The State-of-the-art Technology of Currency Identification: A Comparative Study

1 INTRODUCTION

Currency has become a medium for trading various goods that replaces the ancient barter system. Currency is composed of three important components, namely, coins, banknotes and electronic data. The stability of currency represents a nation's overall strength in economy. Therefore it appears to be significant to protect security of currency's circulations.

However, there exists currency counterfeit that influences the normal stability of currency. Cheaters are able to produce reprographic equipment to copy, scan and distribute fake banknotes that severely affects security of currency. The currency problem requires national reserve banks raise effective technical solutions to cope with them. Even if private banks have their own approaches of handling the threats from counterfeit currency, national reserve banks should officially have the authorization to centralize currency issue and policy establishment.

A counterfeiter's primary objective is to reproduce passable reproductions and mastering security features. Security features are classified into three categories [3][22][23][49][50], (a) immediately detectable through human senses, (b) hidden from normal view of human senses, detectable using basic tools, such as a magnifying glasses or Ultra Violet light, (c) intrinsic characteristics resulting from the manufacturing process and the interaction of raw materials.

As physical banknotes have obvious weaknesses, all paper-like materials are prone to wear and tear, therefore they are possibly exploited by counterfeiters for producing forged banknotes which are hardly recognized by currency examination machines and tools. Therefore banks and cashers are using techniques such as digital image processing, machine vision and pattern recognition that effectively distinguish fake banknotes from the authentic ones [51,52,53]. Software is being trained to recognize specific banknotes using learned knowledge based on computable features, a banknote which does not meet the specified condition is deemed to be either counterfeit or worn-out which affects normal transactions, it will be further examined and may be removed from the circulation. Similarly, if a banknote has such an engraving and printing problem in producing time which has been found out by using the same machine vision technology, it will be disposed before it entered the circulation after manual examinations. Traditional currency recognition software is used to check print quality of new notes [51,52,53]. It is considered to be significant of utilizing print banknotes, quality of notes remains to be authenticated by manual inspections. Cheaters are able to reproduce the forged notes with certain security features by simulating the genuine ones. However, it is impossible for them to distribute the notes with all the security features [12][15][19][24][27][30][33].

Albeit there is a new kind of money which is electronic version of currency, it contains most of the basic security components which are inherited from physical banknotes. Nevertheless, as differences exist in transactions of using physical banknotes and electronic currency, the security and governance should be taken into consideration. In this paper, we will analyze features of currency by using feature extraction and classification techniques in the banknotes of USD (USA Dollar), NZD (New Zealand Dollar) and CNY (Chinese Yuan).

In this paper, we hope to investigate quantitative methods of currency authentication further, a comparative study will be conducted based on the methods illustrated in Table 1 which is based on a published survey paper [51]. By designing and implementing an experiment on these feature extraction methods and classifiers, we expect selecting an existing algorithm that performs the best in distinguishing genuine currency notes from the forgery ones. Our contribution is to conduct comparisons of banknote identification approaches and select an effective identification method from various candidate ones. In this paper, the brief introduction of feature extraction and classifiers as well as the proposed algorithms are presented in Section 2. The explanation of our dataset and the experiment process are described in Section 3. Section 4 will present the analysis of the experimental results. Finally, the conclusion of this paper will be drawn in Section 5.

2 CURRENCY SECURITY COMPUTATIONS

Digital image processing and computer vision have been employed to quality assurance of paper currency in the producing time and currency authentication in the transaction time. Usually the Bureau of Engraving and Printing of the government officially take over production of paper currency and examine the printing procedure. In real transactions, the bank and government of all countries allow cashers to use the Cash Check and Count Machines for cash verification which are granted by government. Any suspicious cashes will be reported to police for further investigations.

Table 1. Prevalent feature extraction and classification algorithms in currency authentication from the previous literatures review [51]

Task	Method
Feature extraction	Canny
	Hough Transform
	PCA
	SURF
	LBP
Classification	LVQ
	GA
	ANN

	SVM
	Adaboost
	HMM

Our aims in this section are to investigate the algorithms that have been employed to the area of currency authentication by using those computable features in Table 1. Our goal is to automatically authenticate banknotes under a camera. By summing up the features and classifiers, this paper compares the results of experiments using these existing approaches such as CPN, SURF or Discrete Wavelet Transform for classification [4][17][20][21] [22] [29] [35][38][40][45][47][48].

