Myanmar Paper Currency Recognition Using GLCM and k-NN

By
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Submitted in Partial Fulfillment of the Requirement for the Degree of Master of Science in Computer Science Assumption University

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ABSTRACT

Automatic currency note recognition invariably depends on the currency note characteristics of a particular country and the extraction of features directly affects the recognition ability. 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. This research aims to present an algorithmic model for automatic classification of currency notes using $k$-Nearest Neighbor ($k$-NN) classifier. A $k$-NN rule is one of the simplest and the most important method in pattern recognition. The proposed algorithmic model is based on textural feature such as Gray Level Co-occurrence Matrix (GLCM). The recognition system is composed of four parts. The skew correction of rotated image is first. The captured image is second preprocessing by reducing data dimensionalities and the third part is extracting its features by using image processing toolbox in MATLAB. According to the GLCM, the work of texture feature extraction is finished. The last one is recognition, in which the core is $k$-Nearest Neighbor classifier. Experimental results are presented on a dataset of 500 images consisting of 5 classes of currency notes which are 100, 200, 500, 1000, and 5000 Kyat notes. It is shown that a good performance can be achieved using $k$-NN classifier algorithm. The recognition system presented in this research indicates that the proposed approach is one of the most effective strategies of identifying currency pattern to read its face value. Although either Myanmar digit or Myanmar word texture image is recognized, Myanmar paper currency amount is correctly shown. So, it is easy to count currency quickly for the staffs that work in the financial organizations and overcome from his/ her serious problems, especially wrong classification.
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CHAPTER 1: 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.

Previous researches proposed a lot of recognition methods. In Thai banknote recognition [2], the slice values which are the digitized characteristics of banknote by the mask set, are extracted from each banknote image. 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. India paper currency recognition [3] 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. 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. ‘Money Talker’ [5] 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.

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. 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.200, 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 GLCM features to get correct accuracy. It is very important to develop automated system to extract feature and recognize Myanmar currency notes are used in different area such as bus station, railway station, shopping mall, ATM machines, and banking.
CHAPTER 2: LITERATURE REVIEW

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. Salient features of the method: 1) Author has used three layer perception for classification and RBF for validation. 2) Three layer perceptron is used for pattern recognition which is very effective tool for classifying paper currency. 3) RBF network has a potential to reject invalid data because it estimates probability distribution of sample data effectively. 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].

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.

In [6] the proposed system “SLCREC” comes up with a solution focusing on minimizing false rejection of notes. Gunaratna, D., Kodikara, N., & Premaratne, H. (2008) proposed a system for Sri Lankan banknote recognition, exploiting several changes in image quality. Hence a special linear transformation function is adapted to wipe out noise patterns from backgrounds without affecting the notes’ characteristic images and re-appear images of interest. Their proposed transformation maps the original gray scale range into a smaller range of 0 to 125. Applying Edge detection
after the transformation provided better robustness for noise and fair representation of edges for new and old damaged notes. A three-layer back propagation ANN used was for edge detection. The implemented system, comprising compressed grayscale range and the three layers BP-ANN, produced suitable results for Sri Lankan currency notes. Currency Recognition task has been categorized into three components. 1) Canny algorithm is used for edge detection because of its low error rate and good ability to localized edge points properly. 2) Three layer back propagation neural network is used for currency classification. 3) The experiments carried out by author showed good classification results and proved that the proposed methodology has the capability of separating classes properly in varying image conditions.

Debnath, K. K., Ahmed, S. U., & Shahjahan, M. (2010) proposed a currency recognition system using an Ensemble Neural Network (ENN) [7]. The individual ANNs in an ENN are trained via Negative Correlation Learning (NCL). The objective of using NCL is to train individuals on different parts or portions of the input patterns in an ensemble. First, they convert the note image into gray scale and then the image is compressed. Then the compressed image is given to system as an input for recognition. The system developed using ENN can easily identify the currency with noise as well as old currency notes. With independent training, there are less chances of misclassification. To prove the efficiency of proposed ENN method author has compared it with the other methods like Hidden Markov Model (HMM), radial basis function (RBF) and Feature Extraction method called SLCRec.

Put forward a new image based technique for Bahraini paper currency recognition based on two classifiers, the weighted Euclidean distance using suitable weights and the Neural Network presented by Ebtesam Althafiri, Muhammad Sarfraz, Muhammad Alfarras (2012) [8]. First of all color image of paper currency having
quality approximately equal to 600 dpi is obtained through scanning process. In preprocessing step four different kinds of images are obtained from color image, viz. the binary image; the gray scale image using Sobel mask; the gray scale image using Prewitt mask; and the gray scale image using Canny mask. Then features are extracted by calculating the sum of pixels of each of the four images. Also, the Euler number is calculated for each of the images then computed the correlation coefficient of input image after converting it to gray scale. After feature extraction paper currency classification is done by using two different methods called Weighted Euclidean Distance (WED) and Neural Networks using feed forward back propagation. The minimum distance classification method by taking the Weighted Euclidean Distance shows 96.4% accuracy rate while the Neural Network with feed forward back propagation classification technique provides almost 85.1% average of accuracy for the best case. Therefore, author concluded that the Weighted Euclidean Distance approach is better than the Neural Network.
CHAPTER 3: SYSTEM DESIGN

In the architecture of Myanmar Paper Currency Recognition (MPCR) system, Myanmar currency notes such as 100, 200, 500, 1000, and 5000 Kyat are accepted as input image. The MPCR system consists of three phases:

- Skew Correction using Hough Transform
- Preprocessing
- Feature Extraction using GLCM
- Recognition using $k$-NN

The recognition of MPCR system will be displayed the result as an output message. The architecture of MPCR is shown in Figure 3-1.

![Diagram](image)

Figure 3-1 System Design of the Currency Recognition.
3.1 Input Image

Input image is Myanmar currency notes. MPCR system is used five classes of Myanmar currency notes such as 100, 200, 500, 1000, and 5000. Input images are shown in Figure 3-2 (a)-(e).
3.2 Skew Correction using Hough Transform

The image of currency note may be skewed while image acquisition process. And it is very important to de-skew the image to its original orientation. Hough transform (HT) is a technique which can be used to isolate features of a particular shape within an image. The classical Hough transform is most commonly used for the detection of regular curves such as lines, circles, ellipses, etc. Presently, HT is widely used in image analysis, computing vision, and pattern recognition. It becomes a standard tool on pattern recognition.
3.3 Preprocessing

Preprocessing is necessary to perform several document analysis operations prior to recognizing text in scanned documents. This phase contains cropping, binarization, noise removal using median filter and resizing with the standard size is (100x180).

3.4 Feature Extraction using GLCM

In this research, Gray Level Co-occurrence Matrix (GLCM) is formulated to obtain statistical texture features. A number of texture features may be extracted from GLCM. Only five GLCM features namely energy, homogeneity, correlation, contrast, and entropy are computed.

3.5 Recognition using k-NN

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. 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.

3.6 Output

Output can be taken on GUI (Graphical User Interface).
CHAPTER 4: SKEW CORRECTION USING HOUGH TRANSFORMATION

The image of currency note may be skewed while image acquisition process. And it is very important to de-skew the image to its original orientation, thus making the image aligned with the $X$ and $Y$ axes.

The Hough Transformation is a powerful global method for detecting edges. It transforms between the Cartesian space and a parameter space in which a straight line or other boundary formulation can be defined. Hough transformation uses in the image skew detection and correction.

