FIRST ORDER STATISTICS AND GLCM BASED FEATURE EXTRACTION FOR RECOGNITION OF MYANMAR PAPER CURRENCY

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Abstract- Paper currency recognition is one of the important applications of pattern recognition. A paper currency recognition system has a wide range of applications such as self receiver machines for automated teller machines and automatic good-selling machines. The paper currency recognition is significant for a number of reasons. a) They become old early than coins; b) The possibility of joining broken currency is greater than that of coin currency; c) Coin currency is restricted to smaller range. In this paper, Myanmar paper currency recognition system based on First Order Statistics, Gray Level Co-occurrence Matrix (GLCM), and k-Nearest Neighbor (k-NN) is presented. Image processing is the most popular and effective method of paper currency recognition. Image processing based paper currency recognition technique consists of few basis steps like image acquisition, its preprocessing, median filter used to remove noise, feature extraction using first order statistics and GLCM, and finally recognition of the currency using k-NN classification.

Index Terms- Currency Recognition, Gray Level Co-occurrence Matrix (GLCM), Image Processing, k-Nearest Neighbor (k-NN)

I. INTRODUCTION

Due to the development of automated cash handling machines, paper currency recognition system has developed as one of the most important applications of pattern recognition. Pattern recognition is important field in computer vision and artificial intelligence.

In 1953, the Union Bank of Burma introduced the first kyat notes, in denominations of 1, 5, 10 and 100 Kyat. In 1958, 20 and 50 Kyat notes were introduced. The 50 and 100 Kyat notes were demonetized on May 15, 1964. Following the change of the country's name to Myanmar on 20 June 1989, new notes began to be issued. This time, the old notes were not demonetized, but simply allowed to fall into disuse through inflation as well as wear and tear. On 01 March 1990, 1 Kyat notes were issued, followed by 200 Kyat notes on 27 March 1990. On 27 March 1994, notes for 20, 50, 100, and 500 Kyat were issued, followed, on 01 May 1995, by new 5 and 10 Kyat notes. 1,000 Kyat notes were introduced in November 1998. 5,000 and 10,000 Kyat notes were introduced on 01 October 2009 and on 15 June 2012. At present, Myanmar currency system has the denomination K.1, K.5, K.10, K.20, K.50, K.100, K.500, K.1000, K.5000 and K.10000 [14]. Myanmar currency notes are having their own features such as denomination, shape, color etc.

In currency circulation, the original information on paper currency may have a loss because paper currency may be worn, blurry, or even damaged. Furthermore the complex designs of different kinds of paper currencies make automatic currency recognition difficult to work well. So it is important how to extract the characteristic information from currency image and select proper recognition algorithms to improve the accuracy of currency recognition. In our system we are extracting first order statistical features and GLCM features to get correct accuracy. It is very important to develop automated system to extract feature and recognize Myanmar currency note in different area such as bus station, railway station, shopping mall, ATM machines and banking.

II. RELATED WORKS

Aoba, M., Kikuchi, T., & Takefuji, Y. (2003) proposed the use of two types of ANNs, including a three-layered perceptron and a Radial Basis Function (RBF) network, for euro banknote recognition. Most of them uses single neural network with hidden layer but there are certain limitation of this networks. Firstly, single NN is not sufficient to train all aspects of currency note. Secondly, decision was made completely from a NN and not from a group of NNs. They also propose using infra-red (IR) and visible images as input data to the system since euro banknotes have quite significant features in IR images [1].

Thai banknote recognition has been discussed by Takeda, F., Sakoobunthu, L., & Satou, H. (2003). The slice values, which are the digitized characteristics of banknote by the mask set, are extracted from each banknote image [2]. These slice values are the summation of non-masked pixel values of each banknote. Then, they used ANN to execute the learning and recognition process. Their system shows some unreliability because of the output fluctuation by the mask set and threshold values.

G.Trupti Pathrabe, Mrs.Swapnili Karmore (2011) presented the method for paper currency recognition using the properties of the HSV (Hue, Saturation and Value) color space with emphasis on the visual perception of the variation in Hue, Saturation and Intensity values of an image pixel [3]. In this technique, Fitting tool of Neural Network is used for the purpose of paper currency verification and recognition. Crucial features from Indian banknotes were extracted by image processing and experimented on Neural Network classifier.