2.1 Computable Features

Despite the current security approaches of currency notes vary as the variances of nations and regions, the authentication is achieved by using multiple models of Human Vision System (HVS) such as security strips and paper watermarks. Basically, the authentication of these notes is in accordance with digital image processing since the geometric patterns on currency notes are designed for currency types and edition distinctions. Therefore it is crucial to investigate the authentication of currency notes synthetically from the point view of visual information such as computer graphics, digital image processing, and computer vision, etc. Based on the given currency features, detection and classification algorithms could be employed to authenticate currency notes, etc.

2.1.1 Canny Edge Detector

Previous research work has extended the knowledge of banknote authentication based on security components by utilizing various feature extraction and classification algorithms. One generally used in feature extraction is Canny edge detector. There are two criteria for evaluating performance of edge detectors [1][38][49]. The first criterion is that a qualified detector needs to have a good signal-to-noise ratio which is able to facilitate the process of edge detector. The other is the accuracy of edge detection which describes precise boundaries of the detected object.

The process of the Canny edge detection encompasses multiple stages. At the first step, an image is processed with a filter to remove insignificant details of the image which is then transferred to a grayscale image. The most widespread use of filters for noise removal in Canny edge detection is Gaussian operator. One concern in setting of the filter is the tune of its width which severely affects the result due to noise. On the next phase the gradient of each pixel is determined.

As edges of an image may be expanded in any directions, the Canny algorithm detects edges in four directions, namely, horizontal, vertical and diagonal directions. The magnitude is called edge strength and calculated by using operators such as Roberts, Prewitt, Sobel which returns two metrics of gradient in two directions. From this, the edge, gradient and direction are obtained by,

$$G = \sqrt{G_x^2 + G_y^2} \tag{1}$$

$$\theta = \arctan(\frac{G_y}{G_x}) \tag{2}$$

where G is the gradient strength and $arctan(\cdot)$ is the arctangent function which is computed for the start of direction. The edge direction angle is rounded to one of four angles representing horizontal, vertical and the two diagonals (0˚, 90˚, 45˚ and 135˚, respectively).

2.1.2 Hough Transform

Hough transform is a technique which is used to extract features of a specific shape from an image [23]. Classical Hough transform is most broadly used for detection of regular patterns such as lines and circles. Despite its domain restrictions, the classical Hough transform retains a myriad of applications as the most manufactured parts contain feature boundaries which are described by regular curves. The main advantage of Hough transform technique is that it is able to avoid influence of gaps in feature boundary detection and is relatively immune to image noise. The Hough transform method performs well in the detection of fake banknotes which have been in circulation. This is because of its ability to detect lines where there are gaps in the captured image, especially for notes which are torn-up or worn-out.

The simplest case of Hough transform is the linear transform for detecting straight lines. In the image, a straight line is described as $y = m \cdot x + b$ where the parameter m is slope of the line, and b is the intercept. For the sake of computations, Hough transform uses a different pair of parameters, denoted as r and θ for the lines in Hough transform. In a polar coordinate system, the parameter r represents the algebraic distance between the line and the origin, while θ is angle of the vector orthogonal to the line and pointing toward the half upper plane. Linear Hough Transform is interpreted as:

$$y = (-\frac{\cos\theta}{\sin\theta})x + (\frac{r}{\sin\theta}) \tag{3}$$

$$r = x \cdot \cos\theta + y \cdot \sin\theta \tag{4}$$

Each line in an image after Hough transform has a value of (r, θ) where $\theta \in [0, 2\pi]$ and $r \geq 0$. The (r, θ) is used to define Hough space for analyzing lines in two dimensions.

2.1.3 PCA

Principal Component Analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components [26][44]. The number of principal components is less than or equal to the number of original variables. This transformation is defined in such a way that the first principal component has the largest possible variance, and each succeeding component in turn has the highest variant possibility under the constraint that it is orthogonal to the preceding components.

