# ANN Based Currency Recognition System using Compressed Gray Scale and Application for Sri Lankan Currency Notes - SLCRec

D. A. K. S. Gunaratna[1, 4], N. D. Kodikara[2, 4], and H. L. Premaratne[3, 4]



***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. Sri Lanka has not been involved in any kind of research or implementation of this kind. The proposed system "SLCRec" comes up with a solution focusing on minimizing false rejection of notes. Sri Lankan currency notes undergo severe changes in image quality in usage. 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. The 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 neural network is presented with the number of edges detected in row order of the notes and classification is accepted in four classes of interest which are 100, 500, 1000 and 2000 rupee notes. The experiments showed good classification results and proved that the proposed methodology has the capability of separating classes properly in varying image conditions.

***Keywords*****—**Artificial intelligence, linear transformation and pattern recognition.

## I. INTRODUCTION

WHILE developments of various methodologies have been proposed by many other countries with regard to automatic recognition of currency notes, this aspect is an issue requiring a feasible and timely solution in the context of Sri Lanka. However one of the major concerns regarding Sri Lankan currency notes is the exposure to high rate of noise when in circulation. Hence any solution given should be able to produce accurate results, whilst adapting to the conditions unique to the notes in Sri Lanka. Furthermore financial institutions are in need of a system that can calculate notes irrespective of the denominations given. If such a system is introduced, it would undoubtedly enhance the socio-economic dimension of Sri Lanka as well. Customer depositing money to his account through an ATM machine could be considered as one such instance.

[1] kalpagunaratna@gmail.com
[2] ndk@ucsc.cmb.ac.lk
[3] hlp@ucsc.cmb.ac.lk
[4] University of Colombo School of Computing, No 35, Reid Avenue, Colombo 07, Sri Lanka

The question raised in this paper is "How are we going to adapt and implement an intelligent recognition system for Sri Lankan currency notes?". At present the answer is in the negative, since there is no identified system to fulfill this requirement and the only available systems which are in use merely count a given set of notes of the same denomination. However the proposed system should also be able to adapt to high noise, which is a critical factor. Hence the task at hand to be solved can be categorized into two components. The first step involves getting characteristic features of Sri Lankan currency images extracted that vary from each denomination. The second step requires using these characteristic features in an intelligent system for recognition.

Sri Lankan currency notes are quite different compared to currency notes of other countries', by their images on the face. These images are quite complex and they reflect ancient heritage and culture of Sri Lanka. One way to address this complexity is to get the outline of basic shapes in the notes, which is called as edge detection. The noise overhead should also be considered appropriately. Hence a special transformation is expected in feature extraction phase. Thus a particular linear transformation function is applied on gray scale images to remove noise, retrieve only relevant characteristic patterns, re-appear prominent shapes in distorted image conditions and have fair representation of edges in almost every image condition making the system robust. A feed forward neural network has been used with BP learning with a hidden layer having number of output nodes representing classes of currency note classification.

## II. RELATED WORK

### *A. Image Processing*

Edge detection has been successfully used with image enhancement technique to classify Chinese banknotes with high accuracy [1]. A linear transformation function has been used to wipe out noise in background.

Masking technique is used with Genetic Algorithms in [2][3]. The type of masking technique used is random masking which is considered as a worldwide banknote recognition concept. Masks are obtained by random numbers and selects optimum mask by applying GA on them. There exists another masking technique called as Axis Symmetric Masks which avoids multiple training patterns as mentioned in

[4].

PCA (Principal Component Analysis) is a technique used to reduce the dimensionality of data sets for analyzing purposes and PCA is considered in [5][6] for compressing image data to be classified.

Wavelet transform has been successfully used in various applications, including object identification, and texture analysis. In general, patterns in a banknote can be considered as textures having certain ranges of spatial frequencies and can be easily decomposed into several frequency sub bands [7].

### B. *Neural Network Structure*

Feed forward neural networks have been used for pattern association, classification and mapping rather than feedback or feed forward and feedback neural networks [11]. Back propagation is a supervised learning technique used for training neural networks. It is most useful in feed forward networks and showed good results with RMBs [1].

