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Bahraini Paper Currency Recognition

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ABSTRACT

This paper presents a new technique to recognize paper currency. Bahrain paper currency has been considered as a special case, although the system can be trained for other currencies too. The recognition of paper currency has been successfully attempted to be recognized from both sides. It uses two classifiers, the weighted Euclidean distance using suitable weights and the Neural Network. The proposed technique is based on extracting some specific features of the paper currency. In addition to finding and extracting features, the technique also includes various preprocessing steps. Various factors like the image size, edge detection, the Euler number and the correlation coefficient play important role in the recognition process. The system, using weighted Euclidean distance, yields results up to 96.4% of accuracy of recognition. Whereas, the two level of feed forward back propagation neural network classifier, which has many conditions that effect on the accuracy rate, can recognize up to 95.5% of accuracy in best case of the recognition.

***Keywords*: Paper currency, recognition, classification, feature extraction, imaging.**

1. Introduction:

There are approximately more than 150 currencies all over the world, each of them looking totally different. By expansion of modern banking services, automatic schemes for paper currency recognition are significant in many applications. The requirements for an automatic banknote recognition system have offered many researchers to build up robust and dependable techniques. Speed and precision of processing are two vital factors in such systems. The existing paper currency recognition methods, in the current literature, involve extraction of features for banknote classification. Paper currency recognition systems should be clever to recognize banknotes from each side and each direction. Since banknotes may be faulty during circulation, the designed system should have an important precision in detecting torn or worn banknotes.

Various authors have worked for paper currency recognition. For example, Wang and Liu (Wang and Liu, Hassanpour, 2008), used an invariant feature extraction for banknote classification which has performed very well when applied to banknote stores. Furthermore, Hassanpouret.el. (Hassanpour, Yaseri, Ardeshiri, 2007), proposed a technique where characteristics of paper currencies include size, color and texture are used in recognition. In this technique, the Marcov Chain concept has been used to model texture of paper currencies as a random process. On the other hand, Pathabe and Bawane (2011), presented a currency recognition system using ensemble neural network (ENN). The individual neural networks in an ENN are skilled via negative correlation learning. Besides this, Takeda and Nishikage (2000), concentrated on enhancing neuro-recognition system to increase the number of recognition patterns using axis symmetrical mask and two image sensors. Zhang et al. (2003) presented a method using linear transform of grey image to diminish the influence of background image noises in order to give prominence to edge information of the image. Debnath et.al (2010) presented a currency recognition system using (ENN) and applied it to 7 different types of Taka (Bangladeshi currency).

This paper proposes new techniques, to recognize paper currency, using two different classifiers. A set of features has been introduced for the recognition purposes. Bahrain paper currency has been selected as a special case for testing the schemes.

The organization of the paper is as follows. In Section 2, Bahrain Paper Currency (BPC) recognition methodology is introduced. The proposed modeling system has been completely discussed in Section 3. Section 4, describes Simulation and results of the proposed paper currency recognition system. Finally, the paper is concluded Section 5.

Fig.1. The National Bank of Bahrain advertising of the fourth issue of BPC.

2. Proposed Methodology

In Feb 2008, the National Bank of Bahrain (Central Bank of Bahrain), presented the fourth issue, a new paper currency for Bahraini Dinar (BD), shown in Fig 1. So, there was a big and timely need to design a Bahrain Paper Currency Recognition System (BCRS).

This system introduces the use of feature extraction in order to classify and recognize the paper currency image by using two main classifiers: the Weighted Euclidean Distance and the neural network.

2.1. Minimum Distance Classification

Distance functions are used to measure the similarity or dissimilarity between two classes of patterns. The smaller the distance between two classes of patterns, the larger is the similarity between them. The minimum distance classification algorithm is computationally simple and commonly used. It can result in classification accuracies that are comparable to other more computationally intensive algorithms like maximum likelihood class.