PCA is the simplest of true eigenvector-based multivariate analyses. Its operation is often thought of as revealing the internal structure of the data in a way that best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space, the PCA supplies us with a lower-dimensional picture, a projection of this object when viewed from its most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced. The PCA is one of the most popular methods for feature extraction of data and it is discussed in documents on multivariate analysis. The most common derivation of the PCA is in terms of a standardized linear projection which maximizes the variance in the projected space.

The PCA is well suited for extracting characteristics from banknotes, as banknotes are high quality documents, much classification data is captured. When embedded smart detection devices into ATM and banknote sorting machines, time is a critical factor as the PCA is used to determine the necessary features, we assure that only the necessary elements are being checked for this purpose.

Traditionally, the PCA is performed on symmetric covariance matrix or symmetric correlation matrix. These matrices are calculated from the data matrix. The covariance matrix contains scaled sums of squares and cross products. A correlation matrix is like a covariance matrix. The principal components are normalized eigenvectors of the covariance matrix of the genes and ordered according to how much of the variation present in the data they contain. Each component is then interpreted as the direction, uncorrelated to previous components, which maximizes variance of the samples when projected onto the component. The dimensionality is reduced to a single dimension by projecting each sample onto the first principal component.

2.1.4 LBP

Local Binary Pattern (LBP) is an operator for texture description and it converts the original image into binary one by using a threshold to choose value of each pixel [16][42]. The LBP value of a certain pixel is calculated by the following Equation (5).

$$LBP(p) = \sum_{i=0}^{7} 2^i \cdot s(g_i - g_p) \tag{5}$$

Where g_p is the value of a pixel p, g_i is the grayscale value of i-th pixel around pixel p which totally has eight neighbors. Threshold of the pixel is given by the function $s(\cdot)$.

The normal process of LBP is:

Step 1. Separate the original picture into cells.
Step 2. Compare one pixel to each of its eight-neighbors following a direction of clockwise.

Step 3. If a central pixel value is greater than the value of adjacent pixels, then this neighbor will be replaced by the value of 1 and vice versa.
Step 4. Make the result of each cell into the histogram so as to demonstrate the frequency of each number
Step 5. Normalize the histogram.
Step 6. Combine histograms of each cell in the image and construct the feature vector for the entire image.

Once the feature vector of LBP is formed, it is then utilized in machine learning algorithm to classify or cluster images. The LBP is broadly used for face recognition and other fields which require texture analysis.

2.2 Classification Algorithms

2.2.1 SVM

In machine learning, Support Vector Machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns for classification and regression analysis [11][34][41][43][46]. Given a set of training examples labelled as one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, makes it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into the same space which belongs to a category based on which side of the gap they fall on.

2.2.2 GA

A Genetic Algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution [10]. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce their children for next generation. Over successive generations, the population evolves toward an optimal solution.

The GA algorithm is applied to solve the problems that are not well suited for standard optimization algorithms, including problems in which the objective function is discontinuous, non-differentiable, stochastic, or highly nonlinear.

The GA algorithm usually starts with a set of solutions (represented by chromosomes) called population. Solutions from one population are taken and used to form a new population. This is motivated by hypnosis that the new population will be better than the old ones. Solutions chosen to form new solutions (offspring) are selected for currency identification according to the fitness - the more suitable they are, the more chances they have to reproduce.

2.2.3 LVQ

A Learning Vector Quantization (LVQ) network has the first competitive layer and a second linear layer [14]. The competitive layer learns to classify input vectors in the same way as the competitive layers of Cluster with Self-Organizing Map Neural Network. The linear layer transforms the competitive layer's classes into target classifications defined by the user. The classes learned by the competitive layer are referred to as subclasses and classes of the linear layer as target classes.

An advantage of LVQ is to create prototypes that are easy to interpret for experts in the respective application domain. The LVQ is applied to multi-class classification problems in a natural way.

2.2.4 SOM

A Self-Organizing Map (SOM) or Self-Organizing Feature Map (SOFM) is a type of Artificial Neural Network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of input space of the training samples, called a map [7][39]. SOMs are different from other ANNs in the sense that they use a neighborhood function to preserve topological properties of the input.