Figure 4-1 Presentation of Cartesian Coordinate to Polar Coordinates

In the polar representation a line is parameterized with $\rho$ and $\theta$ [16], as shown in Figure 4-1. Parameter $\rho$ represents the distance between the line and the origin, and the angle, $\theta$ of the vector from the origin to this closest point, as given by Equation (4.1).

$$\rho = x \cos(\theta) + y \sin(\theta)$$ (4.1)

In this polar parameterization the parameters $\rho$ and $\theta$ are bounded. The angle $\theta$ ranges from 0 to 180 and the radius $\rho$ ranges from 0 to $\sqrt{W^2 + H^2}$, where $W$ and $H$ are the width and height of the image respectively.
4.1 Hough transform algorithm

- Typically use a different parameterization
  \[ \rho = x \cos(\theta) + y \sin(\theta) \]
  - \( \rho \) is the perpendicular distance from the line to the origin
  - \( \theta \) is the angle this perpendicular makes with the x axis

- Basic Hough transform algorithm

1. Initialize \( A[\rho, \theta] = 0 \); \( A \) is called accumulator array

2. for each edge point \( [x, y] \) in the image
   
   for \( \theta = 0 \) to \( 180 \)
   
   \[ \rho = x \cos(\theta) + y \sin(\theta) \]
   
   \[ A[\rho, \theta] = A[\rho, \theta] + 1 \]

3. Find the value(s) of \( (\rho, \theta) \) where \( A[\rho, \theta] \) is maximum

4. The detected line in the image is given by \( \rho = x \cos(\theta) + y \sin(\theta) \)

4.2 Step by Step of Skew Detection and Correction

The skew detection and correction basic step is shown in Figure 4-2.

```
Input Image -> Gray Image -> Canny Edge Detection

Rotated Image -> Angle Calculation -> Hough Transformation
```

Figure 4-2 Currency Note Image Skew Detection and Correction
The computation of the skew angle is achieved using Hough transform to find the most visible lines in the currency note image and their angles, and finally the currency note image will be rotated as shown in Figure 4-3.

Figure 4-3 (a) Original Image, (b) Gray Image, (c) Canny Edge Detected Image, (d) Rotated Image
CHAPTER 5: PREPROCESSING

The preprocessing step is performed directly on the image obtained from the scanner. The key function of preprocessing is to improve the image in ways that increase the chances for success of the other processes. Preprocessing is necessary to perform several document analysis operations prior to recognizing text in scanned documents. This phase contains the following (4) steps. There are

- Cropping Image
- Binarization
- Noise Removing
- Image Resizing

5.1 Cropping Image

When an image is obtained from a scanner, the size of the image is too big. In order to reduce the calculation, the size of the image should be reduced. If the image is smaller, the extraction can be faster and may improve accuracy. 100 Kyat image’s size is normalized 1179 x 559 before cropping image. In the cropping image step, there are two regions such as Myanmar Digit region and Myanmar Word region are auto cropped to get the smaller image. As banknotes are different in size, the locations of cropped regions are not same. For 100 Kyat, the location pixel value of digit region is [ 50, 445, 157, 55 ] and word region is [ 561, 221, 292, 117 ]. Table 5-1 shows the normalized image size and location pixel values of cropped regions. The two cropped regions are shown in Figure 5-1.

![Cropped Image](image)

Figure 5-1 Cropping image.
Table 5-1 Normalized Image Size and Location Pixel Values of Cropped Regions

<table>
<thead>
<tr>
<th>Currency Notes’ image</th>
<th>Normalized Image Size</th>
<th>Digit Region</th>
<th>Word Region</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1179 x 559</td>
<td>[50, 445, 157, 55]</td>
<td>[561, 221, 292, 117]</td>
</tr>
<tr>
<td>200</td>
<td>1486 x 642</td>
<td>[1238, 43, 167, 67]</td>
<td>[400, 264, 432, 176]</td>
</tr>
<tr>
<td>500</td>
<td>1501 x 691</td>
<td>[69, 550, 170, 76]</td>
<td>[649, 262, 395, 179]</td>
</tr>
<tr>
<td>1000</td>
<td>2051 x 839</td>
<td>[1665, 655, 300, 89]</td>
<td>[521, 327, 562, 162]</td>
</tr>
<tr>
<td>5000</td>
<td>1501 x 679</td>
<td>[70, 565, 212, 72]</td>
<td>[850, 169, 280, 234]</td>
</tr>
</tbody>
</table>

5.2 Binarization

In order to make the image texture feature for image binarization processing, the gray-scale image is converted to the binary image. Binarization texture image is shown in Figure 5-2.

Figure 5-2 Binary image.

5.3 Noise Removing

The image acquired by scanner having many kinds of noise. Removing the noise is an important step when image processing is being performed. However noise may affect pattern matching. These noises are removed using 3 x 3 median filter. The filtered image is shown in Figure 5-3.

Figure 5-3 Filtered image.

5.4 Image Resizing

In image resizing step, this system used resized image with the standard size is (100x180). The resized image is shown in Figure 5-4.

Figure 5-4 Resized image.
CHAPTER 6: FEATURE EXTRACTION USING GLCM

Texture is one of the important characteristics used in identifying objects or regions of interest in an image. The textural features based on gray-tone spatial dependencies have a general applicability in image classification. 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]. The fourteen textural features proposed by R. M. Haralick, K. Shanmugam and I. Dinstein [10] contain information about image texture characteristics such as homogeneity, gray-tone linear dependencies, contrast, number and nature of boundaries present and the complexity of the image.

Gray level co-occurrence matrix (GLCM), one of the most known texture analysis methods, estimates image properties related to second-order statistics. GLCM computes the statistical features based on gray level intensities of the image. Such features of the GLCM are useful in texture recognition, image segmentation, image retrieval, color image analysis, image classification, object recognition and texture analysis methods etc.

In this research, texture features are extracted using Gray Level Co-occurrence Matrices (GLCM). It is defined as “A two dimensional histogram of gray levels for a pair of pixels, which are separated by a fixed spatial relationship.” 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 \( \theta \). The information can be extracted from the co-occurrence matrix [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 \(\theta\). The orientation \(\theta\) is quantized in four directions that represent horizontal, diagonal, vertical and anti-diagonal by \(0^\circ, 45^\circ, 90^\circ\) and \(135^\circ\) respectively.

![Schematic diagram of gray level co-occurrence matrix structure](image)

Figure 6-1 Schematic diagram of gray level co-occurrence matrix structure [11].

In Figure 6-1, \(xoy\) 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 \(N_z\) level. Non-normalized frequencies of co-occurrence matrix as functions of distance, \(d\) and angle \(0^\circ, 45^\circ, 90^\circ\) and \(135^\circ\) can be represented respectively as [11] below:

\[
P_{0,d} = \begin{cases} 
(k,l),(m,n) & \in D: \\
\text{ such that } k-m = 0, |l-n| = d, \\
f(k,l) = I_1, f(m,n) = I_2 
\end{cases}
\]  
(6.1)

\[
P_{45,d} = \begin{cases} 
(k,l),(m,n) & \in D: \\
\text{ such that } (k-m = d, |l-n| = -d) \lor \\
(k-m = -d, |l-n| = d), \\
f(k,l) = I_1, f(m,n) = I_2 
\end{cases}
\]  
(6.2)
\[
P_{90^\circ, d} = \left\{ \begin{array}{l}
[(k,l),(m,n)] \in D: \\
k - m = d, |l - n| = 0,
\end{array} \right. \quad f(k,l) = I_1, f(m,n) = I_2
\]

(6.3)

\[
P_{135^\circ, d} = \left\{ \begin{array}{l}
[(k,l),(m,n)] \in D: \\
(k - m = d, |l - n| = d) \lor \\
(k - m = -d, |l - n| = -d),
\end{array} \right. \quad f(k,l) = I_1, f(m,n) = I_2
\]

(6.4)

where \( P_{\theta,d} \) indicates cardinality of set, \( f(k,l) \) is intensity at pixel position \((k,l)\) in the image of order \((M \times N)\) and the order of matrix \(D\) is \((M \times N) \times (M \times N)\) [11].

