Banknote Authentication

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Abstract. Security aspects of banknotes have to be reconsidered constantly and security features have to be improved to take effective measures against counterfeiters. In this paper, we introduce a novel authentication concept for security prints. We use a specialized form of the redundant Fast Wavelet Transform to gain and analyze the spectral components of banknote representations. By evaluating the high-frequency coefficients, we calculate appropriate features that contain characteristics of the selected patterns and allow for class discrimination. We found that use of statistical features is appropriate when analyzing banknotes. The calculated features were fed into a classifier that successfully determined the authenticity of supplied banknotes.

Keywords: banknotes, authentication, Wavelet Transform, Intaglio

1 Introduction

To enable smooth cash transactions, one has to be protected against forged banknotes. Therefore, protection against forgery is and remains an important concern of the money economy. By using advanced and constantly improving techniques, counterfeiters are more and more able to produce copies that resemble genuine banknotes to a very high degree. Hence, security aspects of banknotes have to be reconsidered constantly and features have to be improved.

One of the oldest security features, which is contained by nearly every denomination, is the raised surface. Special printing techniques add a unique structure to banknotes. By using the Intaglio technique, several tons per square cm press a feelable relief into the paper, which is also accompanied by high contrasts and, to some extent, with very fine structures [1]. There is no other print method that can reproduce such sharpness [2]. Being unique in its printing process, it constitutes an authenticity feature for banknotes.

By use of appropriate analytical methods, one can use the Intaglio structures of circulating banknotes for authentication. One possibility is to apply a frequency transformation to the image of a banknote. This way we can split lower and higher frequencies, determine spectral components, and analyze them. A suitable transform is the Wavelet Transform (WT). It has the ability to code discontinuities very well, which are especially found at high-contrast line structures in Intaglio printings. Compared to genuine security prints, counterfeits only possess structures with lower contrast. This leads to different transformation coefficients.

When selecting the regions of interest (ROI), which contain the printing structures relevant for authentication, one has to mind the homogeneity of the textures. Heterogeneous textures can lead to deviations in feature calculation and therefore bias the results.

This paper is organized as follows. In the next section we present the authentication concept for security prints, while in Sect. 3 we describe the classification of object-specific features. In Sect. 4 we discuss the results of our research. Finally, we give an outlook on future studies in Sect. 5.

2 Authentication Concept

In this paper, we use an approach comprising four passes: Image digitization, preprocessing, feature extraction, and classification. In this section, we present information on the former three.

The authentication procedure starts with the digitization of a banknote or a part of it. Afterwards, the images are preprocessed as follows. First of all, the images are prefiltered. Then, the images are transformed by the Wavelet Transform to get their spectral components. After these preprocessing steps, we gain the object-specific features from the wavelet coefficients.

2.1 Image Digitization

For our authentication research, we digitized three specimens by KBA-Giori S.A. that differ in the applied printing technique.

1. Genuine: These specimens resemble techniques used in common banknotes.
2. High-Quality Forgery: Specimens printed with an offset printing press. The printing plates were made by using original image files.
3. Low-Quality Forgery: Specimens printed with an offset printing press. The printing plates were made by using images that were produced by digitizing genuine specimens on a drum scanner.

Exemplarily, we show the same area of the different specimen images in Fig. 1.

We used an industrial camera for digitization. Those cameras are usually used for print inspection. They produce images with 640×480 pixels. Due to the object lens and distance to the investigated object we gained grayscale pictures with a resolution of about 660 dpi.

Our ROIs have an edge length of 400×400 pixels. Generally, it holds "the bigger, the better" under the constraint that the structure of the detail remains homogenous. The reason for this is that bigger details are more robust in respect of translations or disturbances of the motive.

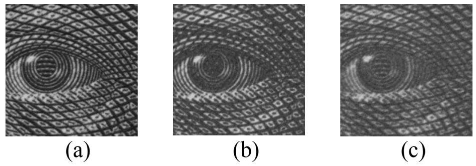

Fig. 1. Different printing techniques for banknote reproduction: (a) Genuine, (b) High-Quality Forgery and (c) Low-Quality Forgery.