2.2.5 HMM

Hidden Markov Model (HMM) which is employed to detect differences between several continuous states, is a widely used algorithm in statistic [9][32][37]. HMM utilized in currency notes authentication is due to its probability presentation in time-varying sequences. Equation (6) indicates the computational process of the HMM.

$$\overline{\lambda} = \arg\max(P(\lambda \mid O_i, i = 1, \cdots t)) \tag{6}$$

where λ is the model to be estimated, O is the observation sequences in training set, P is a probability of O in the model λ. The best model λ^* is selected with the highest probability.

$$P(\lambda^* \mid O) = \max_{\lambda m} P(\lambda_m \mid O) \tag{7}$$

where m is the number of candidate models, O is the given sequence to be trained. The probability is calculated by Bayesian theory:

$$P(\lambda_m \mid O) = \frac{P(\lambda_m) P(O \mid \lambda_m)}{P(O)} \tag{8}$$

In HMM, the model selection is conducted based on the number of states, training iterations and Gaussian components. The number of Gaussian components is iteratively increased in test for determining its most suitable value for certain model establishment. Further, the length of sequence is also a significant parameter to be tested in the experiments.

2.2.6 ANN

Artificial Neural Networks (ANN) are typically organized in layers [2][5][6][8][18] [25] [28] [31]. Layers are made up of a number of interconnected nodes which contain an activation function. Various patterns are presented to the network via input layer, which communicates to one or more hidden layers where the actual process is done via a system of weighted connections.

With the delta rule, as with other types of propagation, learning is a supervised process that occurs with each cycle or epoch (i.e. each time the network is presented with a new input pattern) through a forward activation flow of outputs, and the backwards error propagation of weight adjustments. When a neural network is initially presented with a pattern it makes a random guess as to what it might be. It then sees how far its answer was from the actual one and makes an appropriate adjustment to its connection weights.

Once a neural network is trained to a satisfactory level it may be used as an analytical tool on other data. In order to work for this task, a user no longer specifies any training runs and instead allows the network to work in forward propagation mode only. New inputs are presented as the input pattern where they filter into and are processed by the middle layers as training is taking place. The output of a forward propagation is the predicted model for the data which is then used for further analysis and interpretation.

2.2.7 AdaBoost

AdaBoost (adaptive boosting) is an ensemble learning algorithm that is used for classification or regression [13]. Although the AdaBoost is more resistant to over-fitting than many machine learning algorithms, it is often sensitive to noisy data and outliers.

AdaBoost is also called adaptive because it uses multiple iterations to generate a single composite strong learner. AdaBoost creates the strong learner (a classifier that is well-correlated to the true classifier) by iteratively adding a classifier that is only slightly correlated to the true classifier (a week learner). During each round of training, a new weak learner is added to the ensemble and a weighting vector is adjusted to concentrate on examples that were misclassified in previous rounds. The result is a classifier that has higher accuracy than the weak learners' classifiers.

3 OUR CONTRIBUTIONS

3.1 Data Collection

In order to deal with the ongoing experiments of comparing the precision using various classifiers, a proper dataset is predefined for experiment input. The dataset in this project includes three kinds of currency with three different amounts of values, namely, New Zealand Dollar (NZD: $10, $20, $100), US Dollar (USD: $5, $50, $100) and Chinese Yuan (CNY: ¥10, ¥50, ¥100). The requirements for these samples are in various degrees with clear patterns of identifications on the currency so as to facilitate the process of feature extraction.

The features to be used in classification are Canny edge detector, Hough transform feature, PCA, YIG and LBP. All the features are organized in a form of vectors and each direction of the vector represents a feature. The features are all extracted by using the programming platform Matlab. Figure 1 illustrates the features we used in our experiments.

As there are a considerable number of raw samples which tend to affect the recognition process of the experiment, like experiments in currency authentication, we decide to segment one currency note into six partitions with three divisions in vertical direction and two in horizontal. Figure 2 shows an example of this segmentation.

Each of the 3×2 parts of the currency is treated as a vector which is applied to feature extraction and utilized for the purpose of data collection. Moreover, as dimensions of the sample currency notes are different, the vectors are hard to be integrated into the database. Therefore, we decided to use the PCA for dimension decreasing. On the basis of a trail for testing parameters of components in the PCA, we find that the component number of 50 is suitable for the feature extraction.

