Analysis of Fluorescent Paper Pulps for Detecting Counterfeit Indian Paper Money

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Abstract. The paper itself forms an important security feature for many security paper documents. This work attempts to develop a machine assisted tool for authenticating the paper of a security document. Image processing and pattern recognition principles form the basis of this automatic method. Paper pulps play a crucial role in characterizing a paper material. These pulps are visible in the UV scanned image of the document. Therefore, the pulps are first identified in the UV scanned image. This identification is done by borrowing ideas from rice grain detection method. Once the pulps are detected, shape and color features are extracted from them. Paper pulps coming from fake documents are significantly different from those of genuine documents in their shapes and colors. Using the shape and color features, a multilayer back propagation neural network is used to discriminate paper pulps as genuine or fake. The proposed method is tested with Indian banknote samples. Experiment shows that consideration of paper pulps is one of the crucial tests for authenticating paper money.

Keywords: Computational Forensics, Security document authentication, Banknote,Paper pulp, Image Processing, Pattern Recognition.

1 Introduction

With the advancement of scanning, copying and printing technologies, counterfeiting of security documents (i.e. deeds, postal stamp, ticket, bank check and draft etc.) has become a serious threat to our society. Counterfeiting of bank notes is playing havoc on economy of many countries [4, 2, 3]. As a result, authentication of banknotes has been an area of utmost concern [5, 6]. Though significant study has been conducted in the field of forensic signature or handwriting authentication, little research has been done for authentication of security paper documents [22]. This work is motivated by this research need. Bank notes consist of several security features in order to prevent their counterfeiting. Printing technique, artwork, security thread, watermark, etc. are significant security marks that are embedded in banknotes [7, 8]. The manual authentication of these security features as so far have been done by the forensic question

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document examiners is a time consuming process and an unattractive solution especially when verification of a large number of documents comes into question. An automatic authentication process could provide a viable solution to this problem. A couple of patents on developing automatic method for authentication of currency notes is reported in the literature [9–11] but the technical details of these systems are not readily available because of the commercial reason. This has severely limited us to judge the true potential of the commercial systems. In this area, the reproducible research efforts are still rare in number.

The authors of the paper in [1] proposed a semi-automatic approach for characterizing and distinguishing original and fake Euro notes. Their method is based on the analysis of several areas of a banknote using a Fourier transformed infrared spectrometer with a microscope with an attenuated total reflectance (ATR) objective. They considered four different regions of a note and observed that fake notes were easily identifiable from the analysis of the spectra corresponding to the four regions. However, the authors did not propose any automated scheme for decision-making. Later on, the authors in [12] described another system for authenticating Bangladeshi Bank Notes. They assumed that original currencies under test have the bank name printed in micro letter text. They scanned this part (the region where the bank name should be) using a grid scanner and the textual images are fed in an optical character recognition engine that matches characters with prototypes. Since the fake currencies were assumed not to have the text they show very low matching score. The algorithm is heavily dependent on one feature which makes the system very sensitive. The system would fail miserably if the counterfeiters happen to develop means of duplicating the feature in question. Recently, Roy et. al.[13] presented an authentication method based on detection of printing technique. They tested their method for Indian bank notes where the name of the bank and denomination of the note are printed using intaglio technique. Any deviation from this printing technique was reported as a counterfeiting effort. Later on, they extended their system to consider other security features like artwork, micro print text, security thread, etc. and presented a more robust system for authentication of banknotes [14].

The previous efforts attempted to exploit several security features but the paper material itself was hardly consulted for authenticating the document in question. For any security paper documents including the banknotes, the paper itself plays a crucial role in proving some kind of security to the document [15]. The paper based security is normally achieved by embedding certain special ingredients to the paper material during its manufacturing process. A review on security papers can be found in [16]. Colour optical pulp (or fibre) embedded in the paper is an example. Security fibres may be metallic or photo-chromic. The optical pulp defines a certain kind of characteristics of the paper. They are luminescent under ultraviolet (UV) ray and therefore, visible when the paper is scanned under UV or illuminated light ray. The forensic experts often check the intended paper quality by physical contacts and sometimes, though manually, they check the brightness, illumination and density of the paper pulp in order to authentic the paper of the document in question. This paper attempts to make this process automatic. The preliminary version of this paper was presented in an unreferenced workshop [17]. Here we present an extended and elaborate version of the research.