Using Co-occurrence matrix, features can be defined which quantifies coarseness, smoothness and texture related information that have high discriminatory power. Normalized Co-occurrence matrix is defined as [10] below:

\[
P(I_1, I_2) = \frac{V_{I_1,I_2}}{\sum_{I_1,I_2=0}^{N_g-1} V_{I_1,I_2}}
\]

(6.5)

where \( I_1 \) and \( I_2 \) are reference pixel values and neighbor pixel values, \( P(I_1, I_2) \) is normalized values of Co-occurrence Matrix, \( V_{I_1,I_2} \) is \( \text{th} \) entry in GLCM and \( N_g \) is the number of distinct gray levels in the image.

Gray Level Co-occurrence Matrix of \( \text{Joo (200)} \) is as shown in Figure 6-2.
\begin{array}{cccccccc}
14414 & 256 & 196 & 54 & 48 & 63 & 17 & 119 \\
298 & 22 & 18 & 5 & 5 & 18 & 2 & 5 \\
183 & 54 & 9 & 4 & 0 & 1 & 0 & 9 \\
50 & 12 & 1 & 0 & 0 & 2 & 2 & 9 \\
49 & 1 & 0 & 0 & 0 & 3 & 1 & 20 \\
48 & 0 & 0 & 1 & 4 & 35 & 3 & 44 \\
17 & 1 & 1 & 0 & 0 & 1 & 0 & 8 \\
161 & 27 & 35 & 12 & 17 & 12 & 3 & 3283 \\
\end{array}

Figure 6-2 Gray Level Co-occurrence Matrix of $joo$ (200).

In order to estimate the similarity between different gray level co-occurrence matrices, R. M. Haralick, K. Shanmugam and I. Dinstein [10] proposed 14 statistical features extracted from them. To reduce the computational complexity, only some of these features were selected. In this research, we extracted five of those, energy, homogeneity, correlation, contrast and entropy from the Myanmar currency image. These features are given in the following sections.

6.1 Energy

It measures the textural uniformity that is pixel pair repetitions [10]. It detects disorders in textures. Uniformity reaches a maximum value equal to one. High uniformity values occur when the gray level distribution has a constant or periodic form. Energy has a normalized range. The homogeneous scene contains only a few gray levels, giving a GLCM with a few but relatively high values of $P(I_1, I_2)$. So the sum of squares will be high. Range = [0 1]. Energy equals to 1 means the image is constant. The Energy formula can be given as:

$$Energy = \sum_{I_1, I_2 = 0}^{N-1} P(I_1, I_2)^2 \quad (6.6)$$
where \( I_1 \) and \( I_2 \) are reference pixel values and neighbor pixel values, \( P(I_1,I_2) \) is normalized values of Co-occurrence Matrix and \( N_g \) is the number of distinct gray levels in the image.

### 6.2 Homogeneity

The Homogeneity feature is also called as Inverse Difference Moment [10]. It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. It means that the value of homogeneity decreases if contrast increases while energy is kept constant. Range=\([0 \ 1]\). Homogeneity equals to 1 for a diagonal gray level co-occurrence matrix. The Homogeneity formula can be given as:

\[
\text{Homogeneity} = \frac{N_g-1}{\sum_{I_1,I_2=0}^{N_g-1} \frac{P(I_1,I_2)}{1+|I_1-I_2|^2}}
\]  

(6.7)

where \( I_1 \) and \( I_2 \) are reference pixel values and neighbor pixel values, \( P(I_1,I_2) \) is normalized values of Co-occurrence Matrix and \( N_g \) is the number of distinct gray levels in the image.

### 6.3 Correlation

The correlation texture measures the linear dependency of gray levels on neighboring pixels [10]. Returns a measure of how correlated the pixel is to its neighbor over the whole image. Range = \([-1 \ 1]\]. The meaning to the actual calculated values: 0 is uncorrelated, 1 is perfectly correlated and NaN (Not a number) for a constant image. The Correlation formula can be given as:
Correlation = \sum_{I_1, I_2 = 0}^{N_s-1} \frac{(I_1 - \mu_1)(I_2 - \mu_2)P(I_1, I_2)}{\sigma_1 \sigma_2} \quad (6.8)

In this equation, \(\mu_1, \mu_2, \sigma_1\) and \(\sigma_2\) are the means and standard deviations.

\[
\mu_1 = \sum_{I_1, I_2 = 0}^{N_s-1} I_1 [P(I_1, I_2)]
\]

\[
\mu_2 = \sum_{I_1, I_2 = 0}^{N_s-1} I_2 [P(I_1, I_2)]
\]

\[
\sigma_1 = \sqrt{\sum_{I_1, I_2 = 0}^{N_s-1} P(I_1, I_2)(I_1 - \mu_1)^2}
\]

\[
\sigma_2 = \sqrt{\sum_{I_1, I_2 = 0}^{N_s-1} P(I_1, I_2)(I_2 - \mu_2)^2}
\]

where \(I_1\) and \(I_2\) are reference pixel values and neighbor pixel values, \(P(I_1, I_2)\) is normalized values of Co-occurrence Matrix and \(N_s\) is the number of distinct gray levels in the image.

6.4 Contrast

The contrast feature measures the spatial frequency of an image and is difference moment of GLCM [10]. It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. When \(I_1\) and \(I_2\) are equal, so \((I_1 - I_2) = 0\) and the cell is on the diagonal. The weight function \((I_1 - I_2)^2 = 0\), represents pixels which are entirely similar to the neighbor. The weights continue to increase exponentially as \((I_1 - I_2)\) increases. The function returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. Range = \([0 \text{ (size(GLCM, 1) - 1)^2}]\). If sum of
square variance equals to 0, it means the image is a constant. Contrast is also called 
_Inertia_. The contrast can be given as:

\[
Contrast = \sum_{I_1, I_2=0}^{N_c-1} |I_1 - I_2|^2 P(I_1, I_2)
\]

(6.13)

where \(I_1\) and \(I_2\) are reference pixel values and neighbor pixel values, \(P(I_1, I_2)\) is normalized values of Co-occurrence Matrix and \(N_c\) is the number of distinct gray levels in the image.

### 6.5 Entropy

The Entropy feature measures the disorder or complexity of an image [10]. The entropy is large when the image is not texturally uniform and many GLCM elements have very small values. Complex textures tend to have high entropy. Entropy is strongly, but inversely correlated to energy. The Entropy formula can be given as:

\[
Entropy = - \sum_{I_1, I_2=0}^{N_c-1} P(I_1, I_2) \text{[ln } P(I_1, I_2)\text{]}
\]

(6.14)

where \(I_1\) and \(I_2\) are reference pixel values and neighbor pixel values, \(P(I_1, I_2)\) is normalized values of Co-occurrence Matrix and \(N_c\) is the number of distinct gray levels in the image.