In addition to the parameter tuning in the PCA, we also choose the value of Y in YIQ for color feature extraction in our data preprocessing. YIQ is a better translation of color descriptor of RGB. YIQ is the color space commonly used by the NTSC color TV system [36].

Specifically, Y component in YIQ denotes for the luminance information and the brightness of certain areas. As a preferred brightness descriptor of image and frames, YIQ has shown its outstanding performance in a variety of applications.

In the experiment, Canny edge detector is employed to extract the edge information of a vector and centroid of the detected image by applying Canny edge detector is utilized as the centroid has the ability to briefly describe the pixel distribution of a certain image. The extracted features of an instance are indicated in Table 2.

Figure 1. Various features used in experiments

3.2 Experiment Design

By clearly defining and collecting data from currency notes samples, we dispatch them into eight distinguished classifiers. The two most significant considerations for our experiments are the parametric tuning and result analysis. The parametric tuning methods vary as the difference of algorithms. By identifying the best approach for each algorithm, we will conduct a comparison among these algorithms for determining the most suitable algorithm in currency authentication.

Figure 2. The sample of currency notes

Table 2. The extracted features from training data

No	Canny	Hough	YIQ	LBP	PCA
1	89.313	7.0	0.26404	41.295	8.2653
2	90.127	6.0	0.26479	41.681	8.2653
3	88.837	7.0	0.26534	41.421	8.2653
4	90.806	1.0	0.23128	41.808	8.2653
5	91.066	1.0	0.2394	41.808	8.2653
6	87.657	3.0	0.23392	41.808	4.823
7	88.005	8.0	0.25777	51.661	4.823
8	88.968	5.0	0.26921	52.088	4.823
9	88.387	9.0	0.26862	52.088	4.823
10	85.079	6.0	0.23319	51.803	4.823

We use F-measure shown in Equations (9) as our criterion for comparing all the eight classifiers which combine both precision and recall. Precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. Both precision and recall are therefore based on an understanding and measure of relevance. In this experiment, we expect the rate of currency identification to be as high as possible. On one hand, we hope the prediction precision of correctly classified currency notes in retrieved notes is high; on the other hand, the ratio of correctly identified notes to the number of relevant notes is preferred to be bigger. Therefore, we need both of precision and recall to be as high as possible. By considering both of the value of precision and recall, F-measure is an ideal function for our experiment.

$$F = \frac{(a^2+1)P \cdot R}{a^2(P+R)} \tag{9}$$

when a =1, we have

$$F_1 = \frac{2P \cdot R}{(P+R)} \tag{10}$$

4 RESULTS AND COMPARISONS

4.1 Experiment Results

4.1.1 LVQ

The LVQ is a clustering algorithm for distributing instances into different categories. In this experiment, we pre-define the categories to be 0 and 1 which represent authentic and forgery currency notes respectively. The parameter to be calibrated is learning rate which explains the amount of weights updated. The accuracy is highly dependent on the initialization of the model as well as the learning parameters used shown in Table 3.

4.1.2 GA

Crossover probability tells us how often a crossover will be performed. If there is no crossover, the offspring is exact copy of the parents. If there is a crossover, the offspring is made from parts of parents' chromosome. If the crossover probability is 100%, then all offspring is made by crossover. If it is 0%, the new generation is made from exact copies of chromosomes of old population, crossover is made in hope that new chromosomes will have good parts of old chromosomes and maybe the new chromosomes will be better. However it is good to leave some parts of population survive to next generation.

Mutation probability means how often will be parts of chromosome mutated. If there is no mutation, the offspring is taken after crossover (or copy) without any change. If the mutation is performed, part of chromosome is changed. If the mutation probability is 100%, whole chromosome is different, if it is 0%, nothing is changed.

Population size represents how many chromosomes are in population (in one generation). If there are too few chromosomes, GA has a few possibilities to perform crossover and only a small part of search space is explored. On the other hand, if there are too many chromosomes, GA slows down. Mutation is adopted to prevent falling GA into local extreme, but it should not occur very often, because GA will in fact change to random search.

Table 5 reports the accuracy of each algorithm of different kinds of currency notes. We select the algorithms with the highest precision and compare them to select the most suitable algorithm for authenticate currency note.