The classifier finds the distances from a test input data vectors to all the mean vectors representatives of the target classes. The unknown pattern is assigned to that class from which its distance is smaller than its distances to all other classes. Three types of distance measures, in digital image processing, are often used: Euclidean, city block, and chessboard. The distance between two points P) with coordinates (x,y) and Q with coordinates (u,v) is defined as:

$$d(P,Q) = \sqrt{(x-u)^2 + (y-v)^2} \tag{1}$$

The Eq. 1 can further be generalized in a higher dimension and with a variety of associated parameters as follows:

$$d = \sqrt{p((w_i - wj)^2 + (hi - hj)^2) + q(\sum_{i=1}^{n} (ai - a j)^2) - k * ci} \tag{2}$$

Here in Eq. 2 the p, q and k are the weights of the equation, a is the feature in both images, c is the correlation coefficient, h is the height of the image, and w is the width of the image.

2.2. Neural Networks:

Artificial neural networks have been applied in various application domains for solving real world problems such as feature extraction from complex data sets, direct and parallel implementation of matching and search algorithms, forecasting and prediction in rapidly changing environments, recognition and image processing applications, using multilayer perceptron.

The most popular neural network model is the multilayer perceptron (MLP) (Hassoun, 1995), which is an extension of the single layer perceptron proposed by Rosenblatt (1962). Multilayer perceptions, in general, are feed forward networks, having distinct input, output, and hidden layers. The architecture of multilayered perceptron is used as error back propagation network.

In an hl-class problem, where the patterns are N-dimensional, the input layer consists of N neurons and the output layer consists of A1 neurons. There can be one or more middle or hidden layer(s). No computations are performed at the input layer neurons. The hidden layer neurons sum up, the inputs pass them through the sigmoid non-linearity and fan-out multiple connections to the output layer neurons. In feed forward activation, neurons of the first hidden layer compute their activation and output values and pass these on to the next layer as inputs to the neurons in the output layer, which produce the networks actual response to the input presented to neurons at the input layer. Once the activation proceeds forward from the input to the output neurons, the network's response is compared to the desired output corresponding to each set of labeled pattern samples belonging to each specific class, there is a desired output. The actual response of the neurons at the output layer will deviate from the desired output which may result in an error at the output layer. The error at the output layer is used to compute the error at the hidden layer immediately preceding the output layer and the process continues (Acharya & Ray, 2005).

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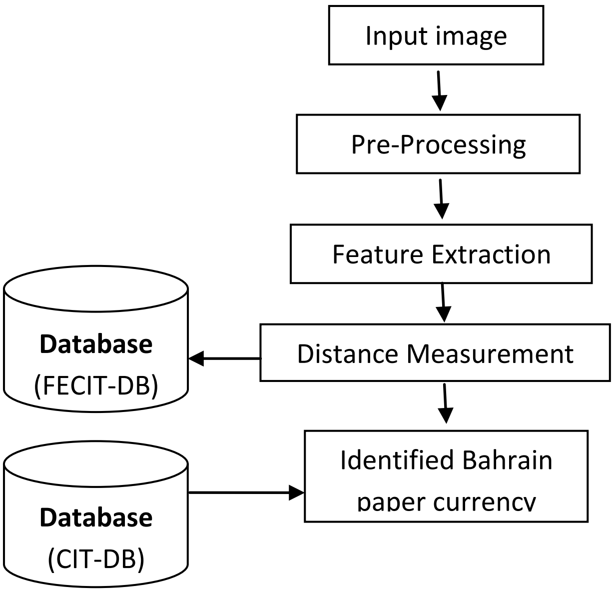

Fig.2. Proposed approach diagram.

3. Modeling System

The BCRS is designed to recognize Bahraini paper currency. The Bahrain paper currency has five different banknotes of values1/2, 1, 5, 10, and 20 BD). Fig. 1 show these banknotes from the front as well as back sides the developed system has various phases including scanning, pre-processing, feature extraction, classification and identification. These phases are explained in the following subsections and the system’s flow can be seen in Fig. 2.

3.1. Preprocessing

The system begins with scanning images for the quality 600 dpi. High quality of 600 dpi has been taken intentionally for better quality; it can be reduced later for faster manipulation and low cost of storage. The colored scanned input image is converted into grayscale and then into black-white image.

