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Deformed Banknote Identification Using Pattern Averaging and Neural Networks

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Abstract: -Neural networks combined with image processing can provide sufficient solutions to problems where automation and machine intelligence is required. An Intelligent Banknote Identification System that is able to recognise clean and deformed banknotes may be used to aid identification by machines or banknote counters. For such as system to be useful in real-life applications it must be also be fast, efficient and simple to use. This paper presents a fast intelligent banknote identification system that is able to recognise clean and deformed banknotes. Banknote image compression using Discrete Cosine Transform (DCT) and Biorthogonal Wavelet Transform (BWT) is used to simulate four levels of banknote deformation. The deformed banknotes will be used to test the trained neural network. A real-life application will be presented where this system is used to identify EURO banknotes and the new Turkish Lira (TL) banknotes. Experimental results suggest that the developed system perfoms well when using highly deformed banknote images as well as clean images; thus providing a fast, efficient system for recognizing banknotes.

Key-Words: - Deformed Banknote Identification, Back Propagation Neural Network, Image Compression, Intelligent Recognition, Pattern Averaging.

1 Introduction

The purpose of implementing pattern recognition using artificial neural networks is to develop a machine that is able to simulate our perception of the objects that we see. We, humans, have the ability to recognize patterns and object by simply seeing a part of an object or a whole object.

Patterns can be defined as a quantitive or structural description of an object or some other entiny of interest. Pattern Recogniton is the process of categorizing any sample of measured or observed data as a member of the several classes or categories. A pattern recognition system may consist of pre-processing, data reduction, segmentation, object or pattern recognition and image understanding [1].

The reliability and success of intelligent systems on pattern recognition depends on the recognition rate of the degraded patterns. Noise can be created artificially by using image processing techniques or can occur naturally within an image such as when capturing images of an old soiled banknote.

The use of image compression has traditionally been used to reduce processing time and storage space. However, in this paper the use of image compression is aimed at simulating various levels of degradation in the pixel values, thus, yeilding different levels of image deformations.

Banknote images contain patterns as well as number to indicate the value of a banknote. An identification system that is able to recognise clean and deformed banknotes using parts of the banknote and not necessarily identifying the value number can be useful in automazing banknote counting machines or cashpoints [2].

The aim of the work presented within this paper is to provide an fast intelligent banknote identification system that is able to recognise banknotes with various levels of deformation. Two compression methods are used DCT and BWT with compression ratios of 50% and 80% to simulate four deformation levels in banknote images. Pattern averaging of the banknote images is used to reduce the amount of data required for meaningful training of the neural network. A Real-life application will be implemented using seven EURO banknotes and six new Turkish Lira (TL) banknotes.

2 Characteristics of the Banknotes

There are 6 banknotes of the new Turkish Liras; 1, 5, 10, 20, 50 and 100 TL, and 7 banknotes of the Euro; 5, 10, 20, 50, 100, 200 and 500 Euro. Each banknote has different sizes, patterns and colors. Figure 1 shows TL and EURO banknote samples.

The banknotes have their values (numbers) printed on front and back, however these values are not detected by our proposed system. Instead, an averaged representation of the banknote patterns is considered for training the neural network to classify the different banknotes and their values. This novel approach aims at solving the problem of unreadable characters or numbers in deformed banknote images.

3 Simulating Banknote Deformation

Different levels of deformation in banknotes may be simulated using banknote image compression. Image compression using DCT and wavelet transforms has been investigated thoroughly [3], [4]. Suggestions were made that DCT provides the most damaged reconstruction of compressed images because of the blocking artifacts at high compression ratios [5], [6]. Thus, DCT compression will be used to simulate extremely and highly deformed banknotes. On the other hand, Wavelet Transforms provide much better reconstruction of compressed images than DCT. Although there are several types of wavelet transforms to compress images, Biorthogonal Wavelet Transform (BWT) is used in this work to simulate low and medium deformation because of its efficient and clear reconstruction of images even at higher compression ratios.

In this paper, compression ratios of 50% and 80% have been applied using DCT and BWT. The result deformed banknote images will be used for testing the trained neural network within the banknote identification system. The efficiency of this identification system will be demonstrated by its ability to recognise deformed banknotes as well as clean bankotes.