Table 3. Results of LVQ clustering

Currency	Learning Rate	F-measure
NZD	0.3	71.3%
USD	0.3	82.3%
CNY	0.3	82.3%

NZD	0.7	83.4%
USD	0.7	85.3%
CNY	0.7	87.4%

Table 4. Results of the GA algorithm

Currency	Population size	Mutation probability	F-measure
NZD	100	50	98.4%
USD	100	50	91.7%
CNY	100	50	83.0%
NZD	50	50	92.8%
USD	50	50	87.4%
CNY	50	50	95.5%

4.2 Analysis

From Table 4, we observe that the GA algorithm is the most suitable one for authenticating currency notes from the view of content-based analysis. While the experiment is conducted by using three different kinds of currency notes and five different features are extracted for the data model establishment, the F-measure result of adopting different classification and cluster algorithm appears to be various from around 40% to as high as 98%.

By tuning the parameters of each algorithm, we firstly select the most suitable set of parameters for each algorithm. While some of the algorithms have only one parameter to be tuned in this experiment, GA and ANN algorithms have two kinds of parameter to tune. As the results of different currency with different parameters are distributed in a large scope, we simply compare each kind of parameter by computing their average value and select the set of parameters with the largest average F-measure to be the best one for a certain algorithm.

Table 5. Comparisons of different algorithms in currency authentication

Currency	LVQ	GA	ANN	SVM	SOM	Adaboost	HMM
NZD 10	83.4%	90.4%	78.2%	86.3%	55.9 %	82.0%	74.0%
USD 5	85.3%	91.7%	76.8%	75.2%	65.3%	50.4%	50.4%
CNY 10	87.4%	83.0%	73.1%	80.6%	62.1%	74.0%	74.0%

After the parametric comparison, it is important to make a contrast of these algorithms and select the best one as the experiment result for currency notes authentication. From Table 5, the GA algorithm has been proved as the most preferable one with the F-measure value at around 90% which is apparently higher than that of the other algorithms.

5 CONCUSION AND FUTURE WORK

In this paper we concentrate authentication problem in banknotes identification and select suitable algorithms for our comparative study. Our contribution is to review the available algorithms [51] which are thought very effective in currency notes authentication. The result explicitly reveals that GA algorithm is the most feasible algorithm in currency authentication.

Our future work is proposed to improve the results. Firstly, the types and the number of samples are expected to be enhanced by taking consideration of more available samples of both genuine ones and forgery ones. Moreover, more features are expected to be adopted since currency notes are protected by various ways of security methods.

REFERENCES

1. Singh, B., Badoni, P., & Verma, K. (2011) Computer vision based currency classification system. International Journal of Computer Applications.
2. Cao B, Liu J (2010) Currency recognition modelling research based on BP neural network improved by gene algorithm. In: Proceedings of the Second International Conference on Computer Modelling and Simulation (ICCMS'10), Washington, DC, USA, pp. 246–250
3. Clarkson W, Weyrich T, Finkelstein A, Heninger N, Halderman JA, Felten EW (2009) Fingerprinting blank paper using commodity scanners. In IEEE Symposium on Security and Privacy, pp. 301–314
4. Daraee F, Mozaffari S (2010) Eroded money notes recognition using wavelet transform. In: Iranian Machine Vision and Image Processing (MVIP'10), pp. 1–5
5. Debnath KK, Ahdikary JK, Shahjahan M (2009) A currency recognition system using negatively correlated neural network ensemble. In: International Conference on Computers and Information Technology (ICCIT '09), pp. 367–372
6. Singh, S., Choudhury, S., Vishal, K., Jawahar, C.V. (2014) Currency Recognition on Mobile Phones. In International Conference on Pattern Recognition (ICPR), pp. 2661 – 2666
7. Dittenbach, M., Merkl, D., & Rauber, A. (2000) The growing hierarchical self-organizing map. In IEEE-INNS-ENNS International Joint Conference on Neural Networks, pp. 6015-6015
8. Demuth, H., & Beale, M. (1993) Neural network toolbox for use with Matlab.
9. Elliott, R. J., Aggoun, L., & Moore, J. B. (1994) Hidden Markov Models. Springer.
10. Davis, L. (Ed.). (1991) Handbook of genetic algorithms. New York: Van Nostrand Reinhold.