Edge detection is of fundamental importance in image analysis. Edges characterize object boundaries and are therefore useful for segmentation, registration, and identification of objects under consideration. Edge points can be thought of as pixel locations of abrupt gray-level change (Shin, 2010). A number of edge detectors based on a single derivative have been developed by various researchers. Amongst them, most important operators are the Robert operator, Sobel operator, Prewitt operator, Canny operator, and Krisch operator (Jain, 1989). For this study, we use Prewitt, Sobel and Canny edge detection methods.

(a) (b) (c) (d)

Fig.3. The edge detection operators applied on Bahrain paper currency: (a) Binary; (b) Sobel; (c) Prewitt; (d) Canny.

3.2. Feature Extraction

In the pre-processing step, we achieve four different kinds of images: the binary image; the gray scale image after applying Sobel mask; the gray scale image after applying Prewitt mask; and the gray scale image after applying Canny mask. Fig. 3 presents a sample of these images. Fig. 4 explains the pre-processing steps. After that, we calculate the sum of pixels of each of the four images. Also, the Euler number is calculated for each of the images .Finally, we compute the correlation coefficient of input image after converting it to gray scale.

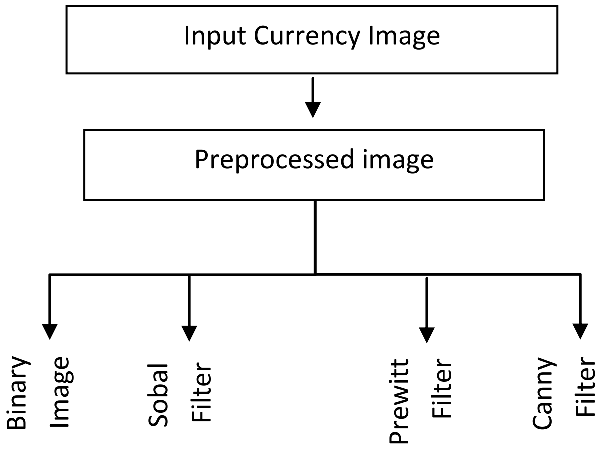

Fig.4. The pre-processing steps.

3.3. Databases

The system considers all kinds of banknotes including eroded, old and the ones with handwritten words or scratches. The main algorithm is described in Fig. 2 One can see that the system deals with two databases: database for the currencies image templates (CIT-DB) of clean, clear and new images collected and arranged according to their values; and the database of the extracted features of the currencies image templates (EFCIT-DB) in (CIT-DB).

3.4. Classification

Two different methods have been used for the classification after all features were extracted. The first one depends on minimum distance classification; we apply the Weighted Euclidean Distance (WED) here. The other is the Neural Networks using feed forward back propagation neural networks..

4. Computer Simulation and Results

The main algorithm starts with acquiring the currency images. The input image is pre-processed by removing noise and converts it to gray scale. The next step, in the algorithm, is extracting the features of each input image. The selected features are the height, width, areas of image after applying three masks of edge detection methods Prewitt, Sobel and Canny filters, and the correlation coefficient. The classification step is handled by the distance measurement using WED. It compares the input image features with those of template features images in the (EFCIT-DB) database. The last step is the identifying currency image that is shown from the (CIT-DB) database.

4.1. Consideration of WED

The WED classifier system is applied on BPC with 110 different input types of currencies. According to algorithm, specified in, as shown in Fig. 2, Table1 provides the computed features in numerical form.In this table,the features z,z1,z2 and z3 denote the areas of the images after applying the edge detection masks. Whereas, eu, eu1, eu2 and eu3 are the Euler numbers for the masked images. These features are obtained for all the Bahrain currency arranged on their values front faces (1/2F, 1F, 5F, 10F and 20F) and back faces (1/2B, 1B, 5B, 10B and 20B).

Fig.5, shows the front side of all BPC 's and their related features extracted as shown in Table 1. In this figure, the currencies are arrange according to their values (1/2F, 1F,5F,10F and 20F). The letter F indicates the front face of the currencies. Similarly, Fig. 6 demonstrates the back sides of the paper currency; the letter B indicates the back side.