LVQ (Learning Vector Quatization) is a supervised classification algorithm. It can be applied to pattern recognition, multi-class classification and data compression tasks, e.g. speech recognition, image processing or customer classification. LVQ algorithms do not approximate density functions of class samples, but directly define class boundaries based on prototypes, nearest-neighbor rule and winner-takes-all paradigm. Italian currency notes have been identified using LVQ based neural network which gave satisfactory results [8]. Applying local PCA with LVQ is another approach considered in [5][6]. In local PCA, input data space is partitioned into regions using self organizing maps first [9] and then apply PCA in these local regions. A system having wavelet transformation [12] also used this structure as the neural network.

Perceptrons are used to identify whether a particular pattern belongs to a given pattern by a threshold value. This threshold is called as verification threshold. However in practical pattern verifications, there arises a problem with threshold values. The class discrimination takes place in feed forward networks by means of separation surfaces in the pattern space that are drawn by the learning algorithm under the purely requirement of discriminating the given examples. These partitions separate input data properly but in some cases these surfaces are not necessarily closed [10].

Autoassociators complement the open separation surfaces problem by reproducing the input at the output. Hence the verification is based on the input-output Euclidean distance [10]. The basic idea is that only the patterns of the class used for training the autoassociator are likely to be reproduced with enough approximation at the output and all other patterns, including false ones, are not likely to be reproduced with the desired approximation.

## III. Design

The proposed system comprises of two components namely image processing component and neural network component. Fig. 1 shows the overall design steps.

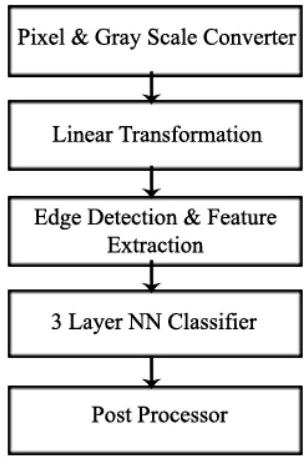


Fig. 1 Design

### A. *Image Processing Component*

First, scanned currency notes are converted into gray scale from file format to pixel values. Converting to gray scale does not reduce the required level of information of currency notes for this instance and colour is not a concern in this research.

Then new set of values have been generated from original gray scale pixel values by having a linear combination of the former values. Transformation function used for this is of kind shown in (1). This function has two constants named as $f_A$ and $f_B$, $x$ is the gray pixel value and $f(x)$ is the resultant transformed pixel value.

$$f(x) = f_A * x + f_B \qquad (1)$$

After the transformation, Edge detection is performed to extract the image's identity as what is used to recognize by the system. Edge detection reflects sharp intensity changes in colors of the image. Then this detected edge information is extracted and arranged in a format required by the neural network.

### B. *Neural Network Component*

There are four classes that come out in the classification phase and they are 100, 500, 1000 and 2000 rupee notes. The neural network is trained with notes representing different operational conditions to each other in color brightness, noise, dust effect, etc for these four classes. Since it is supervised learning, neural network is expected to give expected results when notes with similar or slight differences are presented for classification.

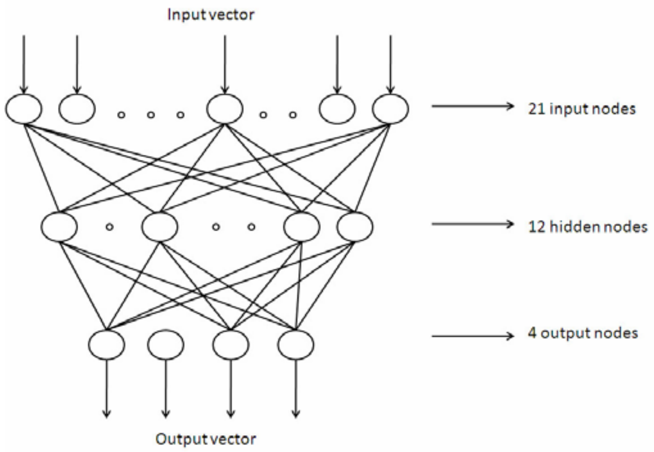


Fig. 2 Network Structure

Neural network consists of 3 layers having one layer each for input, hidden and output layers as shown in Fig. 2 representing 21, 12 and 4 nodes respectively. All input values are normalized and output is taken as either 0 or 1 (0 for no and 1 for yes). Finally the classification is validated by checking dimensions of each denomination as it is unique to each kind. This post processor identifies any misclassification happening by simply checking this feature.