The deformation levels of the banknotes vary according to the compression method, compression ratio and the banknote. The deformation ratio D is defined as follows:

$$D = (D_{min} + D_{max}) / 2 \tag{1}$$

where D_{min} and D_{max} are minimum and maximum deformation ratios of the banknotes and are defined as:

$$D_{min} = ((1 - PSNR_{\min} / 100) * 100) \tag{2}$$

$$D_{max} = ((1 - PSNR_{\max} / 100) * 100) \tag{3}$$

where $PSNR_{min}$ and $PSNR_{max}$ are minimum and maximum Peak signal-to-noise values in the range of $PSNR$ values for a reconstructed banknote image, using one compression method with a certain compression ratio. Table 1 shows the deformation ratios and levels which are defined as: *low*, *medium*, *high* and *extreme*. Figure 2 shows an example of low deformation and extreme deformation of a 5 Euro banknote.

Table 1. Deformation levels of banknote images

Comp. Method	Comp. Ratio	PSNR	Deform. Ratio	Deform. Level
BWT	50%	35.38 - 45.98	60 %	Low
	80%	26.64 - 34.63	70 %	Medium
DCT	50%	18.45 - 27.12	80 %	High
	80%	9.92 - 14.35	90 %	Extreme

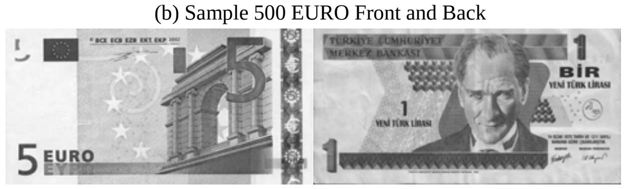
4 Identification System and Neural Network Arbitration

Intelligent identificaton of banknotes is a dual-phase system. The first phase is data preparation via image pre-procesing and the second is neural network training and generalization phase.

Banknote image pre-processing is the data preparation phase where the banknotes are prepared for the training and meaningful learning in minimal time. This phase comprise size reduction image cropping and pattern averaging prior to presentation to the neural network. A block diagram of data preparation phase is shown in Figure 3.

(a) Sample 100 TL Front and Back

(b) Sample 500 EURO Front and Back



(c) Sample 5 EURO and 1 TL Front

Fig. 1. Examples of new Turkish Lira (TL) and EURO banknotes

Original

Low Deformation

Extreme Deformation

Fig. 2. Example of extreme and low deformations of a 5 EURO banknote.

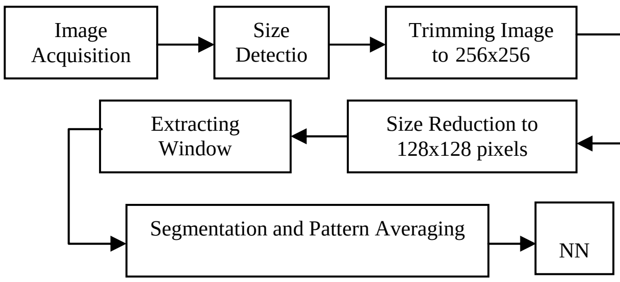


Fig. 3. Block Diagram of Data Preparation Phase

Pattern averaging is the averaging of the defined segments of the image. Our suggestion is that averaging provides efficient representation of the banknote patterns despite the level of deformation. Image segmentation is carried out using 10x10 segments that are averaged and presented as one segment per node at the neural network input. This method is used to minimize the number of input nodes in the neural networks, thus reducing training and run time.

The second phase of the identification system is training the 3-layer back propagation neural network and then once converged, generalizing the trained network. A single neural network is used with 100 input neurons, 25 hidden neurons and 13 output neurons, as shown in Figure 4. During the training phase, initial random weights of values between –0.6 and 0.6 were used. The learning rate and the momentum rate; were adjusted during various experiments in order to achieve the required minimum error value and meaningful learning. An error value of 0.001 was considered as sufficient for this application. Table 2 shows the final parameters of the neural network.

Table 2. Neural network parameters

Input Layer Nodes	100
Hidden Layer Nodes	25
Output Layer Nodes	13
Learning Rate	0.03
Momentum Rate	0.75
Minimum Error	0.001
Iterations	1977
Training Time	31.50 seconds
Run Time	0.02 seconds

5 Results and Discussion

The neural network within the identification system was trained using 26 images of original clean banknotes. The images comprised 12 images of the New Turkish Lira (6 front and 6 back) and 14 images of the EURO (7 front and 7 back). The result of testing the neural network using these training clean banknotes was 100% recognition as would be expected.