The system has been tested on 110 of BPC inputs with different and random types of currencies. Table 2 shows the results after applying the proposed system. The weights, in the WED of the system, have been selected as p=0.5, q=0.0005 and k=10000. The computed results thus are shown in Table2. From the table, we find that the best results are obtained for the currencies on the front side for the values 1/2, 10 and 20. Similarly, the best results for the back side of the currencies are obtained for values 1/2B, 1B and 10B. These results are obtained with 100% accuracy. The lowest recognition accuracy was obtained for the type of value 20 in the back face. The time of recognition for best case was for 1F where the longest time was 20F and 1B. The average accuracy of recognition was found as 96.3% in 2.6 seconds of time.

It is worth noting that the recognition time can be increased further by reducing the size of the input image by taking not a very high resolution and the high quality of image.

Table1.The feature database of all Bahrain paper currency in numerical form.

Type	**z**	**z1**	**z2**	**z3**	**eu**	**eu1**	**eu2**	**eu3**
1/2F	308035	19917	19585	49608	-3210	1997	2265	521
1F	314028	20053	19744	47542	-2745	2355	2605	420
5F	306905	18993	18566	51618	-3913	2604	2853	568
10F	301949	24012	23613	46577	-5889	3567	3811	157
20F	286905	20463	20113	54103	-6675	3563	3460	31
1/2B	296549	18615	18038	45254	-4835	2742	2820	541
1B	294104	18313	17640	44593	-6677	3252	3487	663
5B	294679	18828	18209	47269	-5881	3392	3553	549
10B	293434	17974	17003	50013	-5374	3091	3492	360
20B	306288	16890	16457	50108	-4603	3133	3069	786

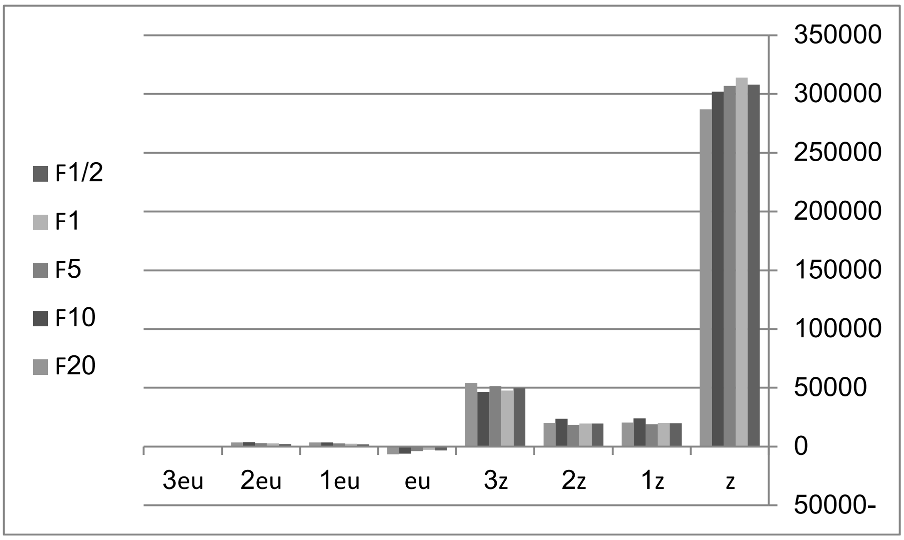

Fig.5. Bahraini paper currency front face according to their extracted features.