The salient contribution of this work is to capture the pulp-based paper security feature in a computational way and then associate these features with the notion of genuine and fake documents. The problem has been viewed from the pattern recognition and artificial intelligence principles. Security aspects are represented as feature vectors and the concept of genuine and fake is defined in the feature space. For extracting features, ideas from rice grain detection [18, 19] in images are borrowed as it closely matches with the present problem of detecting fluorescent paper pulps in images. The features suitable for paper pulps are identified in this work. Moreover, as elimination of foreign body is more difficult in UV scanned images than in rice grain images taken by CCD camera, an improved elimination method has been designed for paper pulp detection. Next, the features are extracted and analysed. Classification is done using neural network. Experiment considers Indian banknotes that make use of pulp based paper as a major security aspect. Involvement of real forensic samples is a significant aspect of this study. The experiment shows the importance of paper pulp in detecting fraudulent documents and attests the proposed approach for authenticating banknotes.

2 Proposed Method

The paper used for printing currency notes is a high quality paper made by 100% cotton. Cotton has given whiteness of paper and folding capability. This paper also gives specific identity by its surface finish and crackling sound. During manufacturing process extra features like watermark, security thread and optical fibre (i.e. pulp) are embedded for additional security aspects. The optical fibres or pulps are of specific color and length. For example, in Indian 500 rupee currency note, these fibres are photo-chromic in nature. It spreads randomly on the notes which are illuminated under UV light source. When a banknote is scanned under UV light, the fluorescent paper pulps are visible in the scanned image. Fig. 1(a) shows a banknote and Fig. 1(b) shows the UV scanned image of the banknote. One may see the fluorescent paper pulps visible in the image in Fig. 1(b). The bright spots in the scanned image correspond to the paper pulps present in the note. These pulps play crucial role in authenticating the paper. In a counterfeit note, if the paper is very different from the genuine one, these pulps may not be seen at all. In a high quality counterfeiting, these pulps came as very bright spots and their shapes show significant difference with respect to the pulp marks of the genuine. Therefore, the illumination and shape of these paper pulps are important in characterizing a note paper as genuine or fake.

Our overall approach is divided into a number of stages: (i) detect pulps in a UV scanned banknote, (ii) extract features from the detected pulps, (iii) train a NN classifier based training samples that include both genuine and fake notes.

(a)

(b)

Fig. 1. (a) A 500 rupee Indian banknote (b) UV scanned image of the note

Once the classifier is trained, we use this for classification which is configured as 2-class (genuine vs. fake) problem.

2.1 Detection of Paper Pulps

Detection of paper pulps has two stages: identification and verification. During identification phase, detected pulps may be mixed with several foreign (non-pulp) elements mostly coming from background artworks. So removal of foreign particles is done during verification stage.

Identification of Paper Pulps: Paper pulps are identified in a UV scanned image by following a 7-step method as given in Algorithm-1. The UV scanned image is represented in RGB color space. As the pulps are mostly blue in color, we convert the RGB image to CMY (Step-2 of the algorithm) and consider the cyan part of the resultant image at Step-3. Next, median filtering is applied at Step-4 to eliminate small unwanted particles. The centroids obtained at Step-7 indicate individual position of pulps in the image. At this stage, all detected points do not correspond to paper pulps. Many other particles which are same as pulp are identified at this stage. These foreign bodies come from background artwork of the banknote. So the next step is to eliminate these foreign elements and identify only the pulps in the image. This elimination is done by the following process.

Elimination of Non-pulp Elements: The method described in Algorithm-2 eliminates the non-pulp particles from the detected set of pulps. In Algorithm-1, the centroids detected at Step-7 correspond to paper pulps. Here, around each centroid an m-by-m pixel-window is considered on the initial RGB image (Step-1 of

Algorithm 1. PULP IDENTIFICATION

Begin
Step 1: Acquire the currency note image (RGB) by UV light
Step 2: Image Complement (RGB − > CMY)
Step 3: Extract cyan image
Step 4: Apply median filter
Step 5: Convert binary image by OTSU thresholding
Step 6: Connected component labelling of background pixels
Step 7: Compute centroid of each component
End