## IV. Application and Results

Extraction of features is the most important step in this research due to high rate of noise effect present in Sri Lankan currency notes. Everything else will not function well if this is not handled properly. Therefore edge detection alone is not sufficient for the task. A noise removal technique has to be used without effecting the basic features of images which are important later in the process but loss of lesser features can be accepted for the betterment of recognition rates. In fact each and every feature is not going to effect the classification when the patterns of Sri Lankan notes are analyzed. Considering all of them makes them noisy and confusing.

### A. Analysis of Shapes

Denominations that are considered for this research and all the denominations of Sri Lankan currency have different identifiable shapes on them. In fact, the idea of making these identifiable shapes is to make human identification easy and fast. Whenever a person sees a currency note, his eyes tend to find those shapes, color and the printed value altogether. There are very complex images that include ancient objects, symbols and animals. For example, the elephant in traditional fancy dress at Daladha Perahara printed on 1000 rupee note can be considered.

A simple analysis was carried out having educated people of undergraduates, graduates and research students to get an idea of how Sri Lankan citizens identify notes and we show the results obtained. According to us, most of the people recognize Sri Lankan currency notes by color and overall image composition which is taken into consideration in this research.

TABLE I
HUMAN IDENTIFICATION PATTERN

| Attention | Preference | % |
|---|---|---|
| Only look at a part of the note | 5 | 9 |
| Look for hidden patterns | 2 | 3 |
| Look at the printed value | 8 | 14 |
| Look at the overall image composition | 13 | 23 |
| Identify by color | 17 | 30 |
| Look at the size of the currency note | 6 | 10 |
| Feel the currency note | 5 | 9 |
| Look for a specific image | 1 | 2 |

### B. Edge Detection and Linear Transformation

Edge detection and linear transformation both interact with each other very closely in this system and the transformation is applied on gray converted currency images before they are forwarded for edge detection.


Fig. 3 Comparison of edge detection with and without linear transformation

First, the edge detection is configured to perform to the level it is expected to output edges and then linear transformation is adjusted to get more favourable edge detection which will separate the classification classes from each other apart. In Fig. 3, (a) is the edge detection with linear transformation and (b) is without linear transformation. It is important to notice that the Fig. 3 is a sample of a 500 rupee note which is very good in condition. Marked areas of Fig. 3 are to illustrate the reappearance happening because of the linear transformation in addition to the prominent shape outlining. By comparing (a) and (b) in Fig. 3 it can be said that for a newly printed note, edge detection together with linear transformation gives better appearance. In fact, the use of linear transformation helps to keep notes look similar in varying conditions.

After evaluating both these techniques together over different image conditions, edge detection is slightly adjusted to compensate for the reappearance happening in addition to noise removal of linear transformation. In Fig. 4 it is shown how the linear transformation brings new and old notes into a common representation without noise for better feature extraction. Fig. 4 (a) shows an old distorted image condition and (b) shows a good image condition in gray and transformed image formats.

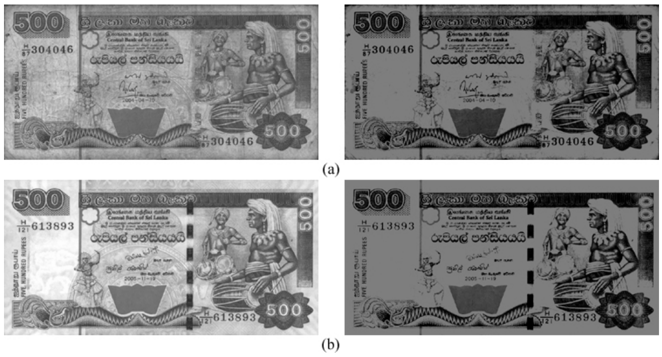

Fig. 4 Linear Transformation in varying image conditions

## V. Implementation

It is important to discuss the need of compressing the original gray scale scope of pixel values and requirement there for Sri Lankan currency notes with respect to linear transformation and edge detection.

### A. Edge Detection

There are several techniques available for edge detection and "Canny" algorithm is used for several reasons as bellow.