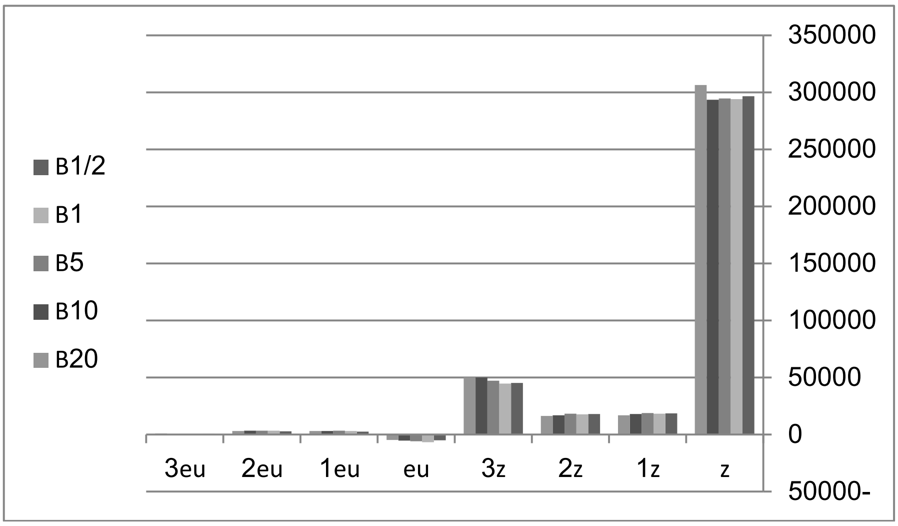

Fig.6. Bahraini paper currency back face according to their extracted features.

Fig. 7 shows the results of BPC recognition using WED, for different and random input samples of 110 Bahrain paper currencies. Table 2 demonstrates the statistics of the nature of the results.

Table 2.The system results of Bahrain paper currency samples using WED.

Currency Type	Sample Input	Recognition Result	Accuracy rate	Time taken
1/2 BD-F	23	23	100%	2.35sec
1 BD-F	17	16	94.18%	2.1sec
5 BD-F	5	4	80%	2.8sec
10 BD-F	5	5	100%	2.7sec sec
20 BD-F	4	4	100%	2.8sec
1/2 BD-B	23	23	100%	2.7sec
1 BD-B	19	19	100%	2.8sec
5 BD-B	5	4	80%	2.6sec
10 BD-B	5	5	100%	2.6sec
20 BD-B	4	3	75%	2.6sec
Average	**110**	**106**	**96.36%**	**2.6sec**

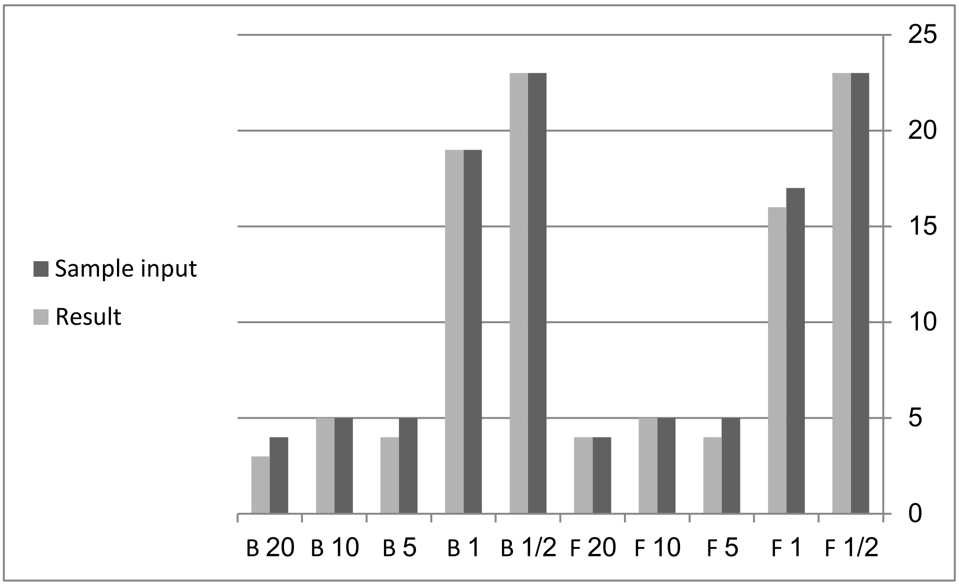

Fig.7. Results of BPC recognition using WED classifier.

It is important to mention here that when the weights were reduced to 50%, 98.2% of accuracy was achieved in time2.7sec. Similarly, when the weights were increased up to 50%, 96.36% of accuracy in time 1.77 sec.