Algorithm-2). The value of m is sufficiently large to completely contain a pulp mark within the window. The gray level co-occurrence matrix (GLCM) [20] is computed for each pixel window at Step-2. For this purpose, we transform the gray image to k ($k < 256$) level image (I). Let s≡(x,y) be the position of a pixel in I and t≡(△x,△y) be a translation vector. Then the co-occurrence matrix M_t is calculated as,

$$M_t = card(s, s + t) \in R^2 \mid I[s] = i, I[s + t] = j \qquad (1)$$

Where co-occurrence matrix M_t is a (k x k) matrix whose (i,j)-th element indicates the number of pixel pairs separated by the translation vector t (here, t = 1) that have the pair of gray levels (i, j). Texture features are extracted at Step-3. An artificial neural network (ANN) is used at Step-4 to discriminate pulp from non-pulp elements. A set of training samples is separately identified for the training this ANN. The features extracted at Step-3 are tagged with pulp and non-pulp identification for training the ANN. In our experiment, the values of m and k are set to 60 and 8 (i.e. the image transforms to 8 levels). These values are fitted empirically. Fig.2 shows the detection of pulp in Fig. 2(a) and then elimination of non-pulp elements to give final result in Fig. 2(b). Fig. 3(a) shows detection of an individual pulp.

Algorithm 2. ELIMINATION OF NON-PULP ELEMENTS

Begin
Step 1: Around each centroid as detected at Step 7 of Algorithm-I, $m \times m$ sub-image is cropped from the initial RGB image.
Step 2: For each such sub-image, compute Gray Level Co-occurrence Matrix (GLCM) [20] under consideration of two adjacent pixels on four directions 0 °, 45 °, 90 °,and 135 ° .
Step 3: Generate texture level four statistical features i.e. contrast, correlation, energy and homogeneity from each co-occurrence matrix.
Step 4: Configure an artificial neural Network (ANN) for discriminating pulps from non-pulp particles.
End

2.2 Feature Extraction from Pulps

Two aspects, namely, shape and color of pulps are considered for feature extraction. Regions of interest are found around the detected pulps. One such example

(a)

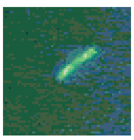
(b)

Fig. 2. Identification of pulps: (a) detected pulps after execution of Algorithm-1 (b) pulps after elimination of foreign bodies by Algorithm-2

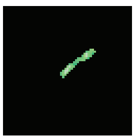
is shown in Fig. 3(b). Feature are extracted from this region of interest. Image analysis techniques used for extraction of features. In total, 10 features are extracted: 4 features coming from shape properties and the remaining 6 features are from color properties of the pulp particles. The four shape features are computed as follows:

(i) Area (f_1): This feature calculates the number of pixels inside pulp identified by a connected component (refer Step 6 of Algorithm-1).

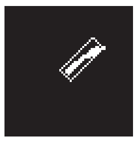
(ii) Rectangular Aspect Ratio (f_2): This feature is given by the ratio of the length and width of the rectangular bounding box of the pulp particle. Fig. 3(c) shows how the rectangular bounding box of a detected pulp is identified.



(a)



(b)



(c)

Fig. 3. Rectangular box around a pulp: (a) Pulp detection, (b) Region of interest and (c) identification of the rectangular box around the pulp

(iii) Pulp Aspect Ratio (f_3): The pulp aspect ratio is computed as the ratio of the lengths of the major and minor axes. The length (d_{max}) of the major axis is measured as the distance between the end points of the longest line that could be drawn through the pulp particle. Similarly, the length (d_{min}) of the minor axis is the distance between the end points of the longest line that could be drawn inside the pulp and is perpendicular to the major axis.

(iv) Shape Factor (f_4): This feature is defined as follows:$f_4 = \frac{d_{rms}}{\bar{d}}$; where, d_{rms} is the root means squared deviation and is defined as, $\sqrt{\frac{(d_{max}-\bar{d})^2+(\bar{d}-d_{min})^2}{2}}$. The mean diameter of the pulp is denoted by $\bar{d}$ and computed as $\frac{(d_{max}-d_{min})}{2}$.