1) Low error rate.
2) Edge points are well localized.
3) Only one response to a single edge

A normal home used scanner of "Plustek Optic Pro ST28" brand is used for scanning the currency notes. By experiment and to fulfill the image requirements it has been decided that the lower and upper thresholds of canny are selected as 50 and 230 respectively. Non-maxima suppression threshold is set to 200; Gaussian kernel which is used to smooth edges is assigned the value of 15 and is used with a standard deviation of 1.2.

### B. Linear Transformation

The main feature of this is to avoid noise appearing on images to some extent and that prevents minor features appearing which makes the images noisy otherwise. An argument can be made that not taking these minor features into consideration is neglecting the purpose of printing them on currency notes which is to make forging difficult. But the research is considering only on false rejection and not about identifying forged notes. In fact if all the possible edges are tried then the four classes of currency note features may overlap with each other because of excessive features being detected. Since linear transformation is used to remove noise interference, edge detection is performed after applying transformation on gray converted image pixels. The transformation is as shown in (1). $f_A$ and $f_B$ are constants and they are assigned values of 1.75 and -130 respectively, $x$ is the gray converted pixel value and $f(x)$ is the resultant transformed image. The constant values were decided according to the Sri Lankan currency note characteristics after conducting several neural network training iterations. The algorithm used for this transformation is as follows,

1) Take a pixel value and multiply it by the constant $f_A$.
2) If multiplication caused the value of $x$ to exceed 255 then assign 255 to $x$.
3) Subtract $f_B$ from $x$.
4) If the value of $x$ is now less than 0 then assign 0 to $x$.
5) Repeat the procedure for all the pixels in the image.

When above determined linear transformation is applied on image pixel values, the original range of 0 to 255 is modified into the range of 0 to 125 as shown in Fig. 4. This happens due to the constraint imposed by the step number 2 and 3 of the algorithm.

$$0 \le i - 130$$
$$130 \le i, i = x * f_A, f_A = 1.75$$
$$130/1.75 \le x$$
$$74.3 \le x, x_{\min} = 74.3$$
$$255 \ge i$$
$$255 \ge x * f_A, f_A = 1.75$$
$$255/1.75 \ge x$$
$$145.7 \ge x, x_{\max} = 145.7$$

By calculation it can be shown as above that the range of gray image pixels which are affected by this configured linear transformation is from 74.3 to 145.7. This pixel range of 74.3 to 145.7 is mapped in the gray scale from 0 to 125 and other pixels which are below 74.3 and above 145.7 are assigned 0 and 125 respectively.

An argument can be made that this multiplication is unnecessary and only addition will be enough to remove the noise effect in the upper gray pixel values but the fact to consider is that these images are not in good shape all the time. Therefore reappearance for some extent is also needed and this multiplication provides that capability well for this context. But a higher multiplication factor would give rise to slight intensity changes which is not expected to be reappeared in such complex patterns. Therefore, compression of gray scale range is used to avoid a higher multiplication factor.

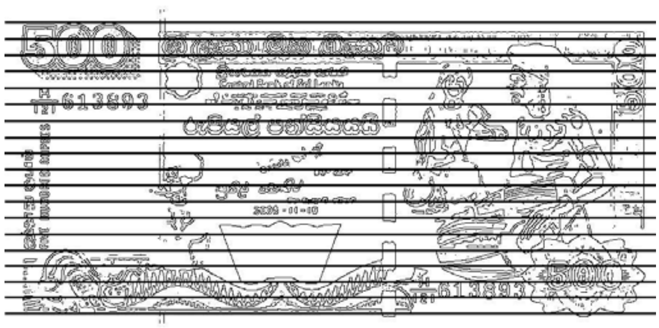

Fig. 5 Feature extraction

### C. Feature Extraction

Extraction of features is done by dividing an edge detected image into 20 rows along the height direction as in Fig. 5 and taking the sum of edge pixels that fall in that region. Using horizontal partitions give additional advantage over vertical partitions when upside down orientation of notes is considered. These 20 row values are normalized and together with a bias of value 1are arranged in a 21 dimensional vector to be presented to the neural network input.

### *D. Classification*

Each currency note is divided into 20 horizontal partitions along height direction and this number is determined after training and testing the neural network for several numbers of partitions. Size of these partitions is not fixed and they change for each kind of currency note as whole image sizes differ from each denomination. Input to the network is the 21 dimensional vector formatted in feature extraction phase.

$$P(t) = \frac{1}{1+e^{-t}} \tag{2}$$

A sigmoid function has been used for output and hidden layers to make the learning comfortable as shown in (2). This sigmoid function is used in wherever a weighted sum is calculated in output and hidden layers. Once errors are calculated, they are propagated backwards and weights are updated accordingly.

