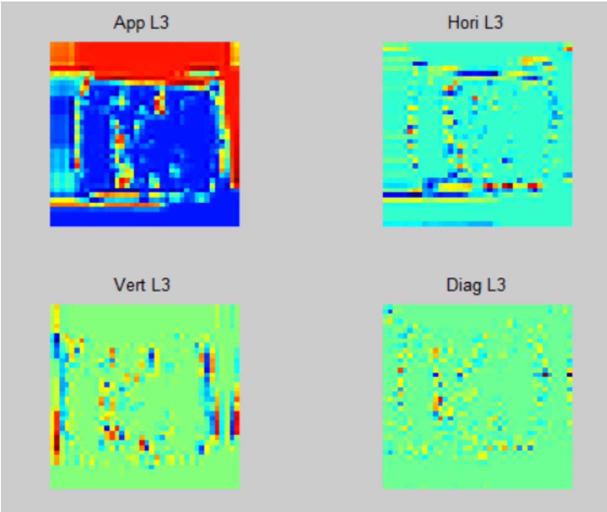


Figure.7 Line 3 Detection

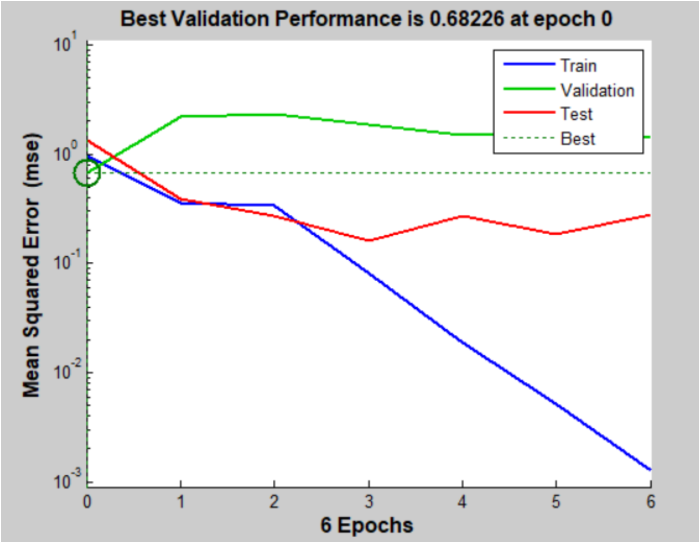


Figure.8 Mean Square Error

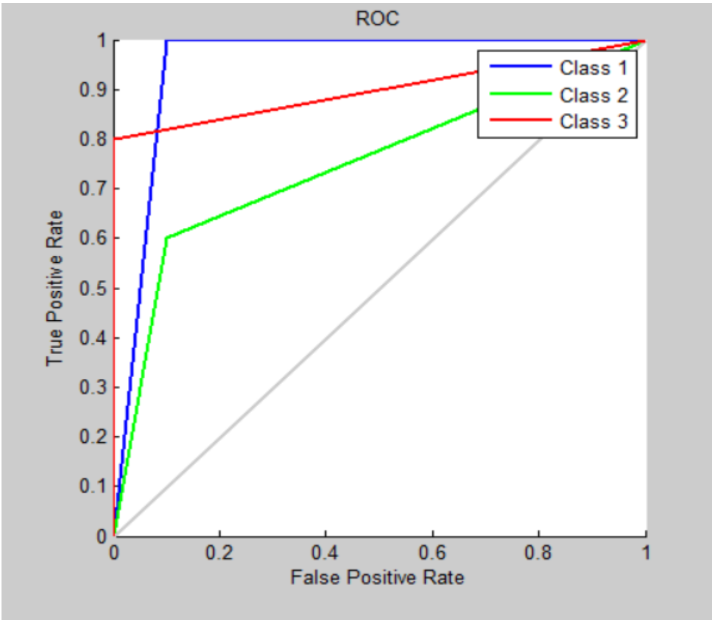


Figure.9 True and False Positive Rate

ADVANTAGES

- 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 key point 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.
- The proposed approach is evaluated extensively on four different datasets, containing currency that are of different denominations and from different countries.

APPLICATIONS:

Advanced Driver Assistance Systems (ADAS)

ADAS includes safety features such as lane departure warning, forward collision warning, and adaptive cruise control. These systems rely on environmental perception to assist drivers in maintaining control and avoiding accidents. Fog detection enhances visibility assessments, ensuring the system accurately detects lanes and obstacles in adverse weather. Free space segmentation helps determine drivable areas, improving decision-making. Enhancing these aspects makes ADAS more reliable in foggy conditions, reducing accident risks.

Autonomous Vehicles

Self-driving cars require precise environmental perception for safe navigation. Fog detection helps identify low-visibility conditions, allowing the vehicle to adjust speed and route accordingly. Free space segmentation enables the vehicle to distinguish drivable areas from obstacles, ensuring a smooth driving path. These technologies work together to maintain safety and efficiency in challenging weather. By improving fog detection and segmentation, autonomous vehicles can operate more reliably in real-world conditions.

Traffic Management Systems

Real-time fog detection data plays a vital role in traffic management by identifying hazardous road conditions. Traffic control centres can use this data to adjust signal timings, issue warnings to drivers, and deploy emergency services when necessary. Accurate fog detection helps reduce accident risks by informing drivers of potential dangers in advance. Free space segmentation ensures efficient rerouting in case of road blockages. These improvements contribute to overall traffic safety and smoother road operations.

CONCLUSION

A fake currency detection method exploiting the characteristics of currency image is proposed in this paper. The currency image is represented in the dissimilarity space, whose dimension is determined by the number of prototypes. Each dimension corresponds to the dissimilarity between the currency image under consideration and a prototype. In order to compute the dissimilarity between two currency 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 efficiently based on the characteristics of the currency.

We also propose a post processing method to remove mismatched keypoints. Since the number of fake currency is very limited in real life, we conduct one-class learning. It is distinguished by the ability to train the classifier using genuine currency samples only. The proposed approach is evaluated on four different currency 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 currency, some genuine currency images are needed for training. Yet, for some rare currency, 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 currency, 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. Currency 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 currency utilizing currency-derived signals containing different harmonic components. U.S. Patent, No. 4,971,187, Nov. 20, 1990.

[4] K. Okada. Method and apparatus for discriminating currency 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 currency. Forensic Science International, 89(1): 21-26, 1997.

[6] M. Hida, H. Sato and H. Sugawara, et al. Classification of counterfeit currency using multivariate analysis with Xray diffraction 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 currency detector. Sensors, 9(9): 7083-7096, 2009.

[8] K. Sun, B.Y. Feng and P. Atighechian, et al. Detection of counterfeit currency 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 currency recognition. IEEE Transactions on Neural Networks, 3(2): 272-279, 1992.

[12] J. Kim and V. Pavlovic. Ancient currency 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 currency 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.