The following demonstrates these features; consider an example of a 4x4 gray-scale image in Figure 6-3.
Figure 6-3 (a) 4x4 gray scale image; (b) Co-occurrence matrix; (c) Normalized Co-occurrence matrix; (d) General form of GLCM.

Figure 6-3(a) is a 4x4 gray scale image. Figure 6-3(b) is Co-occurrence matrix of the image following vertical direction ($\theta = 90^\circ$ and $\theta = 270^\circ$) with distance $d = 1$. Figure 6-3(c) is Co-occurrence matrix after normalization (each entry is divided by the total number of possible pairs, i.e., 24). Figure 6-3(d) is the general form of GLCM. Based on Figure 6-2, the following calculate five texture features of Haralick’s formula [10].

Energy = $(0.250)^2 + (0.000)^2 + (0.083)^2 + (0.000)^2 + (0.000)^2 + (0.167)^2 + (0.083)^2 + (0.000)^2 + (0.083)^2 + (0.083)^2 + (0.083)^2 + (0.000)^2 + (0.000)^2 + (0.083)^2 + (0.083)^2 + (0.083)^2 + (0.000)^2 + (0.000)^2 + (0.083)^2 + (0.083)^2 + (0.083)^2 + (0.000)^2 + (0.083)/(1 + (0 - 0)^2) + [0.000/(1 + (0 - 1)^2)] + [0.083/(1 + (0 - 2)^2)]

Homogeneity = 0.1386
\[ + \frac{0.000}{1 + (0 - 3)^2} + \frac{0.000}{1 + (1 - 0)^2} + \frac{0.167}{1 + (1 - 1)^2} \]
\[ + \frac{0.083}{1 + (1 - 2)^2} + \frac{0.000}{1 + (1 - 3)^2} + \frac{0.083}{1 + (2 - 0)^2} \]
\[ + \frac{0.083}{1 + (2 - 1)^2} + \frac{0.083}{1 + (2 - 2)^2} + \frac{0.083}{1 + (2 - 3)^2} \]
\[ + \frac{0.000}{1 + (3 - 0)^2} + \frac{0.000}{1 + (3 - 1)^2} + \frac{0.083}{1 + (3 - 2)^2} \]
\[ + \frac{0.000}{1 + (3 - 3)^2} \]
\[ = 0.6992 \]

Mean (\( \mu \)) = \[ [0 \times 0.250] + [0 \times 0.000] + [0 \times 0.083] + [0 \times 0.000] \]
\[ + [1 \times 0.000] + [1 \times 0.167] + [1 \times 0.083] + [1 \times 0.000] \]
\[ + [2 \times 0.083] + [2 \times 0.083] + [2 \times 0.083] + [2 \times 0.083] \]
\[ + [3 \times 0.000] + [3 \times 0.000] + [3 \times 0.083] + [3 \times 0.000] \]
\[ = 1.1630 \]

Standard Deviation (\( \sigma \)) = \[ [(0 - 1.163)^2 \times 0.250] + [(0 - 1.163)^2 \times 0.000] \]
\[ + [(0 - 1.163)^2 \times 0.083] + [(0 - 1.163)^2 \times 0.000] \]
\[ + [(1 - 1.163)^2 \times 0.000] + [(1 - 1.163)^2 \times 0.167] \]
\[ + [(1 - 1.163)^2 \times 0.083] + [(1 - 1.163)^2 \times 0.000] \]
\[ + [(2 - 1.163)^2 \times 0.083] + [(2 - 1.163)^2 \times 0.083] \]
\[ + [(2 - 1.163)^2 \times 0.083] + [(2 - 1.163)^2 \times 0.083] \]
\[ + [(3 - 1.163)^2 \times 0.000] + [(3 - 1.163)^2 \times 0.000] \]
\[ + [(3 - 1.163)^2 \times 0.083] + [(3 - 1.163)^2 \times 0.000] \]^{1/2}
\[ = \{0.9697\}^{1/2} = 0.9847 \]

Correlation = \[ [(0 - 1.163) \times (0 - 1.163) \times 0.250] + [(0 - 1.163) \times (1 - 1.163) \times 0.000] \]
\[
+ [(0 - 1.163) \times (2 - 1.163) \times 0.083] + [(0 - 1.163) \times (3 - 1.163) \times 0.000] \\
+ [(1 - 1.163) \times (0 - 1.163) \times 0.000] + [(1 - 1.163) \times (1 - 1.163) \times 0.167] \\
+ [(1 - 1.163) \times (2 - 1.163) \times 0.083] + [(1 - 1.163) \times (3 - 1.163) \times 0.000] \\
+ [(2 - 1.163) \times (0 - 1.163) \times 0.083] + [(2 - 1.163) \times (1 - 1.163) \times 0.083] \\
+ [(2 - 1.163) \times (2 - 1.163) \times 0.083] + [(2 - 1.163) \times (3 - 1.163) \times 0.083] \\
+ [(3 - 1.163) \times (0 - 1.163) \times 0.000] + [(3 - 1.163) \times (1 - 1.163) \times 0.000] \\
+ [(3 - 1.163) \times (2 - 1.163) \times 0.083] \\
+ [(3 - 1.163) \times (3 - 1.163) \times 0.000)] / 0.9697 = 0.4865
\]

**Contrast** = 
\[
[(0 - 0)^2 \times 0.250] + [(0 - 1)^2 \times 0.000] + [(0 - 2)^2 \times 0.083] + [(0 - 3)^2 \times 0.000] \\
+ [(1 - 0)^2 \times 0.000] + [(1 - 1)^2 \times 0.167] + [(1 - 2)^2 \times 0.083] + [(1 - 3)^2 \times 0.000] \\
+ [(2 - 0)^2 \times 0.250] + [(2 - 1)^2 \times 0.000] + [(2 - 2)^2 \times 0.083] + [(2 - 3)^2 \times 0.083] \\
+ [(3 - 0)^2 \times 0.000] + [(3 - 1)^2 \times 0.000] + [(3 - 2)^2 \times 0.083] + [(3 - 3)^2 \times 0.000] \\
= 0.9960
\]

**Entropy** = 
\[
- [0.250 \times \ln(0.250)] + [0.000] + [0.083 \times \ln(0.083)] + [0.000] \\
+ [0.000] + [0.167 \times \ln(0.167)] + [0.083 \times \ln(0.083)] + [0.000] \\
+ [0.083 \times \ln(0.083)] + [0.083 \times \ln(0.083)] + [0.083 \times \ln(0.083)] + [0.000] \\
+ [0.000] + [0.000] + [0.083 \times \ln(0.083)] + [0.000] \\
= 2.0915
\]
Table 6-1 Texture Feature of 4x4 image

<table>
<thead>
<tr>
<th>No.</th>
<th>Texture Feature</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Energy</td>
<td>0.1386</td>
</tr>
<tr>
<td>2</td>
<td>Homogeneity</td>
<td>0.6992</td>
</tr>
<tr>
<td>3</td>
<td>Correlation</td>
<td>0.4865</td>
</tr>
<tr>
<td>4</td>
<td>Contrast</td>
<td>0.9960</td>
</tr>
<tr>
<td>5</td>
<td>Entropy</td>
<td>2.0915</td>
</tr>
</tbody>
</table>

All features are functions of the distance $d$ and the orientation $\theta$. 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.