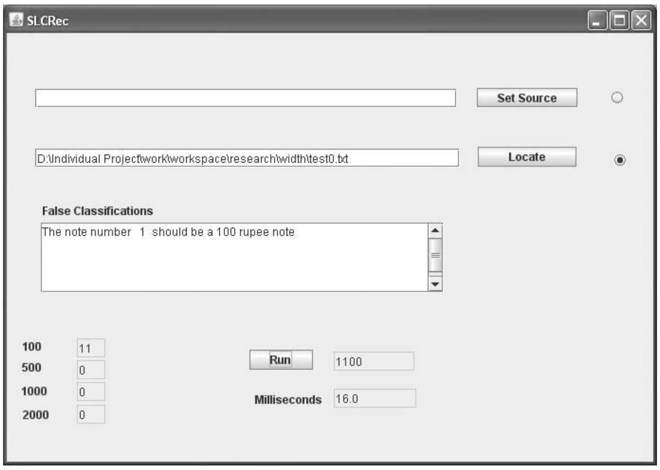


Fig. 6 Graphical interface of the implementation

In addition to weight matrices, some random thresholds have been initialized in output and hidden layers where they are updated with weight matrix. The memory of the neural network can be considered as the combination of weight matrix and thresholds. These threshold and matrix values are initialized at random in the range of -0.5 to +0.5 in training. A momentum is added to the training phase to have the neural network behave as if it is in unsaturated area and generalized delta rule has been used in back propagation learning.

Learning rate is taken as 0.7 and momentum as 0.5 in the learning phase of *SLCRec* and learning seemed to be converging well in these circumstances. Network is trained until MSE is around 3%. Classification is taken as the highest number among four classes which is also greater than 0.5. If no class is greater than 0.5, it is taken as a failure of classification. Sizes of the currency notes are taken into consideration for validating the classifications in the post processing step. For example, it can be verified whether a classified note is actually of that type by checking its size against recognized class. Graphical interface of the implementation of *SLCRec* is shown in Fig. 6 and the system is implemented using Java programming language.

## VI. Results

What is needed to analyze here mostly is the possibility of false rejection and false classification. Minimizing these as much as possible would give the system more reliability and confidence in users.

TABLE II
CLASSIFICATION RESULTS

| | 100 rupee note | 500 rupee note | 1000 rupee note | 2000 rupee note |
|---|---|---|---|---|
| Training Set | 100% | 100% | 100% | 100% |
| Testing Set | 100% | 100% | 100% | 100% |
| False Classification | 0 | 0 | 0 | 0 |


Fig. 7 Training set feature distribution using norm values

Results shown in II illustrate the success of the system implemented on Sri Lankan currency notes and it is for face side in both directions (normal and upside down). For training, 30 (30x2 in both directions) sample images from each denomination has been taken representing various operational conditions and 40 (40x2 in both directions) for testing. The image quality variation of the training set is as shown in Fig. 7. The norm values of 20 dimensional feature set of each denomination are taken as the characteristic feature of the distribution and image sample variance is maintained in testing set as well. In fact the variation shown within each denomination is lower than actual as norm is calculated after applying linear transformation.

The system showed similar performances for reverse sides as well when it is trained even though it is not expected to perform in those conditions as the research objective is to focus on face side of notes. But when the network is trained at once for both face and reverse sides including 4 orientation sides for a denomination, network tends to misclassify very few notes. In fact the configuration of the system made to work with all denominations does not provide excellent edge detection for reverse side of 100 rupee notes at times. This is due to low printing quality of 100 rupee notes.

On average the performance of the implemented system is around 200 milliseconds per note. The tested computer is of Intel Core 2 Duo @2.66 GHz and 1 GB of ram. False classification for all denominations is 0 and hence this implementation can be considered as reliable in the consumers' perspective by analysing the results obtained. These positive results will probably lead Sri Lanka to develop its own currency recognition system in near future.

### *A. Analysis*

The linear transformation introduced in this research differs from others [1] by the range it defines. Here the range is compressed and hence the system was able to use a lesser multiplication constant in (1) such as 1.75 which suited well for complex patterns in Sri Lankan currency notes.