(v) Colour Features: The brightness and illumination of paper pulps give significant clue about the paper quality. They change with the change in paper material. Therefore, features extracted from color space play crucial role in discriminating pulps coming from genuine or fake paper. We consider HSI color space for extracting color features The average Hue, Saturation and Intensity of the pulp pixels give three features f_5, f_6, and f_7. Similarly, their variances are computed and give another three features (f_8, f_9, and f_{10}).

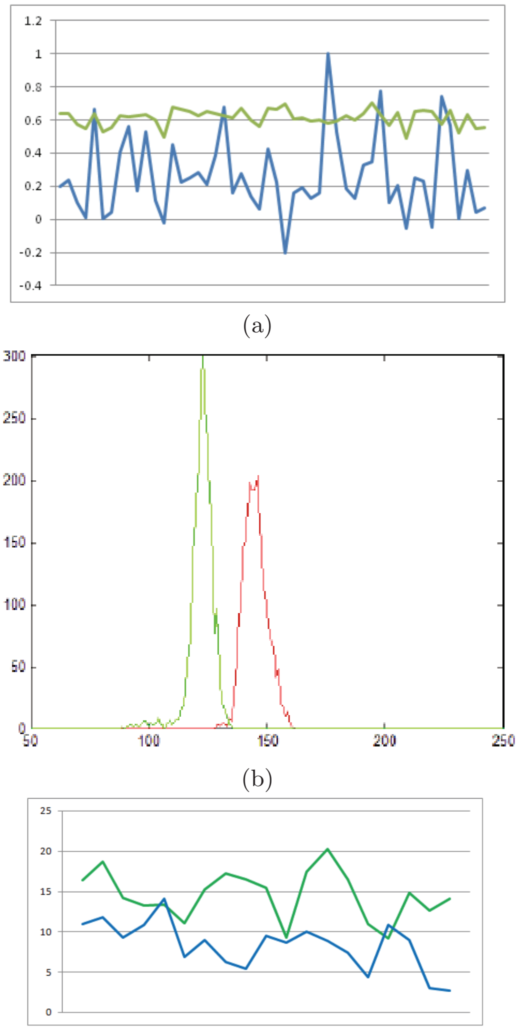
The above features are considered after consulting with the forensic experts. Many of these features they use for manual inspection of the paper in question. It is noted that these features show significant discriminatory power in differentiating genuine and fake samples. This is highlighted in Sec. 3 where experimental results are shown. Fig. 4 shows the discriminatory power of three features, the first one refers to pulp aspect ratio (f_3), the second refers to the average hue (f_5) coming from color space analysis and the third, i.e., shape factor (f_4) coming from shape analysis.

2.3 Training of the Classifier

Initially a neural classifier is configured to discriminate whether a pulp is part of genuine or fake paper. A back propagation neural network (BPNN) is used for this purpose. Multilayer perceptron is used where input layer is consisting of 10 nodes corresponding to 10 features as described in Sec. 2.2. The output layer has just 1 node as the classification problem is binary in nature. Only one hidden layer is used and the number of nodes in the hidden layer is computed as: N=($\frac{I+O}{2} + \sqrt{y}$);where N=number of nodes in hidden layer; I=number of input features; O=number of outputs; and y=number of patterns in the training set. The multilayer feed forward network model with back propagation (BP) algorithm for training is employed for classification task. A gradient descent method is used to find the optimized set of connection weights that are updated as per the following equation:

$$W_{t+1} = W_t + \alpha \left(\frac{\partial E}{\partial W} \right) \Bigg|_{W_t} + \beta \Big\{ W_t - W_{t-1} \Big\} \qquad (2)$$

where W_t is weight at the current iteration, W_{t+1} is weight in the next iteration, E is the error term which is calculated as $E=\frac{1}{2}(T-O)^2$; T is Target and



(c)

Fig. 4. Discriminatory power of the extracted features: (a) distribution of the pulp aspect ratio (f_3) for pulps from genuine and fake banknotes (blue line is for samples from fake currency); (b) distribution of average hue (f_5) of pulp pixels coming from genuine (green line) and fake (red line) banknote samples; (c) distribution of the shape factor (f_4) for pulps from genuine (green line) and fake banknotes (blue line)

O is Output. The parameters α and β are the learning rate and momentum, respectively. A four-fold cross validation is used for the classification task. The efficiency of the BPNN is evaluated using 3 performance measures i.e. Confusion Matrix, Performance Plot, and ROC plot. The graphical representation of confusion matrix, performance plot and ROC plot in each fold is investigated.