Kagehiro, T., Nagayoshi, H., & Sako, H. (2006) used a hierarchical method for high-speed classification of US banknotes, with 99% accuracy. A number of discrete points are selected from the overall image and the average of the pixel at each point and its adjacent pixels is taken as the observed value for each point [4]. They used about 32,850 samples from 12 kinds of US banknote. The banknote is classified by measuring the distance between the template vectors and the feature vectors from the observation points for use in classification. High-speed processing is realized by using low-dimensionality vectors; therefore, the computational costs decrease.

Hinwood, A., Preston, P., Suaning, G., & Lowell, N. (2006), aiming to assist blind Australians [5], proposed 'Money Talker', which takes advantage of the different patterns and colors on Australian banknotes and recognizes them with an electronic device. They showed the light reflection and transmission properties for color feature recognition. Different colored lights were used for detecting distinct ranges of values, depending on the color of the note by corresponding sensors. Their system should be accurate, easy to use, inexpensive, quick and portable at the same time. They reported the execution time is about three seconds for single note recognition. The total accuracy of their device is 99.4% for the whole dataset.

However, each country uses its own banknotes which are different in size, color and texture. This means that a banknote recognition system should be designed especially for each country, which can help to reduce the total cost of the system. We also focused on our country's banknotes and proposed our system.

III. SYSTEM OVERVIEW

The system will be programmed based on MATLAB and includes a user-friendly interface. The main steps in the system are image acquisition, preprocessing, removing noise, feature extraction, recognition and result. There are 5 denominations of Myanmar paper currency in our system. Each note has different size and different color as shown in Table I.

This system is designed to reduce the human effort and to avoid the purchase of expensive hardware. The system will extract the features of the test image and will match with the features stored in training database (mat file). If the features match it will display the amount of currency. Fig. 1 shows the proposed system of the banknote recognition system.

A. Image Acquisition

There are various ways to acquire image such as with the help of camera or scanner. Its main aim is that acquired image should retain all the features. In this step, we scan images of different type of currency each of good quality and bad quality with good clarity.

TABLE I. MYANMAR PAPER CURRENCIES

Value and Dimension	Front Side	Back Side
100 Kyat 145x 70mm		
200 Kyat 150x 70mm		
500 Kyat 150x 70mm		
1000 Kyat 150x 70mm		
5000 Kyat 150x 70mm		

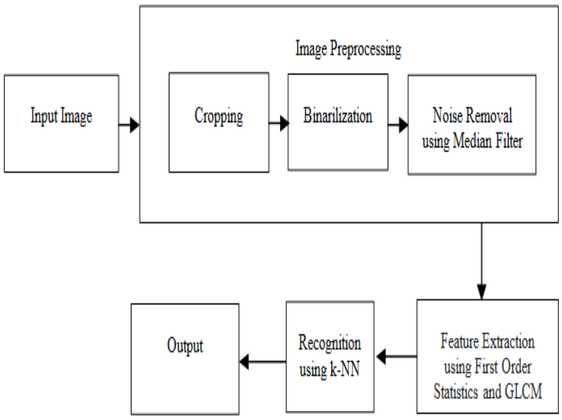

Fig. 1. **System diagram of the currency recognition.**

B. Image Preprocessing

The image to be proposed must be put in a format appropriate for digital computing. It includes transformation of image from one format into other. It also involves cropping, binarilization and noise removal using median filter.

C. Feature Extraction

In this paper, first order statistics and second order statistics or Gray Level Co-occurrence Matrix (GLCM) are formulated to obtain statistical texture features. A number of texture features may be extracted from the first and second order statistics. Only four first order features namely mean, standard deviation, skewness, and kurtosis, and five second order features namely energy, homogeneity, correlation, contrast, and entropy are computed.