The other important factor to mention in this research is that after the linear transformation, actual pixel range does not matter as only edges are expected to be detected and removal of unwanted patterns and noise is the only consideration. When currency notes are in use for a long period of time, their gray converted images become darker than newly printed ones and getting the lower boundary of the multiplication range higher seems to be extremely advantageous. Currency notes seemed to have good printing quality except for 100 rupee notes and reverse side of 100 rupee notes does not produce fine edge detection for the configuration adapted for all notes.

$$Indicator = \mathrm{Re}\,d + Blue - 2 * Green \quad (3)$$

Sri Lankan currency notes are printed in different color codes for each denomination. But the difficulty of getting an RGB indicator is due to color distortion happening while in circulation. When notes get old some color classes tend to overlap with each other. For example, red component of 2000 rupee note is clearly separable from 100 rupee note and when notes get old these two overlap with each other making this feature unusable. But there exists a way to get an indicator from calculating values according to a formula as shown in (3). This feature is not used in this proposed system as it is not intended to have a color code for identification but this will be useful in other researches regarding currency notes of Sri Lanka.

## VII. Conclusion and Future Work

The implemented system comprising of compressed gray scale range and the three layers BPNN produced good results for Sri Lankan currency notes. Even though the system objective is not to identify forged notes, it can be achieved by a counting plug-in. These counting machines are used in banks to count a given set of notes and they can identify forged notes by checking notes' standard density. But these can only count the number but not the value.

Generalization of the network does not perform so well as one sided trained network. Hence as a future enhancement, deciding the relevant side of the note has to be done and then loading relevant neural network will give fine results for all sides. Genetic Algorithms and Masks may be used to improve efficiency more. The possibility of using color codes is discussed in addition and improving on that is another enhancement to this system or any other system related to currency recognition of Sri Lanka.

Still there is no way to deposit money to a bank without an intermediate person at a bank in Sri Lanka and even though there seems to be machines to accept money, they all rely on future verification with the customer. The achievements of this research are more than enough in this area to consider about this fact and to make the system work in the community.

## References

[1] E. Zhang, B. Jiang, J. Duan and Z. Bian, "Research on paper currency recognition by neural networks", in Proc. *2nd International Conf. Machine Learning and Cybernetics*, Xi'an, 2003, pp 2193-2196.

[2] F. Takeda and S. Omatu, "A neuro-paper currency recognition method using optimized masks by genetic algorithm". In Proc. *IEEE International Conference on Systems, Man and Cybernetics*, 1995, pp 4367-4371.

[3] F. Takeda and S. Omatu. *Image Processing and Pattern Recognition*, Academic Press, 1998, pp 133-160.

[4] F. Takeda and T. Nishikage, "Multiple kinds of paper currency recognition using neural network and application for euro currency". In Proc. *IEEE International Joint Conference on Neural Networks*, 2000, pp 143-147.

[5] A. Ahmadi, S. Omatu, and T. Kosaka, "A study on evaluating and improving the reliability of bank note neuro-classifiers". In Proc. *SICE Annual Conference*, Japan, 2003, pp 2550-2554.

[6] A. Ahmadi, S. Omatu, and T. Kosaka. "Improvement of the reliability of bank note classifier machines", 2004, pp 1313-1316.

[7] E. Choia, J. Lee, and J. Yooni. "Feature extraction for banknote classification using wavelet transform", In Proc. *18th International Conference on Pattern Recognition*, 2006, pp 934-937.

[8] S. Omatu, T.Fujinaka, T. Kosaka, H. Yanagimoto, and M. Yoshioka. "Italian lira classification by lvq". In Proc. *International Joint Conference on Neural Networks, IJCNN*, 2001, pp 2947-2951.

[9] T. Kohonen. *Self Organizing maps*. Springer, Berlin, 1995.

[10] M. Gori, A. Frosini and P. Priami." A neural network-based model for paper currency recognition and verification", pages 1482-1490, 1996.

[11] B Yegnanarayan. *Artificial Neural Networks*. New Delhi110 001, Prentice-Hall of India, 2005.

[12] J. Smokelin. "Wavelet feature extraction for image pattern recognition". In Proc. *SPIE*, volume 2751, 1996, pp 110-121.