4.2. Noisy images

Sometimes used currencies may have various handwritten text or scratches on any side of it. For example, Fig. 8 demonstrates some of the paper currencies in such forms.

Fig.8. Cases of noisy Bahrain paper currency with handwritten words and scratches.

After applying the WED classifier on the images, as shown in Fig. 8, the system was able to recognize images (i),(ii) and (v), whereas the images(iii), (iv) and (vi), were not recognized. This indicates that the input should be clean enough for successful system requirements.

4.3. Reduction of Features Set

An experiment was made by minimizing the features set to five only: the four Euler numbers and the correlation coefficient. This was done to find out about which features have the high impact in the recognition process. Table 3 shows the results of the proposed approach. The best results of accuracy were achieved for all the currency types except 5F, 20F and 20B. The time of recognition, for each currency image, was found very close. The lowest time was noted for the currency of values 1/2B and 20B. The average recognition rate was found to be 93.6% of accuracy in time 2.1 sec.

Table 3.System results of BPC with reduced features using WED.

Currency type	Sample	Recognition Results	Accuracy rate	Time taken
1/2 BD-F	23	23	100%	2.1sec
1 BD-F	17	17	100%	2.0 sec
5 BD-F	5	2	40%	2.1sec
10 BD-F	5	5	100%	2.0 sec
20 BD-F	4	1	25%	2.1 sec
1/2 BD-B	23	23	100%	1.9 sec
1 BD-B	19	19	100%	2.0 sec
5 BD-B	5	5	100%	2.3 sec
10 BD-B	5	5	100%	1.9 sec
20 BD-B	4	3	75%	2.0se 07sec
Average	**110**	**103**	**93.6%**	**2.1sec**

4.4. Neural Network

In addition to WED, the classifier of neural network was also attempted in the developed system. As many as 100 samples of random and different Bahrain paper currency were fed to two-layer feed-forward network, with sigmoid, hidden and output neurons. It was able to classify vectors arbitrarily well using 20 neurons in its hidden layer. We tried the system on different cases depending on some variables that affected on the final results. The variables under consideration were: number of hidden neurons, number of training samples, number of validation samples and the number of testing samples.

Table 4. System results of using two layers of feed forward back propagation neural networks classification of BPC, with 20 hidden neurons.

Training Samples	Validation Samples	Testing Samples	Recognition Rate
90	5	5	95.5%
80	10	10	93.75%
70	15	15	86.45%
60	20	20	83.89%
50	25	25	81.33%
40	30	30	78.3%
30	35	35	74.73%

The main system was tested ten training times on different testing and training number of samples. We considered numbers of 90, 80, 70, 60, 50, 40 and 30 for training of input samples which produced the results as shown in Table4. It can be observed, in Table that when a size of 90 as training samples, size of 5 as validation samples, and size of 5 as testing samples were under consideration, it provided 95.5% of accuracy after applying the proposed NN. When the training samples reduced to be 80 with 10 for validating and 10 for testing samples, the accuracy rate reduced to 93.75%. Similarly going on this way, one can see from Table 4, the recognition rate is dropping down continuously. So much so, the lowest

accuracy rate is observed as 74.73% for 30 of training samples, 35 of validation samples and 35 of testing samples.
So from Table4, we found that the best case was achieved for using 90 training samples and the worst was observed for the 30 training samples. So we conclude that the more training samples, the more increasing percentage of accuracy rate will be obtained.

5. Conclusion

This paper proposes an approach for recognizing Bahrain paper currency. The technique used preprocessing steps including applying edge detection masks with Sobel, Prewitt and Canny operators. Then extracting some features based on edge detection filters and Euler number and the correlation coefficient. The recognition uses two classifiers based on two categories. The minimum distance classification was used by taking the weighted Euclidean Distance with 96.4% accuracy rate. The Neural Network with feed forward back propagation was used as another classification technique. It provides almost 85.1% average of accuracy for the best case .Therefore; we find that the WED approach is better than the Neural Network.

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