The root-mean-square-error (RMSE) is also studied both at the individual pulp and document (i.e. whole paper currency) levels.

2.4 Authentication of Banknotes

Finally, authentication of banknotes is done based on the pulp level authentication. For example, if p number pulps are detected in a UV scanned image of a banknote, each pulp undergoes checking for its authenticity. The neural network described in Sec. 2.3 is used for this purpose. If majority of the pulps show a particular type (genuine or fake), the banknote turns out of that category.

3 Experiment

3.1 Dataset

The experiment considers 200 samples of banknotes. All of these are not real samples. We got some real samples from the forensic experts who labelled genuine and fake notes. We extracted features from these labelled notes and labelled the feature vectors as genuine or fake. From these feature vectors, later, we synthetically generated other samples so that we get 100 samples for each genuine and fake classes. We assumed the distribution to be Gaussian to generate the synthetic samples. Each real sample is scanned using *VSC5000* UV scanner. The resolution of scanning was set at 200 dpi. It is noted that each genuine currency note image contains about 15 pulps (this number normally varies from 11 to 17). In fake samples, this number does not vary significantly. In 200 banknotes including both the genuine and fake samples, a total of 3124 pulps were detected. The pulps coming from genuine banknotes are labelled as genuine sample and the pulps originated from the fake banknotes are treated as fake samples.

Identification of the pulps above is done following a semi-automatic process. Sec. 2.1 describes a two-stage method for pulp identification. Though the first stage does not require any training, the second stage of this method requires training of a Neural Net. The stage one of the pulp detection algorithm is initially executed for 50 banknotes and extracted pulps are manually tagged as pulp or foreign to train the net. Next, this trained net is used to detect pulps in the remaining 150 notes. It is observed that the net gives about 90% accuracy in discriminating detected pulps as true pulp or foreign element. The errors are then manually corrected to make the dataset suitable for the subsequent experiments.

From each pulp, a 10-dimensional feature vector is extracted. Among 3124 feature vectors, 1602 are labelled as genuine and 1522 are tagged as fake. Tagging of each pulp is quite easy as all the pulps extracted from a banknote take the label of that note. The whole dataset is divided into 4 subsets for conducting a four-fold cross validation test. The numbers of samples in training, validation and test sets are in 2:1:1 ratio.

Table 1. Confidence in Pulp Level

It. No.	Confidence Interval		Classification of pulps					
	Genuine	Fake	Genuine Samples			Fake Samples		
			G	F	C	F	G	C
1	(0.975,1.025)	(-0.0150,0.0150)	47	02	01	45	03	02
2	(0.970,1.029)	(-0.0128,0.0128)	49	01	00	46	01	03
3	(0.969,1.030)	(-0.0182,0.0182)	44	03	03	47	03	00
4	(0.970,1.029)	(-0.0250,0.0250)	48	00	02	43	02	05
Avg.(%)			94%	3%	3%	90.5%	4.5%	5%