6.6 Image Feature Extraction Algorithm

**Input:** Synthesized image obtained from preprocessing phase.

**Output:** Image Features $f_1, f_2, f_3, f_4$ for each image where $I$, $i \in D$ is the collection of synthesized image.

1. For each image $I$, $i \in D$ do
2. Compute the grey level Co-occurrence Matrices $glcm$ in an $n \times n$ neighborhood of the current pixel $x_k$
3. $glcm = graycomatrix(Image I)$
4. For each $glcm$ extract the four features defined by Haralick
5. End for
6. Store the features $f_i$ in a file.
CHAPTER 7: 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]:

- Determine parameter $k =$ number of nearest neighbors
- Calculate the distance between the query-instance and all the training samples

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:

$$D(X, Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

(7.1)

where $X$ and $Y$ are two records with $n$ attributes.

- Sort the distance and determine nearest neighbors based on the $k$-th minimum distance
- Gather the category of the nearest neighbors
- Use simple majority of the category of nearest neighbors as the prediction value of the query instance.

The Equation (7.1) measures the distance between $X$ and the point $Y$, in terms of take the difference between the corresponding values of that attribute in record $X$ and in record $Y$.

Flow chart for $k$-Nearest Neighbor ($k$-NN) algorithm is shown in Figure 7-1.

![Flow chart for $k$-Nearest Neighbor ($k$-NN) algorithm](image)

Figure 7-1 Flow chart for $k$-Nearest Neighbor ($k$-NN) algorithm
7.1 Assumption in k-NN

k-NN assumes that the data is in a feature space. More exactly, the data points are in a metric space.

The training examples are vectors in a multidimensional feature space, each with a class label.

The training phase of the algorithm consists only of storing the feature vectors and class labels of the training samples.

In the classification phase, $k$ is a user-defined constant, and an unlabelled vector (a query or test point) is classified by assigning the label which is most frequent among the $k$ training samples nearest to that query point.

Usually Euclidean distance is used as the distance metric.

7.2 k-NN Implementation

The data file was converted into a two-dimensional array where each instance was represented by a row and each attribute of that instance was represented by a column of that row. For the calculation purpose the values of the whole dataset were converted into a numeric form.

The leave-one-out validation technique was applied to the k-NN variants, one row was considered as a test instance and all others as training instances. This was repeated for each row. The distance between the test instance and each instance in the training set was calculated by using Euclidean distance measure.

The nearest instance to the test instance was the one which has the lowest distance value. Since $k$-NN involves taking more than one nearest neighbor, different numbers of neighbors were taken: $k=1$ where only the nearest one was taken, $k=4$ where four neighbors were taken in order to observe the behavior of even number of neighbors and $k=5$ taking five neighbors.
The class values of the neighboring instances were observed and the class that appeared the most times was taken as the predicted class of the test case. For \( k=1 \) the single neighbors class was taken as the predicted value.

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 research \( k=1 \)) 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.

### 7.3 Demonstrating the General Concept of \( k\)-NN Algorithm

Test = [5 6 7]; // test has three columns- assume as (x1, x2, x3)

Class1 = [1 2 3; 1.1 2.3 3.4; 5 6 7]; // each has three column (y1, y2, y3)

Class2 = [5.6 6 7; 5.3 6.5 7; 2 4 5];

Euclidence= sqrt((y1-x1)^2 + (y2-x2)^2 + (y3-x3)^2)

E1(test, train1)= sqrt((1-5)^2 + (2-6)^2 + (3-7)^2) = 6.9

E2(test, train2)= sqrt((1.1-5)^2 + (2.3-6)^2 + (3.4-7)^2) = 6.5

E3(test, train3)= sqrt((5-5)^2 + (6-6)^2 + (7-7)^2) = 0

E4(test, train4)= sqrt((5.6-5)^2 + (6-6)^2 + (7-7)^2) = 0.6

E5(test, train5)= sqrt((5.3-5)^2 + (6.5-6)^2 + (7-7)^2) = 0.58

E6(test, train6)= sqrt((2-5)^2 + (4-6)^2 + (5-7)^2) = 4.1

Mid_dist = [0 0.58 0.6 4.1 6.5 6.9]

For 1KNN,

Mid_dist 0 is class1, train3 data

So, Test data belong to class1

For 3KNN,

Mid_dist = [0 0.58 0.6]
Dist 0 belong to class 1
Dist 0.58 belong to class 2
Dist 0.6 belong to class 2

So, Test data belong to class 2 rather than 1

3KNN output class is 2.

(a) 1-nearest neighbor  
(b) 3-nearest neighbor

Figure 7-2 Demonstration of k-nearest neighbor of a record x are data points that have the k-smallest distance to x

7.4 Myanmar Paper Currency Recognition using k-NN

Test = [1];

train1 = [t1>0.55 && t2<0.95 && t3>0.86 && t4>1.19 && t5<0.99];
train2 = [t1>0.51 && t2>0.89 && t3<0.94 && t4<1.8 && t5>0.54];
train3 = [t1>0.52 && t2<0.94 && t3<0.92 && t4>1.18 && t5<0.96];
train4 = [t1>0.5 && t2>0.9 && t3<0.93 && t4<1.99 && t5<1];
train5 = [t1>0.47 && t2>0.87 && t3<0.91 && t4<2.4 && t5>0.39];

Training = [train1; train2; train3; train4; train5];

If input image == 100, train1 is 1 and then train2=train3=train4=train5=0;
So, Training = [1; 0; 0; 0; 0]

Euclidean = sqrt((y1-x1)^2)
E1 = sqrt((1-1)^2) = 0
E2 = sqrt((0-1)^2) = 1
E3 = sqrt((0-1)^2) = 1
E4 = sqrt((0-1)^2) = 1
E5 = sqrt((0-1)^2) = 1
Min_dist=[0 1 1 1 1];

For 1KNN,

Mid_dist 0 is class1, train1 data

So, Test data belong to class1

1KNN output class is 1
CHAPTER 8: EXPECTING RESULT

8.1 Datasets

Algorithm of the proposed methods was implemented using MATLAB from Math Works, Inc. The performance of these techniques was evaluated using scanned real paper currency images. The dataset used in our experiment is collected by our self. We scanned the currency images from Central Bank of Myanmar [14].

To access the performance of the proposed method, the technique was applied on a dataset of 500 banknotes observe images of 5 different denominations, each containing 100 distinct images.

8.2 Results

Table 8-1 shows the example of selected 5 Myanmar Currency Notes’ GLCM features values. Each note includes two recognition regions which are Myanmar digits such as ‘ဗား (100)’, ‘ဗား (200)’, ‘ဗား (500)’, ‘ဗား (1000)’, ‘ဗား (5000)’, and Myanmar words such as ‘တစ်သိန်း (one hundred kyat)’, ‘ပိုင်း (two hundred kyat)’, ‘ပါ (five hundred kyat)’, ‘တစ်ထောင် (one thousand kyat)’, ‘စို (five thousand kyat)’.