D. Recognition

After getting features of currencies, it is essential to recognize the pattern of currencies on the base of the features, which should be practiced by an effective recognition system called classifier. The k-Nearest Neighbor (k-NN) based recognition scheme is used here for currency recognition. In pattern recognition, the k-NN is well known method used for classification.

E. Output

Output can be taken on GUI (Graphical User Interface).

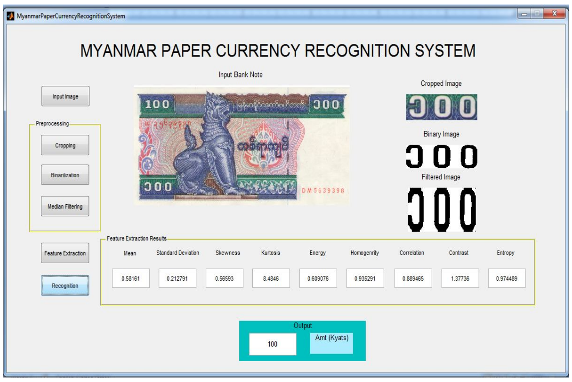

Fig. 2. **Graphical user interface of myanmar paper currency recognition.**

IV. FEATURE EXTRACTION

Feature extraction is a method of capturing visual content of images for indexing and retrieval. Feature extraction is used to denote a piece of information which is relevant for solving the computational task related to a certain application [10]. There are two types of texture features measure. They are first order and second order. In the first order, texture measures are statistics calculated from an individual pixel and do not consider pixel neighbor relationships [13]. In the second order, measures consider the relationship between neighbor relationships. The Gray Level Co-occurrence Matrix (GLCM) is a second order texture calculation.

A. First Order Statistics

Let random variable I represents the gray levels of image region. The first-order histogram P(I) is defined as [13]:

$$P(I)=\frac{number\ of\ pixels\ with\ gray\ level\ (I)}{total\ number\ of\ pixels\ in\ the\ region} \qquad (1)$$

Based on the definition of P(I), the Mean m_1 and Central Moments μ_k of I are given by

$$m_1 = E[I^1] = \sum_{I=0}^{N_g-1} I^1 P(I) \qquad (2)$$

$$\mu_k = E[(I-E[I])^k] = \sum_{I=0}^{N_g-1} (I-m_1)^k P(I), k = 2,3,4 \qquad (3)$$

where N_g is the number of possible gray levels [13]. The most frequently used central moments are Variance, Skewness and Kurtosis given by μ_2, μ_3, and μ_4 respectively. The Variance is a measure of the histogram width that measures the deviation of gray levels from the Mean. Standard Deviation is $\mu^{1/2}$ and can be used in edge sharpening, as intensity level get changes at the edge of image by large value. Skewness is a measure of the degree of histogram asymmetry around the Mean, and Kurtosis is a measure of the histogram sharpness. In our system, mean, standard deviation, skewness and kurtosis are used.

B. Second Order Statistics or GLCM

The features generated from the first-order statistics provide information related to the gray-level distribution of the image. However they do not give any information about the relative positions of the various gray levels within the image. These features will not be able to measure whether all low-value gray levels are positioned together, or they are interchanged with the high-value gray levels. An occurrence of some gray-level configuration can be described by a matrix of relative frequencies $P_{\theta,d}(I_1, I_2)$. It describes how frequently two pixels with gray-levels I_1, I_2 appear in the window separated by a distance d in direction θ. The information can be extracted from the co-occurrence matrix that measures second-order image statistics [10], where the pixels are considered in pairs. The co-occurrence matrix is a function of two parameters: relative distance measured in pixel numbers (d) and their relative orientation θ. The orientation θ is quantized in four directions that represent horizontal, diagonal, vertical and anti-diagonal by 0°, 45°, 90° and 135° respectively.