To ensure that a banknote detail is appropriate for our authentication method, we have to test it for homogeneity. Inhomogeneity is the first sign for incompatibility to our approach. In our case, it means that the detail contains several different kinds of Intaglio structure. We test for homogeneity of the ROI by splitting the detail in 8×8 blocks $\mathbf{R}_i$ with

$$\mathbf{R}_i\,(n,m) = x\,(n + b \cdot i, m + b \cdot i) \tag{1}$$

and $n \in \mathbb{N}, m \in \mathbb{N}, n \leq b, m \leq b, b : 8 \mid b$, $i_{max} = \frac{N}{b} = \frac{M}{b}$. b describes the edge length of the blocks and can be varied at will. After the splitting we calculate the mean gray value of each block:

$$\overline{R}(i) = \frac{1}{b^2} \sum_{n}^{n=b} \sum_{m}^{m=b} \mathbf{R}_i\,(n,m). \tag{2}$$

Figure 2 shows two ROIs and their according mean gray values visually as an example.

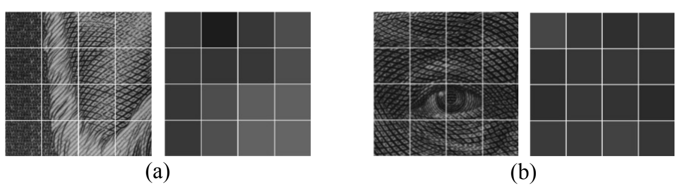

Fig. 2. ROI, devided into blocks (left hand side) and resulting mean values (right hand side): ROI (a) is inhomogeneous and contains—in contrast to specimen detail (b)—more different printing structures. Such banknote details are inadequate for our implemented algorithms. On the contrary, detail (b) can be used for authentication.

We can detect the existence of different printing structures by evaluating the two mean value matrices. For this purpose we calculate the standard deviation σ from the block means $\overline{R}$ and the value from the median filter. For error-prone input data, the latter supplys value stability [3,4].

For discrimination of the images, we use a support vector machine (SVM) with a second order polynomial kernel (cf. Fig. 3) [5].

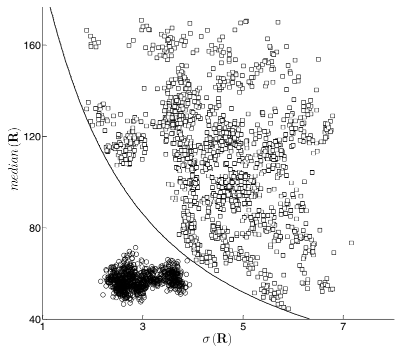

Fig. 3. Feature space, spanned over median and standard deviation of the mean value matrices: Homogeneous ROIs (circles) compose a compact cluster and are unambiguously seperable from the inhomogeneous details (squares).

2.2 Wavelet Transform

To recognize local features, it is important that the signal transformation is shift invariant. This means a signal shift by Δ samples may lead to a shift of scaling or detail coefficients, but not to a modification of their values. This property guarantees that a scale diagram does not depend on the selection of the zero point on a scale. Using the Fast Wavelet Transform (FWT), we lose the property due to its inherent subsampling. Consequently, wavelet coefficients show a high dependency on signal shifts. By subsampling when progressing to the next transformation scale, we also run the risk of forfeiting important information on edges. Hence, it is crucial to apply a signal transformation that is shift invariant. To get a shift invariant transformation, it suggests itself to do the transformation without the subsampling of a signal $s[k]$ [6,7]. This condition is met by the shift-invariant Wavelet Transform (SWT). For shifted, but otherwise identical signals, SWTs provide shifted and otherwise identical wavelet coefficients. Because we do not subsample the coefficients, we gain a redundant signal representation [7,8].

For transforming two-dimensional banknote images into spectral descriptions, we apply two one-dimensional transformations. This is valid because images are separable signals [9].

To transform a two-dimensional signal $\mathbf{x}$, we employ the one-dimensional transformation algorithm alternately on the image rows n and the image columns m. This results in a square matrix $\mathbf{x^1}$ with the dimensions $(2n \times 2m)$:

$$\mathbf{x}^1 = \begin{bmatrix} \mathbf{A}_y \\ \mathbf{D}_y \end{bmatrix} = \begin{bmatrix} \mathbf{A}^1 & \mathbf{cV}^1 \\ \mathbf{cH}^1 & \mathbf{cD}^1 \end{bmatrix}. \tag{3}$$

Now, we divide the wavelet-transformed signal into four sub-images: Scaling coefficients $\mathbf{A}$ and vertical detail coefficients $\mathbf{cV}$ belong to $\mathbf{A_y}$, and horizontal as well as diagonal detail coefficients ($\mathbf{cH}$ and $\mathbf{cD}$) are comprised in $\mathbf{D_y}$ [10].