We compare the performance of our method on the 5 classes of currency dataset. The comparative analysis can be seen in Table 8-2.
Table 8-1 GLCM Feature Values of Myanmar Currency Notes

<table>
<thead>
<tr>
<th>Notes</th>
<th>Recognition Regions</th>
<th>GLCM Features</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Energy</td>
</tr>
<tr>
<td>100</td>
<td>ပါးပါးပါးပါး</td>
<td>0.5540</td>
</tr>
<tr>
<td></td>
<td>ကလကလကလက</td>
<td>0.4794</td>
</tr>
<tr>
<td>200</td>
<td>ပါးပါးပါးပါး</td>
<td>0.5724</td>
</tr>
<tr>
<td></td>
<td>ဒေလက်</td>
<td>0.4821</td>
</tr>
<tr>
<td>500</td>
<td>ပါးပါးပါးပါး</td>
<td>0.5366</td>
</tr>
<tr>
<td></td>
<td>ပါးပါးပါးပါး</td>
<td>0.4640</td>
</tr>
<tr>
<td>1000</td>
<td>ပါးပါးပါးပါး</td>
<td>0.5018</td>
</tr>
<tr>
<td></td>
<td>ပါးပါးပါးပါး</td>
<td>0.4683</td>
</tr>
<tr>
<td>5000</td>
<td>ပါးပါးပါးပါး</td>
<td>0.5179</td>
</tr>
<tr>
<td></td>
<td>ပါးပါးပါးပါး</td>
<td>0.4888</td>
</tr>
</tbody>
</table>

Performance rate(%) = 100 * \left(\frac{\text{Number of correct predition}}{\text{Number of data}}\right) \quad (8.1)
Table 8-2 The Results of Experiment

<table>
<thead>
<tr>
<th>Myanmar Currency Notes (Kyat)</th>
<th>100</th>
<th>200</th>
<th>500</th>
<th>1000</th>
<th>5000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Images</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Recognition Regions</td>
<td>300</td>
<td>100</td>
<td>500</td>
<td>3000</td>
<td>5000</td>
</tr>
<tr>
<td>Correct Images</td>
<td>100</td>
<td>99</td>
<td>100</td>
<td>98</td>
<td>99</td>
</tr>
<tr>
<td>Wrong Image</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Recognition Rate (%)</td>
<td>100</td>
<td>99</td>
<td>100</td>
<td>98</td>
<td>99</td>
</tr>
<tr>
<td>Recognition Time (s)</td>
<td>0.1046</td>
<td>0.0966</td>
<td>0.0907</td>
<td>0.0956</td>
<td>0.0966</td>
</tr>
</tbody>
</table>

8.3 Comparison with Previous Works

Detecting and identifying the currency notes using edge detection, segmentation and artificial neural networks system [16] describes an easy and robust computer vision based currency image segmentation and classification using image processing technology. The input currency image samples of different countries are segmented using an edge detection segmentation algorithm. This helped to segment different currency images. The next step is classification and recognition of samples. For this step a feed forward back propagation neural network model is used for the classification and recognition of the segmented image samples. The edge detection algorithm worked as expected. It was fairly simple to implement and the results for image segmentation are impressive. In the totally 16 (8 for front side and 8 for back side of note respectively) features are calculated. After testing of all images, GLCM texture feature’s overall recognition rate of accuracy is 92.16%. As can be seen by the results, the number of partitions used in the segmentation has a very large effect on
the output. The algorithm also runs quickly enough that real-time image segmentation could be done with this segmentation algorithm. The approach performs well in currency segmentation and classification, the simplicity of this method makes it more efficient and therefore it can be used extensively in banks.

In [17], an empirical approach for automated digital currency identification is formulated and a prototype is developed. A two parts feature vector is formulated consisting of color features and GLCM texture features. The note in question is classified against a FNN classifier because FNN takes all the common features of real banknotes into consideration and reach the ideal accuracy, finally measurement of the similarity between template vector and suspect note vector is output. When classifying notes against the FNN classifier, 98.6% accuracy rate is achieved on recall from outside of the training. Compared to the Adaboost 53%, PRFN 95.7% and CNN 94.3%, it is concluded that when considering all variables of this study, the FNN classifier gives the highest accuracy. Notes within the training set match to the pre-selected template image vector within the range of 99.44% - 99.99% for the output similarity measure.

In this research we present the results on the full 500 Myanmar currency note images dataset consisting of 5 categories. Although either Myanmar digit or Myanmar word texture image is recognized, Myanmar paper currency amount is correctly shown. So, the GLCM features achieve a maximum performance of 99.2% with Euclidean distance measure and being $k=1$ for $k$-NN classifier.

A comparison of various methods with each other is tabulated in Table 8-3 in terms of recognition rate. It is important to mention that GLCM method uses different paper currencies. It is observed that the proposed method is capable to recognize as good as other methods do.
Table 8-3 Comparison of Different Paper Currencies’ Accuracy

<table>
<thead>
<tr>
<th>Methods</th>
<th>Currency</th>
<th>Recognition Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed GLCM and k-NN</td>
<td>Myanmar</td>
<td>95.2</td>
</tr>
<tr>
<td>GLCM and ANN [16]</td>
<td>Europe, India, Oman, UAE, USA</td>
<td>92.16</td>
</tr>
<tr>
<td>GLCM and FNN [17]</td>
<td>USA</td>
<td>98.6</td>
</tr>
</tbody>
</table>

8.4 GUI of Myanmar Paper Currency Recognition System

Graphical User Interface of Myanmar Paper Currency Recognition System is as shown in Figure 8-1.

Figure 8-1 Graphical User Interface of Myanmar Paper Currency Recognition
CHAPTER 9: CONCLUSION

In this research we have proposed a texture feature based currency recognition method. In this work we have considered Gray Level Co-occurrence and $k$-NN classifier for recognition. The algorithm make use of the partial texture difference of Myanmar paper currency. Also we have created our own dataset of Myanmar currencies of 5 classes of 500 currency images. The experimental results have shown that the method can accurately identify the currency amount and can satisfy the Myanmar currency recognition real-time demand.

Although either Myanmar digit or Myanmar word texture image is recognized, Myanmar paper currency amount is correctly shown. So, it is easy to count currency quickly for the staffs that work in the financial organizations and overcome from his/her serious problems, especially wrong classification. But MPCR system cannot check whether the currency is valid or invalid. Although other regions of currency are damaged, currency amount is shown correctly if the two of recognized regions are not damaged. The recognition system is perfect system if the system can check the valid currency. Thus additional research will be needed.
REFERENCES


Myanmar Paper Currency Recognition Using GLCM and k-NN

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Abstract—Paper currency recognition depends on the currency note characteristics of a particular country and the extraction of the features directly affects the recognition ability. 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.

This paper aims to present an algorithmic model for automatic classification of currency notes using k-Nearest Neighbor (k-NN) classifier. A k-NN rule is one of the simplest and the most important method in pattern recognition. The proposed algorithmic model is based on textural feature such as Gray Level Co-occurrence Matrix (GLCM). The recognition system is composed of four parts. The first part of the work is to extract the image of each currency note. The second part of the work is to preprocess the captured image by reducing data dimensionality and the third part is extracting its features by using image processing toolbox in MATLAB. According to the GLCM, the work of texture feature extraction is finished. The last one is recognition, in which the core is k-Nearest Neighbor classifier. Experimental results are presented on a dataset of 500 images consisting of 5 classes of currency notes which are 100, 200, 500, 1000, and 5000 Kyat notes. It is shown that a good performance can be achieved using k-NN classifier algorithm. The recognition system presented in this paper indicates that the proposed approach is one of the most effective strategies of identifying currency pattern to read its face value.