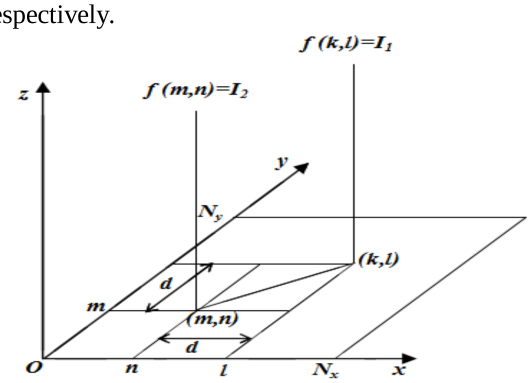

Fig. 3. **Schematic diagram of gray level co-occurrence matrix structure.**

In Fig. 3, xoy is the coordinate plane of the image pixel, the gray coordinate is z axis, the total number of pixels in x direction and y direction are N_x and N_y, and the highest gray level of the images is N_g level. Non-normalized frequencies of co-occurrence matrix as functions of distance, d and angle 0°, 45°, 90° and 135° can be represented respectively as

$$P_{0^\circ,d}=\left|\left\{\begin{array}{c}[(k,l),(m,n)]\in D:\\ k-m=0,|l-n|=d,\\ f(k,l)=I_1,\ f(m,n)=I_2\end{array}\right\}\right| \tag{4}$$

$$P_{45^\circ,d}=\left|\left\{\begin{array}{c}[(k,l),(m,n)]\in D:\\ (k-m=d,|l-n|=-d)\vee\\ (k-m=-d,|l-n|=d),\\ f(k,l)=I_1,\ f(m,n)=I_2\end{array}\right\}\right| \tag{5}$$

$$P_{90^\circ,d}=\left|\left\{\begin{array}{c}[(k,l),(m,n)]\in D:\\ k-m=d,|l-n|=0,\\ f(k,l)=I_1,\ f(m,n)=I_2\end{array}\right\}\right| \tag{6}$$

$$P_{135^\circ,d}=\left|\left\{\begin{array}{c}[(k,l),(m,n)]\in D:\\ (k-m=d,|l-n|=d)\vee\\ (k-m=-d,|l-n|=-d),\\ f(k,l)=I_1,\ f(m,n)=I_2\end{array}\right\}\right| \tag{7}$$

where |{…}| refers to cardinality of set, f(k, l) is intensity at pixel position (k, l) in the image of order (M x N) and the order of matrix D is (M x N) x (M x N) [10].

Using Co-occurrence matrix, features can be defined which quantifies coarseness, smoothness and texture related information that have high discriminatory power. Among them [10], Energy, Homogeneity, Correlation, Contrast, and Entropy are few such measures which are given by:

$$Energy=\sum_{I_1,I_2}P(I_1,I_2)^2 \tag{8}$$

$$Homogeneity=\sum_{I_1,I}\frac{P(I_1,I_2)}{1+|I_1-I_2|^2} \tag{9}$$

$$Correlation=\sum_{I_1,I_2}\frac{(I_1-\mu_1)(I_2-\mu_2)P(I_1,I_2)}{\sigma_1\sigma_2} \tag{10}$$

$$Contrast=\sum_{I_1,I_2}|I_1-I_2|^2\ P(I_1,I_2) \tag{11}$$

$$Entropy=\sum_{I_1,I_2}P(I_1,I_2)\log P(I_1,I_2) \tag{12}$$

Energy is a feature that measures the smoothness of the image. The less smooth the region is, the more uniformly distributed $P(I_1, I_2)$ and the lower will be the value of energy. Homogeneity is a measure that takes high values for low-contrast images. Correlation is a measure of correlation between pixels in two different directions. In (10), μ_1, μ_2 and σ_1, σ_2 are the mean and standard deviations of $P(I_1,I_2)$. Contrast is a measure of local level variations which takes high values for image of high contrast. Entropy is a measure of randomness and takes low values for smooth images. Together all these features provide high discriminative power to distinguish two different kind of images.

To demonstrate these features, we consider an example of a 4x4 gray-scale image in Fig. 4.