The difference between the banknote images used for training and those used for testing is that the testing images were deformed at different deformation levels which were simulated by image compression.

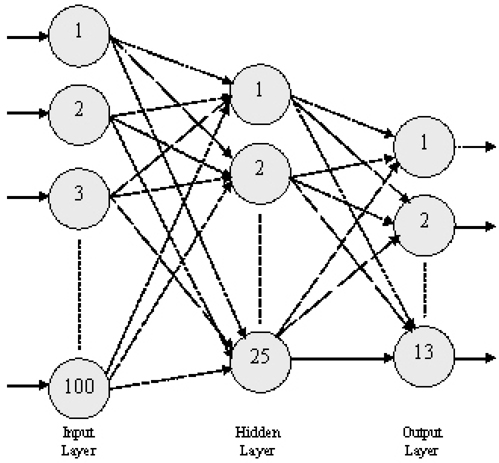


Fig. 4. Classifying Neural Network Topology

The trained neural network was tested using 104 deformed banknote images that were obtained by compressing images of the 26 training images, thus simulating the 4 deformation levels; namely *low*, *medium*, *high* and *extreme* deformation.

Testing the network using *low* and *medium* deformation of the banknotes yielded successful results with 100% recognition of these deformed banknotes that were not presented to the network during training. All 104 deformed banknote images were correctly recognized at the *low* and *medium* deformation levels (BWT compression).

Simulating banknote deformation using DCT compression provides *high* and *extreme* deformation levels. The results of testing the trained neural network using these levels of deformation yielded successful results where all deformed Turkish Lira (TL) banknotes were correctly identified despite the *high* and *extreme* deformation. Similar successful results were also obtained in identifying the deformed EURO banknotes at the *high* deformation level where all deformed EURO banknotes were correctly identified.

However, when using the *extreme* level of deformation of the EURO banknote images, only 12 out of 14 banknotes were recognized, which is a sufficient result when considering the *extreme* deformation of the banknote images. Figure 5 shows the deformation occurring on the 5 and 200 Euro banknotes. Figure 6 shows the deformation occurring on the 5 and 10 TL banknotes. The original banknote images were used for training the neural network, whereas the deformed banknote images were used for testing the network. In summary, 102 out of the 104 testing banknote images that were not presented to the neural network during training were successfully recognized providing an overall recognition rate of 98%.

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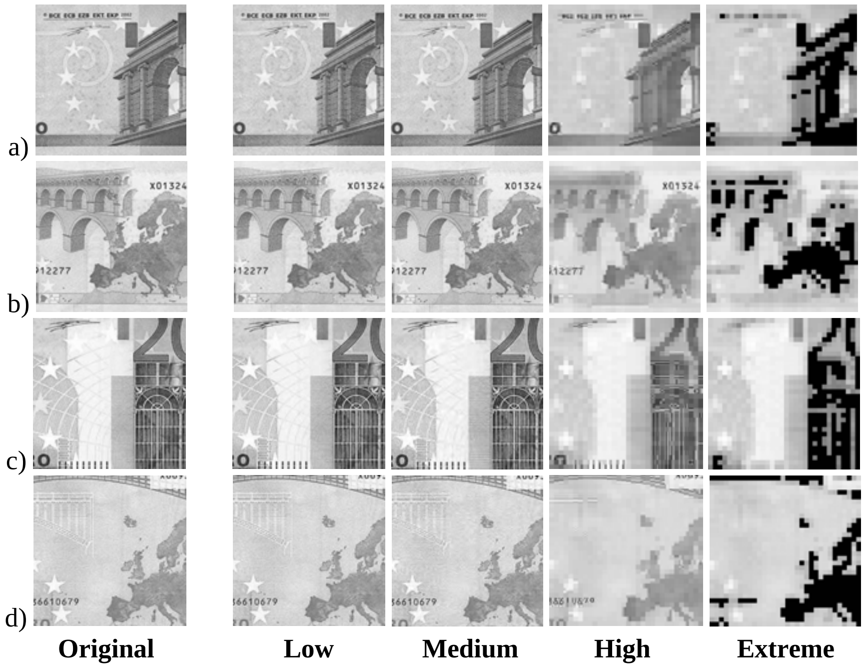