It.: Iteration, G: Genuine, F: Fake, C: Confusion, Accu.: Accuracy

Table 2. Pulp Level Authentication

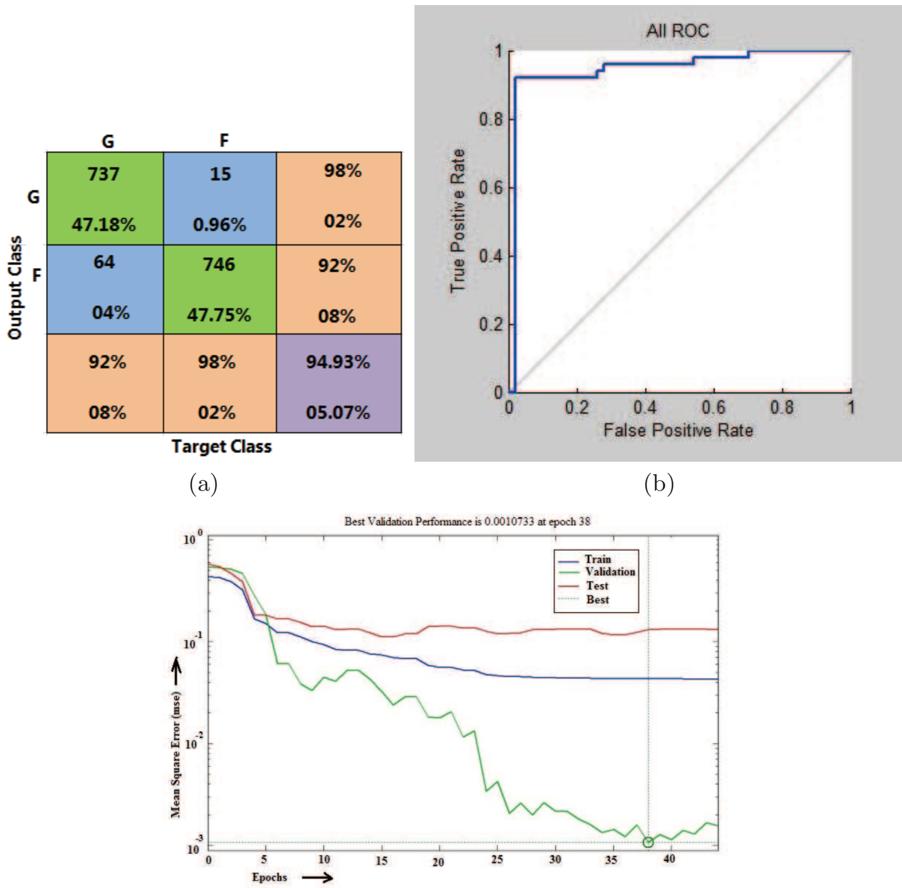
Fold	#Epoch (Best validation at epoch no.)	MSE (Min)	Gradient	Classification accuracy	
				Training	Test
Fold 1	44 (38)	0.00107300	0.00291	94.93%	90.00%
Fold 2	27 (21)	0.00784510	0.00924	92.88%	88.67%
Fold 3	27 (21)	0.07414200	0.03070	90.91%	88.11%
Fold 4	34 (28)	0.06693800	0.04040	89.94%	86.88%
Avg.	33	0.03749952	0.02081	92.16%	88.41%

3.2 Pulp Level Authentication

As mentioned earlier that a neural network is used for discriminating each pulp as genuine or fake. The parameters of the back-propagation neural network are as follows: maximum number of epochs: 1000, minimum MSE value: 0.001, learning rate (α): 0.9, momentum (β): 0.1. Two early stopping conditions were used: (a) total mean squared error (MSE)$\leq$ 0.001 (b) training stopped after 1000 epochs.

At first, recognition of individual pulps is evaluated without mixing genuine and fake pulps together. In evaluating this, we find out two confidence intervals, one for the genuine pulps and the other for the fake pulps. These two confidence intervals are calculated as $1 \pm [\sigma.Z_{\frac{\alpha}{2}}]$ and $0 \pm [\sigma.Z_{\frac{\alpha}{2}}]$, respectively where σ is the standard deviation of pulp recognition accuracy (say, r), i.e. $\sigma = \sqrt{(\frac{r.(1-r)}{n})}$, where n is the total number of pulps; $\frac{\alpha}{2}$ represents the area in each of the two tails of the standard normal distribution curve and $Z_{\frac{\alpha}{2}}$ is the two-tailed normal score for the probability of error α. Following these confidence intervals, Table-1 shows the result for recognition of pulp types at 94% confidence level.

Next all the pulps are mixed together and recognition of their types using the neural net is evaluated. Table-2 reports this result. It is noted that about 88% pulps are accurately classified as genuine or fake by the neural net and this accuracy is achieved at quite low MSE, i.e. 0.037. Fig. 5 graphically shows the behaviour of the neural net. The results are plotted for fold-1. However, similar characteristic curves were observed for other folds. Fig. 5(a) shows the confusion matrix. The ROC plot is shown in Fig. 5(b). As the ROC plot hugs more the left and top edges, it guarantees better accuracy. Fig. 5(c) shows the



(a) (b)

(c)

Fig. 5. Behaviour of the neural net in classifying pulps: (a) confusion matrix, (b) ROC plot and (c) performance plot

performance plotted with mean square error (MSE) value against each epoch. The performance plot shows that with the increase of the number of epoch, the MSE value during training gradually decreases and the best validation is achieved at epoch number 38.