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

(a)

6	0	2	0
0	4	2	0
2	2	2	2
0	0	2	0

(b)

0.25	0	0.083	0
0	0.167	0.083	0
0.083	0.083	0.083	0.083
0	0	0.083	0

(c)

Reference pixel value (I_1)	Neighbor pixel value (I_2)			
	0	1	2	3
0	(0,0)	(0,1)	(0,2)	(0,3)
1	(1,0)	(1,1)	(1,2)	(1,3)
2	(2,0)	(2,1)	(2,2)	(2,3)
3	(3,0)	(3,1)	(3,2)	(3,3)

(d)

Fig. 4. **(a) 4x4 gray scale image; (b) Co-occurrence matrix; (c) Normalized Co-occurrence matrix; (d) General form of GLCM. Fig. 4(b) is Co-occurrence matrix of the image following vertical direction (θ= 90° and θ= 270°) with distance d = 1. Fig. 4(c) is Co-occurrence matrix after normalization (each entry is divided by the total number of possible pairs, 24). We will calculate five texture features following Haralick's formula [10].**

Energy=$(0.25)^2+(0.083)^2+(0.167)^2+(0.083)^2+(0.083)^2+(0.083)^2+(0.083)^2+(0.083)^2+(0.083)^2=0.1386$

Homogeneity=0.25+(0.083/5)+0.167+(0.083/2)+(0.083/5) +(0.083/2)+0.083+(0.083/2)+(0.083/2) = 0.6992

Correlation=[((–1.163)^{2}x0.25)+((–1.163)x0.837x0.083) +((–0.163)x(–0.163)x0.167)+((–0.163)x(0.837)x0.083) +((0.837)x(–1.163)x0.083)+(0.837)x(–0.163)x0.083) +((0.837)x(0.837)x0.083)+((0.837)x(1.837)x0.083) +((1.837)x(0.837)x 0.083)]/0.9697 = 0.4865

Contrast=(4x0.083)+0.083+(4x0.083)+0.083+0.083+0.083 =0.9960

Entropy=(0.25xln(0.25))+(0.083xln(0.083))+0.167xln(0.167) +(0.083xln(0.083))+(0.083xln(0.083))+(0.083xln(0.083)) +(0.083xln(0.083))+(0.083xln(0.083))+(0.083xln(0.083)) =2.0915

TABLE II. **TEXTURE FEATURE OF 4X4 IMAGE**

No.	Texture Feature	Value
1	Energy	0.1386
2	Homogeneity	0.6992
3	Correlation	0.4865
4	Contrast	0.9960
5	Entropy	2.0915

All features are functions of the distance d and the orientation θ. Thus, if an image is rotated, the values of the features will be different. In practice, for each d the resulting values for the four directions are averaged out. This will generate features that will be rotations invariant.

V. THE K-NEAREST NEIGHBOR (K-NN) CLASSIFICATION

The k-Nearest Neighbor classifier computes the distance from the unlabeled data to every training data point and selects the best k neighbors with the shortest distance [15]. Suppose, given some data instance which belongs to one of the two categories or a class, and the goal is to determine which class the new data belongs to, is the problem of classification. Distance is a key word in this algorithm. Each object in the space is represented by position vectors in a multidimensional feature space and the Euclidean distance is used to calculate distance between two vector positions. The k-nearest neighbor algorithm is sensitive to the local structure of the data. The k-Nearest Neighbor is one of those algorithms that are very simple to understand but works incredibly well in practice.

Step by step on how to compute k-Nearest Neighbor (k-NN) Algorithm as follows [15]:

1) Determine parameter k = number of nearest neighbors
2) Calculate the distance between the query-instance and all the training samples
3) The Euclidean distance between X=(x_1, x_2, x_3,..,x_n) and Y=(y_1,y_2, y_3,…,y_n) is defined as:

$$D(x,y)=\sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \tag{13}$$

4) Sort the distance and determine nearest neighbors based on the k^{th} minimum distance
5) Gather the category of the nearest neighbor
6) Use simple majority of the category of nearest neighbors as the prediction value of the query instance

In order to determine the optimum k corresponding to the best accuracy, a simple way is to alter the k from 1 to a large enough value (in this paper k=1) and choosing the k for which the best accuracy is obtained for all test features. Since, the classification accuracy of a pattern recognition system not only depends on features extraction method but also on the choice of classifier.