Fig. 5. Original and deformed banknote images of a) 5 Euro front b) 5 Euro back c) 200 Euro front d) 200 Euro back

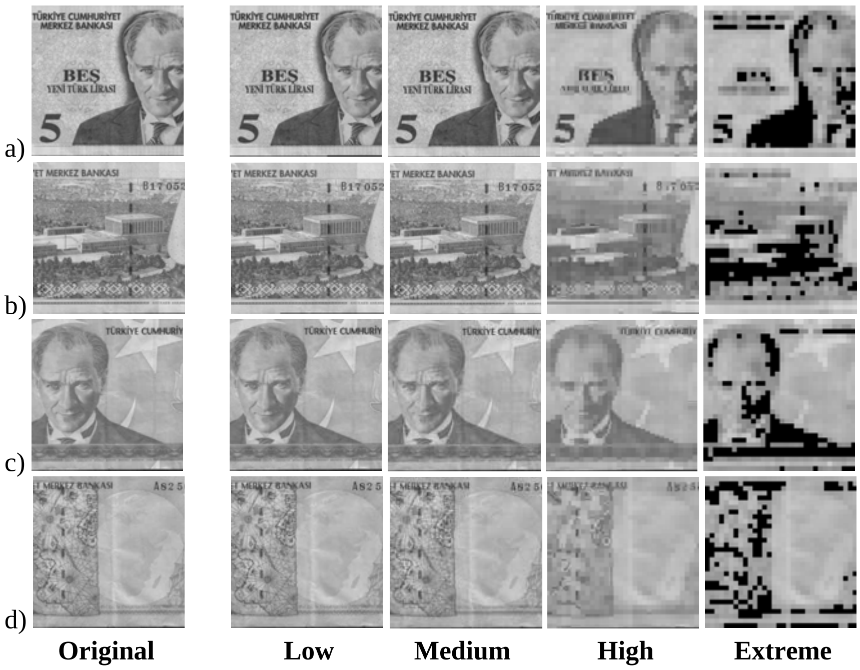

Fig. 6. Original and deformed banknote images of a) 5 TL front b) 5 TL back c) 10 TL front d) 10 TL back

Table 3. Recognition rates of various deformation level

	Low Deformation	Medium Deformation	High Deformation	Extreme Deformation	Total
EURO	14/14 (100%)	14/14 (100%)	14/14 (100%)	12/14 (85.71%)	54/56 (96.42%)
TL	12/12 (100%)	12/12 (100%)	12/12 (100%)	12/12 (100%)	48/48 (100%)
Total	26/26 (100%)	26/26 (100%)	26/26 (100%)	24/26 (92.30%)	**102/104 (98.07%)**

The recognition of all original clean banknotes yielded 100% correct identification. This successful identification outcome shows the robustness of our intelligent banknote identification system in recognizing both deformed and clean banknotes. It also suggests; using pattern averaging to be an efficient method for presenting images to a neural network, where meaningful learning can be achieved. Table 3 shows a summary of the results of testing the neural network using deformed banknotes.

6 Conclusion

In this paper, an intelligent banknote identification system that is able to recognize clean and deformed banknotes is presented. Banknote deformation is simulated at various levels using two image compression methods; namely biorthogonal wavelet transform (BWT) and discrete cosine transform (DCT) compressions, thus providing four deformation levels: “low”, “medium”, “high” and “extreme”. The developed system uses image pre-processing and pattern averaging prior to training a neural network using 26 clean banknote images. We suggest that the use of pattern averaging provides sufficient representation of a banknote character and results in meaningful learning as has been demonstrated when testing the trained neural network. Testing was implemented using 104 deformed banknote images at various levels.

A real life application has been presented using the Euro banknotes and the new Turkish Lira banknotes. Training time of 31.5 seconds and testing (run) time of 0.02 seconds show a fast efficient intelligent system for recognizing clean and deformed banknotes with an overall 98% recognition rate.

The developed intelligent banknote identification system can also be used with any other banknotes, providing neural network training is performed using these new banknotes.

Future work includes further investigation of the efficiency of pattern averaging as a means for data presentation to a neural network, using more deformation levels that will be simulated via image compression.

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