3.3 Authentication of Banknotes Using Pulp

Pulp level authentication result is used to authenticate a banknote as described in Sec. 2.4. Let p be the number of pulps detected in the UV scanned image of bank-note after execution of Algorithm-2 (Sec. 2). Each of these p pulps is authenticated using the neural network as reported in Sec. 3.2. The individual authentication scores are then consulted to determine the nature of the banknote.

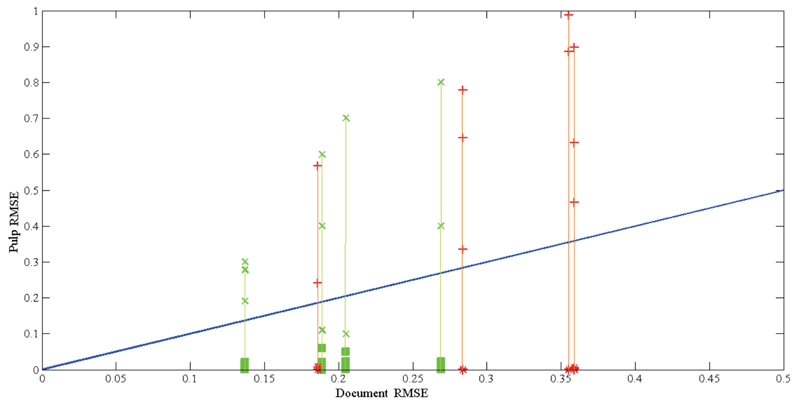


Fig. 6. Banknote classification using paper pulps

In Sec. 3.2, we have checked that the classifier can authenticate the paper pulps with about 88% accuracy. Keeping this accuracy in mind, we decided that at least 75% of the pulps in a banknote should be of similar type (genuine or fake) to label the banknote with that type. If it happens that 75% paper pulps do not show agreement in their class label, the system rejects that banknote and calls for manual intervention. For example, if a banknote normally shows 16 paper pulps, at least 12 pulps should have the same class (genuine or fake) for the system to take decision about the category of the banknote.

The above method was tested for authentication of 200 banknotes divided into 4 groups for conducting a 4-fold cross-validation task. The banknotes of the first two folds participated in training of the neural net. Actually, the pulps inside them are used to train the classifier. The third fold is used for validation purpose. The banknotes in the fourth set are authenticated using the trained classifier. It is observed that out of 200 banknotes 199 samples were correctly classified based on their paper pulp. In one case (which is actually a genuine sample), the system fails to decide as some of its paper pulps are degraded because of the degradation of the paper of the banknote. This banknote is an old one and had been folded at many places. For all other cases, 75% or more paper pulps are rightly authenticated for their class and hence, the system could take accurate decision.

Fig. 6 plots errors in recognizing pulp types as well as document types for eight representative banknotes (genuine samples are marked with green color and red color is used to mark fake samples). The 45° line is shown using the blue color. It is noted that for each banknote there are some pulps for which types are not recognized properly. Misclassified pulps are marked with '×' for genuine and '+' for fake samples. For these pulps RMSE value is higher. However, as the majority of the pulps in a banknote are classified properly, the overall document level (i.e. at banknote level) RMSE value is quite low. Therefore, banknote note types are correctly identified.

4 Conclusion

This paper reports an experiment in the context of machine aided authentication of security paper documents. The role of paper pulps is investigated in order to authenticate a paper in question. To the best of our knowledge, this is one of pioneering efforts for involving paper pulp for developing automatic authentication of security paper documents. Experiments with banknotes strongly attest the viability of the proposed method. As availability of real forensic data in large scale is a hurdle in every country, a small set of real forensic samples is used to develop and verify the system. The future of this research would consider a separate dataset to test the generality of the approach. Though the present study shows the role of paper pulps for banknotes, we advocate that the proposed approach can be used as a part of the whole system for authenticating paper documents. This is because the full authentication should use other security features too. For example, for authenticating banknotes other salient security features like watermark, security thread, background artwork, printing process, etc. are to be validated [14], [21].

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