11. Gaubatz MD, Simske SJ (2009) Printer-scanner identification via analysis of structured security deterrents. In: IEEE International Workshop on Information Forensics and Security (WIFS'09), pp. 151–155
12. Gaubatz MD, Simske SJ, Gibson S (2009) Distortion metrics for predicting authentication functionality of printed security deterrents. In: 16th IEEE International Conference on Image Processing (ICIP'09), Washington, DC, USA, pp. 1489–1492
13. Geusebroek J-M, Markus P, Balke P (2011) Learning banknote fitness for sorting. In: International Conference on Pattern Analysis and Intelligent Robotics (ICPAIR'11), 1: 41–46
14. Gou H, Li X, Li X, Yi J (2011) A reliable classification method for paper currency based on LVQ neural network. In: Advances in Computer Science and Education Applications. Springer, 202: 243–247
15. Grijalva F, Rodriguez JC, Larco J, Orozco L (2010) Smartphone recognition of the US banknotes' denomination for visually impaired people. In: IEEE ANDESCON, pp. 1–6
16. Guo J, Zhao Y, Cai A (2010) A reliable method for paper currency recognition based on LBP. In: 2nd IEEE International Conference on Network Infrastructure and Digital Content, Washington, DC, USA, pp. 359–363
17. Hasanuzzaman FM, Yang X, Tian Y (2011) Robust and effective component-based banknote recognition by SURF features. In: 20th Annual Wireless and Optical Communications Conference (WOCC'11), pp. 1–6
18. Hagan, M. T., Demuth, H. B., & Beale, M. H. (1996) Neural network design, Boston: PWS
19. Hasanuzzaman FM, Yang X, Tian Y (2012) Robust and effective component-based banknote recognition for the blind. IEEE Trans Syst Man Cybern C Appl Rev (99): 1–10
20. Hrishikesh C, Shefali S (2009) Printed document watermarking using phase modulation. In International Conference on Emerging Trends in Engineering and Technology (ICETET).
21. Huang S, Wu JK (2007) Optical watermarking for printed document authentication. IEEE Transactions on Information Forensic and Security 2(2): 164–173
22. Ishigaki T, Higuchi T (2008) Dynamic spectrum classification by divergence-based kernel machines and its application to the detection of worn-out banknotes. In IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP'08). Washington, DC, USA, pp. 1873–1876
23. Illingworth, J., & Kittler, J. (1988) A survey of the Hough transform. Computer vision, graphics, and image processing, 44(1): 87-116.
24. Jin Y, Song L, Tang X, Du M (2008) A hierarchical approach for banknote image processing using homogeneity and FFD model. IEEE Signal Process Letter, 15: 425–428.
25. Jing L, Shuang L, Jin MS, Wei W (2010) About CNY number identification with genetic evolution neural network. In: International Conference on Computer, Mechatronics, Control and Electronic Engineering (CMCE'10), Washington D.C. USA, pp. 286–288