VI. EXPERIMENTAL RESULT

During the initial training phase, a database was complied consisting of 89 currency note observe images. We scanned all currency notes and use them as our experimental samples. The database includes 18 K100, 18 K200, 16 K500, 22 K1000 and 15 K5000. Table III and Table IV show first order statistics and GLCM feature extraction values for randomly selected 10 Myanmar currency notes.

TABLE III. MYANMAR CURRENCY NOTES' FIRST ORDER STATISTICS FEATURE EXTRACTION VALUES

Currency Notes	First Order Statistics Features			
	Mean	Standard Deviation	Skewness	Kurtosis
1	0.585	0.206	-0.04	6.731
2	0.582	0.213	0.566	8.485
3	0.725	0.21	0.102	4.088
4	0.62	0.161	1.137	13.30
5	0.701	0.177	-1.738	16.43
6	0.722	0.194	-1.063	93.21
7	0.777	0.190	-2.346	25.12
8	0.804	0.200	-5.949	62.52
9	0.741	0.177	-2.427	34.17
10	0.598	0.130	-0.681	68.14

The recognition experiments evaluated in our testing, the proposed algorithm achieves 100% true recognition accuracy for all five categories. The experimental results have shown in Table V.

TABLE IV. MYANMAR CURRENCY NOTES' GLCM FEATURE EXTRACTION VALUES

Currency Notes	GLCM Features				
	Energy	*Homogeneity*	*Correlation*	*Contrast*	*Entropy*
1	0.596	0.932	0.884	1.460	0.857
2	0.609	0.935	0.890	1.377	0.975
3	0.586	0.948	0.932	1.012	0.758
4	0.604	0.945	0.919	1.072	0.835
5	0.546	0.922	0.897	1.463	0.544
6	0.560	0.935	0.918	1.201	0.877
7	0.502	0.914	0.899	1.585	0.662
8	0.543	0.937	0.926	1.187	0.965
9	0.481	0.894	0.861	2.130	0.758
10	0.487	0.877	0.816	2.395	0.449

TABLE V. RESULTS OF MYANMAR PAPER CURRENCY RECOGNITION

No.	Recognition Region	Image Correctly Recognized/ Total Images	Recognition Rate (%)
1	100	18/18	100
2	200	18/18	100
3	500	16/16	100
4	1000	22/22	100
5	5000	15/15	100

A comparison of various methods with each other is tabulated in Table VI in terms of recognition rate. It is important to mention that different methods use different paper currencies. It is observed that the proposed method is capable to recognize as good as other methods do.

TABLE VI. COMPARISON OF VARIOUS METHODS

Methods	Currency	Recognition Rate (%)
Hierarchical [4]	US	99
Money Talker [5]	Australian	99.4
SLCRec [6]	Sri Lanka	100
ENN [7]	Bangladesh	100
Proposed First Order Statistics and GLCM	Myanmar	100

Fig. 5. **One hundred kyat with recognition region.**

Fig. 6. **Two hundred kyats with recognition region.**

Fig. 7. **Five hundred kyats with recognition region.**

Fig. 8. **One thousand kyats with recognition region.**

Fig. 9. **Five thousand kyats with recognition region.**

CONCLUSION

Recognition of Myanmar Paper Currency involve two main steps, first step is the process of feature extraction which is done based on first order statistics and grey level co-occurrence matrix (GLCM) which is the second-order statistics that can be used to analyze images as a texture. The second step, recognition is mainly done using classifier technique called as k-nearest neighbor (k-NN) which assigns classification based on majority of vote of neighboring clusters. Therefore proposed approach got a better results and recognition rate of 100%.

The proposed recognition algorithm does not include position correction. In banknote counting machines, the origin position of the distinctive points may be changed when banknotes are not perfectly inserted into the counting machine. This occurs frequently and thus additional research will be needed.

Our future work includes recognizing also other regions of Myanmar paper currency such as wpf&musyf (one hundred kyats), ESpf&musyf (two hundred kyats), ig;&musyf (five hundred kyats), wpfaxmifusyf (one thousand kyats), ig;axmifusyf (five thousand kyats), and getting same accuracy by using other classification methods.

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