Keywords—Pattern Recognition; Feature Extraction; GLCM; Nearest Neighbor Classifier; Myanmar Paper Currency

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.

Previous researches proposed a lot of recognition methods. In Thai banknote recognition [1], the slice values which are the digitized characteristics of banknote by the mask set, are extracted from each banknote image. 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. 'Money Talker' [2] 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. India paper currency recognition [3] 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. 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.

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. 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 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 [15]. Myanmar currency notes are having their own features such as denomination, shape, color etc.

This system can be used in ATM machines, Auto-seller machines and Bank money-counters. The main objective of this is to develop an intelligent system for Myanmar paper currency that could recognize the currency note accurately.

II. SYSTEM DESIGN

In the architecture of Myanmar Paper Currency Recognition (MPCR) system, Myanmar currency notes such
as 100, 200, 500, 1000, and 5000 Kyat are accepted as input images. The MPCR system consists of four phases:

- Skew Correction using Hough Transform
- Preprocessing
- Feature Extraction using GLCM
- Recognition using k-NN

The recognition of MPCR system will be displayed the result as an output message. The system design of MPCR is shown in Fig. 1.

![System Design of Myanmar Paper Currency Recognition](image)

**Fig. 1. System Design of Myanmar Paper Currency Recognition.**

Input image is Myanmar currency note. MPCR system is used five classes of Myanmar currency notes such as 100, 200, 500, 1000, and 5000. Input images are shown in Fig. 2.

**III. SKEW CORRECTION USING HOUGH TRANSFORM**

The image of currency note may be skewed while image acquisition process. And it is very important to de-skew the image to its original orientation thus making the image aligned with the X and Y axes.

Hough Transform is a powerful global method for detecting edges [14]. It transforms between the Cartesian space and a parameter space in which a straight line or other boundary formulation can be defined. Hough transformation uses in the image skew detection and correction.

![Presentation of Cartesian Coordinate to Polar Coordinates](image)

**Fig. 3. Presentation of Cartesian Coordinate to Polar Coordinates.**

In the polar representation a line is parameterized with \( \rho \) and \( \theta \) [14], as shown in Fig. 3. Parameter \( \rho \) represents the distance between the line and the origin, and the angle, \( \theta \) of the vector from the origin to this closest point, as given by follows:

\[
\rho = x \cos(\theta) + y \sin(\theta)
\]

(1)

In this polar parameterization the parameters \( \rho \) and \( \theta \) are bounded. The angle \( \theta \) ranges from 0 to 180 and the radius \( \rho \) ranges from 0 to \( \sqrt{W^2 + H^2} \), where \( W \) and \( H \) are the width and height of the image respectively.
A. Hough Transform Algorithm
- Typically use a different parameterization
  \[ \rho = x \cos(\theta) + y \sin(\theta) \]
  - \( \rho \) is the perpendicular distance from the line to the origin.
  - \( \theta \) is the angle this perpendicular makes with the x axis.
- Basic Hough Transform Algorithm
  1) Initialize \( A[\rho, \theta] \rightarrow 0 \); \( A \) is called accumulator array
  2) for each edge point \( I[x, y] \) in the image
     for \( \theta = 0 \) to 180
        \[ \rho = x \cos(\theta) + y \sin(\theta) \]
        \[ A[\rho, \theta] = A[\rho, \theta] + 1 \]
  3) Find the value(s) of \( (\rho, \theta) \) where \( A[\rho, \theta] \) is maximum
  4) The detected line in the image is given by \( \rho = x \cos(\theta) + y \sin(\theta) \).

B. Step by Step of Skew Detection and Correction
The skew detection and correction basic step is shown in Fig. 4.

**Fig. 4.** Step by Step of Skew Detection and Correction.

The computation of the skew angle is achieved using Hough transform to find the most visible lines in the currency note image and their angles, and finally the currency note image will be rotated as shown in Fig. 5.

**Fig. 5.** (a) Original Image, (b) Gray Image, (c) Canny Edge Detected Image, (d) Rotated Image.

IV. PREPROCESSING

The preprocessing step is performed directly on the image obtained from the scanner. The key function of preprocessing is to improve the image in ways that increase the chances for success of the other processes. Preprocessing is necessary to perform several document analysis operations prior to recognizing text in scanned documents. This phase contains the following (4) steps. There are
- Cropping Image
- Binarization
- Noise Removing
- Image Resizing

A. Cropping Image

When an image is obtained from a scanner, the size of the image is too big. In order to reduce the calculation, the size of the image should be reduced. If the image is smaller, the extraction can be faster and may improve accuracy. 100 Kyat image's size is normalized 1179 x 559 before image cropping. In the cropping image step, there are two regions such as Myanmar Digit region and Myanmar Word region are auto cropped to get the smaller image. As banknotes are different in size, the locations of cropped regions are not same. For 100 Kyat, the location pixel value of digit region is \([50, 445, 157, 55]\) and word region is \([561, 221, 292, 117]\). The two cropped regions are shown in Fig. 6.

**Fig. 6.** Cropping Image.

B. Binarization

In order to make the image texture feature for image binarization processing, the gray-scale image is converted to the binary image. Binarization texture image is shown in Fig. 7.

**Fig. 7.** Binary Image.

C. Noise Removing

The image acquired by scanner having many kinds of noise. Removing the noise is an important step when image processing is being performed. However noise may affect pattern matching. These noises are removed using \(3 \times 3\) median filter. The filtered image is shown in Fig. 8.

**Fig. 8.** Filtered Image.
D. Image Resizing

In image resizing step, this system used resized image with the standard size is (100x180). The resized image is shown in Fig. 9.

![Resized Image](image-url)

Fig. 9. Resized Image.

V. FEATURE EXTRACTION OF IMAGE USING GLCM

Gray level co-occurrence matrix (GLCM), one of the most known texture analysis methods, estimates image properties related to second-order statistics. GLCM computes the statistical features based on gray level intensities of the image. Such features of the GLCM are useful in texture recognition, image segmentation, image retrieval, color image analysis, image classification, object recognition and texture analysis methods etc.

In order to estimate the similarity between different gray level co-occurrence matrices, R. M. Haralick, K. Shanmugan and I. Dinstein [10] proposed 14 statistical features extracted from them. To reduce the computational complexity, only some of these features were selected. In this paper, we extracted five of those, energy, homogeneity, correlation, contrast, and entropy from the Myanmar currency image. In all the equations, \( P(i, j) \) stands for \((i, j)\)th entry or value in a normalized GLCM. Each entry \((i, j)\) in GLCM corresponds to the number of occurrences of the pair of gray levels \(i\) and \(j\) which are a distance \(d\) apart in original image. \(N_g\) is the number of gray levels in the image.

A. Energy

\[
\text{Energy} = \sum_{i,j=0}^{N_g-1} P(i,j)^2
\]

The energy function measures the homogeneity of an image, and provides the sum of squared elements in the GLCM. The homogeneous scene contains only a few gray levels, giving a GLCM with a few but relatively high values of \(P(i, j)\). So the sum of squares will be high. Range = [0, 1]. Energy equals to 1 means the image is constant. It also called Angular Second Moment.

B. Homogeneity

\[
\text{Homogeneity} = \sum_{i,j=0}^{N_g-1} \frac{1}{1+(i-j)^2} P(i,j)
\]

It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. Range = [0, 1]. A diagonal gray level co-occurrence matrix gives homogeneity of 1. It becomes large if local textures only have minimal changes.