26. Jolliffe, I. (2005). Principal component analysis. John Wiley & Sons, Ltd.
27. Kersten J (2010) The art of making money: the story of a master counterfeiter. Penguin Group, USA
28. Li L, Yu-tang Y, Yu X, Liang P (2010) Serial number extracting and recognizing applied in paper currency sorting system based on RBF Network. In: International Conference on Computational Intelligence and Software Engineering (CiSE'10), pp. 1–4
29. Li Z, Zhou X, Chen Y (2009) Research for the intelligent CNY sorter based on ANN. In: 9th International Conference on Electronic Measurement and Instruments (ICEMI'09), pp. 1–103
30. Nishimura K (2009) Banknote recognition based on continuous change in strictness of examination. In IEEE ICCAS-SICE, pp. 5347–5350
31. Omatu S, Yoshioka M, Kosaka Y (2009) Reliable banknote classification using neural networks. In International Conference on Advanced Engineering Computing and Applications in Sciences (ADVCOMP'09), pp. 35–40
32. Rabiner, L., & Juang, B. H. (1986). An introduction to hidden Markov models. IEEE ASSP (Magazine), 3(1): 4-16
33. Roy, A., Halder, B., & Garain, U. (2010, December). Authentication of currency notes through printing technique verification. In the Seventh Indian Conference on Computer Vision, Graphics and Image Processing, pp. 383-390
34. Ryu S-J, Lee H-Y, Cho I-W, Lee H-K (2008) Document forgery detection with SVM classifier and image quality measures. In Proceedings of the 9th Pacific Rim Conference on Multimedia (PCM'08), pp. 486–495
35. Sajal RF, Kamruzzaman M, Jewel FA (2008) A machine vision based automatic system for real time recognition and sorting of Bangladeshi bank notes. In International Conference on Computer and Information Technology (ICCIT'08), pp. 533–535
36. Schwarz, M. W., Cowan, W. B., & Beatty, J. C. (1987). An experimental comparison of RGB, YIQ, LAB, HSV, and opponent color models. ACM Transactions on Graphics (TOG), 6(2): 123-158
37. Shan G, Peng L, Jiafeng L, Xianglong T (2009) The design of HMM based banknote recognition system. In: IEEE International Conference on Intelligent Computing and Intelligent Systems (ICIS'09), 4: 106–110
38. Singh B, Badoni P, Verma K (2011) Computer vision based currency classification system. Int J Comput Appl 16(4): 34–38
39. Marc M. Van Hulle (2012). Self-organizing Maps. Handbook of Natural Computing, pp. 585-622
40. Sun B, Li J (2008) Recognition for the banknotes grade based on CPN. In International Conference on Computer Science and Software Engineering, pp. 90–93
41. Sun B, Li J (2008) The recognition of new and old banknotes based on SVM. In International Symposium on Intelligent Information Technology Application (IITA'08), pp. 95–98

42. Wang, X., Han, T. X., & Yan, S. (2009) An HOG-LBP human detector with partial occlusion handling. In IEEE International Conference on Computer Vision, pp. 32-39
43. Wenhong L, Wenjuan T, Xiyan C, Zhen G (2010) Application of Support Vector Machine (SVM) on serial number identification of CNY. In: 8th World Congress on Intelligent Control and Automation (WCICA). Washington, DC, USA, pp. 6262–6266
44. Wold, S., Esbensen, K., & Geladi, P. (1987) Principal component analysis. Chemometrics and intelligent laboratory systems, 2(1): 37-52.
45. Wu Q, Zhang Y, Ma Z, Wang Z, Jin B (2009) A banknote orientation recognition method with BP network. In: Proceedings of the 2009 WRI Global Congress on Intelligent Systems (GCIS'09), Washington, DC, USA, pp. 3–9
46. Yeh CY, Su WP, Lee SJ (2011) Employing multiple-kernel support vector machines for counterfeit banknote recognition. In: IEEE Applied Soft Computing, 11(1): 1439–1447
47. Yoshida K, Kamruzzaman M, Jewel FA, Sajal RF (2007) Design and implementation of a machine vision based but low cost stand alone system for real time counterfeit Bangladeshi bank notes detection. In International Conference on Computer and Information Technology (ICCIT'07), pp. 1–5
48. Zhou W, Xie G, Liu B (2008) The application of mixed GA-BP algorithm on remote sensing image classification. In Joint Conference on GIS and Built Environment: Classification of Remote Sensing Images, 7147(1).
49. Zhang, Y., & Rockettt, P. I. (2006) The Bayesian operating point of the Canny edge detector. IEEE Transactions on Image Processing, 15(11), pp. 3409-3416.
50. Zhang J, Ma L, Wang Y (2007) Fair e-cash system without trustees for multiple banks. In: International Conference on Computational Intelligence and Security Workshops (CISW'07), pp. 585–587
51. Chambers J, Yan W, Garhwal A, Kankanhalli M. (2014) Currency security and forensics: a survey, Springer Multimedia Tools and Applications, 2014.
52. Yan W, Chambers J. (2013) An empirical approach for digital currency forensics. IEEE ISCAS, pp. 2988-2991
53. Chambers J. (2013) Digital Currency Forensics, Master Degree Thesis, Auckland University of Technology, New Zealand.