C. Correlation

\[
\text{Correlation} = \frac{\sum_{i,j=0}^{N_g-1} (i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j}
\]

The correlation texture measures the linear dependency of gray levels on neighboring pixels. Returns a measure of how correlated the pixel is to its neighbor over the whole image. Range = [-1, 1]. The meaning to the actual calculated values: 0 is uncorrelated, 1 is perfectly correlated and NaN (Not a number) for a constant image. In this equation, \(\mu_i, \mu_j, \sigma_i\) and \(\sigma_j\) are the means and standard deviations.

\[
\mu_i = \sum_{j=0}^{N_g-1} j P(i,j)
\]

\[
\mu_j = \sum_{i=0}^{N_g-1} i P(i,j)
\]

\[
\sigma_i^2 = \sum_{j=0}^{N_g-1} (j-\mu_j)^2 P(i,j)
\]

\[
\sigma_j^2 = \sum_{i=0}^{N_g-1} (i-\mu_i)^2 P(i,j)
\]

D. Contrast

\[
\text{Contrast} = \sum_{i,j=0}^{N_g-1} (i-j)^2 P(i,j)
\]

The contrast measures the local variations in the GLCM. When \(i\) and \(j\) are equal, so \((i-j) = 0\) and the cell is on the diagonal. The weight function \((i-j)^2\) represents pixels which are entirely similar to the neighbor. The weights continue to increase exponentially as \((i-j)\) increases. The function returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. Range = \([0, (\text{size(GLCM, 1) - 1})^2]\). If contrast equals to 0, it means the image is a constant. Contrast is also called Inertia.

E. Entropy

\[
\text{Entropy} = -\sum_{i,j=0}^{N_g-1} P(i,j) \ln P(i,j)
\]

Entropy measures the disorder of an image and it achieves its largest value when all elements in matrix are equal. When the image is not textually uniform many GLCM elements have very small values, which imply that entropy is very large. Therefore, entropy is inversely proportional to GLCM energy.

TABLE I. shows the example of selected 5 Myanmar Currency Notes’ GLCM features values. Each note includes two recognition regions which are Myanmar digits such as 'တိုက်(100)', 'တိုက်(200)', 'တိုက်(500)', 'တိုက်(1000)', 'တိုက်(5000)', and Myanmar words such as 'စီးပွားရေး(one hundred kyat)', 'စီးပွားရေး(two hundred kyat)', 'စီးပွားရေး(five hundred kyat)', 'စီးပွားရေး(one thousand kyat)', 'စီးပွားရေး(five thousand kyat)'.

*UPT–1969*
VI. RECOGNITION USING K-NEXT NEAREST NEIGHBOR

The k-nearest neighbor (k-NN) algorithm is a method for classifying objects based on closest training examples in the feature space. k-NN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. The k-nearest neighbor algorithm was originally proposed by Cover and Hart in 1968 [13].

The k-nearest neighbor algorithm is amongst the simplest of all machine learning algorithms: an object is classified by a majority vote of its neighbors, with the object being assigned to the class most common amongst its k-nearest neighbors (k is a positive integer). If k = 1 (in this paper), then the object is simply assigned to the class of its nearest neighbor. For larger values of k, the algorithm assigns the most common value among the k nearest training examples. Any ties can be broken at random. The k-nearest neighbor algorithm used neighborhood classification as the prediction value of the new query instance.

The neighbors are taken from a set of objects for which the correct classification is known. Basically, an object is classified by the "distance" from its neighbors, with the object being assigned to the class most common among its k distance-nearest neighbors. Distance is a key word in this algorithm. Each object in the space is represented by position vectors in a multi-dimensional feature space and the Euclidean distance is used to calculate distance between two vector positions. Euclidean distance between \( X = (x_1, x_2, \ldots, x_n) \) and \( Y = (y_1, y_2, \ldots, y_n) \) is defined as:

\[
D(X, Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}
\]  

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.

Flow chart for k-Nearest Neighbor (k-NN) algorithm is shown in Fig. 10.

Fig. 10. Flow chart for k-Nearest Neighbor (k-NN) algorithm.

VII. EXPERIMENTAL RESULTS

A. Dataset

Algorithm of the proposed methods was implemented using MATLAB from Math Works, Inc. The performance of these techniques was evaluated using scanned real paper currency images. The dataset used in our experiment is collected by our self. We scanned the currency images from Central Bank of Myanmar [15].

To access the performance of the proposed method, the technique was applied on a dataset of 500 banknotes of 5 different denominations, each containing 100 distinct images.

B. Results

We compare the performance of our method on the 5 classes of currency dataset. The comparative analysis can be seen in TABLE II.

In this paper we present the results on the full 500 Myanmar currency note images dataset consisting of 5 categories. Although either Myanmar digit or Myanmar word texture image is recognized, Myanmar paper currency amount is correctly shown. So, the GLCM features achieve a
The maximum performance of 99.2% with Euclidean distance measure and being k=1 for k-NN classifier.

\[
\text{Performance rate(\%)} = 100 \times \frac{\text{Number of correct prediction}}{\text{Number of data}}
\]  

TABLE II. THE RESULTS OF EXPERIMENT

<table>
<thead>
<tr>
<th>Myanmar Currency Notes (Kyat)</th>
<th>100</th>
<th>200</th>
<th>500</th>
<th>1000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Images</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Recognition Regions</td>
<td>000</td>
<td>000</td>
<td>000</td>
<td>000</td>
</tr>
<tr>
<td>Correct Images</td>
<td>100</td>
<td>99</td>
<td>100</td>
<td>98</td>
</tr>
<tr>
<td>Wrong Images</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Recognition Rate (%)</td>
<td>100</td>
<td>99</td>
<td>100</td>
<td>98</td>
</tr>
<tr>
<td>Recognition Time (s)</td>
<td>0.1046</td>
<td>0.0966</td>
<td>0.0907</td>
<td>0.0956</td>
</tr>
</tbody>
</table>

C. Comparison with Previous Works

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

TABLE III. COMPARISON OF DIFFERENT PAPER CURRENCIES' ACCURACY

<table>
<thead>
<tr>
<th>Methods</th>
<th>Currency</th>
<th>Recognition Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed GLCM and k-NN</td>
<td>Myanmar</td>
<td>99.2</td>
</tr>
<tr>
<td>GLCM and ANN [16]</td>
<td>Europe, India, Oman, UAE, USA</td>
<td>92.16</td>
</tr>
<tr>
<td>GLCM and FNN [17]</td>
<td>USA</td>
<td>98.6</td>
</tr>
</tbody>
</table>

VIII. CONCLUSION

In this paper we have proposed a texture feature based currency recognition method. In this work we have considered Gray Level Co-occurrence Matrix and k-NN classifier for recognition. The algorithm make use of the partial texture difference of Myanmar paper currency. Also we have created our own dataset of Myanmar currencies of 5 classes of 500 currency images. The experimental results have shown that the method can accurately identify the currency amount and can satisfy the Myanmar currency recognition real-time demand.

The following facts are recommended for further extensions with this related field (1) MPCR system can use other feature extraction method. (2) In processing step, the system can be extended on the purpose of better accuracy and efficiency. (3) In further work, this system can be extended to use for other Myanmar currency notes.

REFERENCES