The detail matrices **cV**, **cH**, and **cD** describe the same structure of the wavelet-transformed signal of the image. To reduce computation time for evaluation, we combine the detail coefficients to the detail matrix

$$\mathbf{cG} = (\mathbf{cV} + \mathbf{cH} + \mathbf{cD}) \cdot \alpha \tag{4}$$

with α being a scale factor. This way, all recognized structure transitions are united in one matrix. Please note that you cannot retrieve the signal from the united detail coefficients **cG**. When authenticating banknotes, though, this aspect is irrelevant.

To do a Wavelet Transform, we need a wavelet that fits to the application. We achieved good results with Daubechies wavelets with two vanishing moments (db 2 wavelet). These wavelets are well suited for spectral analysis of fine Intaglio structures because of their compact support.

Due to the scaling coefficients of the db 2 filter, low-pass filtering of continuous signals can lead to negative values [6]. In our multiresolution analysis, we make use of this effect that amplifies edges. Therefore it improves our capability to distinguish between structures of different printing techniques.

2.3 Feature Extraction

We found that calculation of statistical features of wavelet coefficients is advantageous. In Fig. 4 we show different histograms of SWT coefficients. One can easily see that the grayscale frequency distribution of genuine banknotes differ considerably from forged ones.

By calculating descriptive measures on standardized histograms $H_n(p)$ we are able to draw global conclusions on the image structure. We retrieve the following statistical features for further analysis of the wavelet coefficients: Variance σ^2 depicts the amplitude distribution of the wavelet coefficients around the histogram center. Skewness E describes the symmetry of the distribution around the center. Excess C tells the deviation relative to the Gaussian distribution [11,12]. In Fig. 5 we show the feature space containing the object classes that are to be classified.

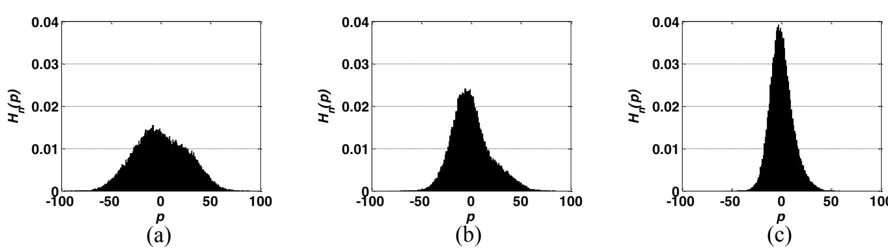

Fig. 4. Histograms of wavelet coefficients after a SWT: (a) Genuine, (b) High-Quality Forgery, and (c) Low-Quality Forgery. The grayscale frequency distribution of genuine banknotes differ considerably from forged ones.

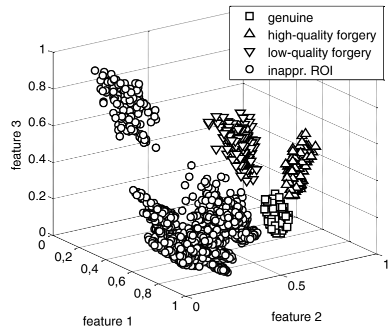

Fig. 5. Feature space, spanned over σ^2 (feature 1), E (feature 2), and C (feature 3).

3 Classification

In classification, we distinguish four different clusters: "Genuine", "High-Quality Forgery", "Low-Quality Forgery", and "Inappropriate ROI". The latter describes regions on a banknote that contain no or insufficient structures and thus being inappropriate for authentication. "Inappropriate ROI" clusters could belong to every banknote type. We selected them empirically with our expert knowledge.

Figure 5 shows that this case of classification is not a linearly separable problem. We separate these non-linearly separable data sets by the use of an SVM. For multi-class classification we employ a one-against-all classification approach [5]. Please note that an object is bijectively assigned to a class only when its class affiliation appears only once in all classification processes. When a feature vector gets assigned to several or no classes, it is discarded. According to the authentication procedure this means that it was not possible to assign the detail bijectively or it is unsuitable.

We determined the classification kernel in a way that the authentication process is applicable to other denominations. In Fig. 5 we can see that the individual object clusters show a certain direction. Our approach is to enhance the class borders in such a manner that they stretch or open into the preferred direction. Thus, we can broaden the area of validity of the classes to cover a multiplicity of denominations. For such a problem inhomogeneous polynomial kernels are a good choice. They are able to meet the required characteristics of the cluster parting planes by few support vectors [5].

4 Research Results

In the learning phase, we trained the system with features of 1489 training objects. In the subsequent testing phase, another 1551 objects were processed.

In Fig. 6 we can see that the areas of validity of the classes are enhanced according to the demands. In the testing phase, every object was assigned correctly, with two exceptions. Since those exceptions were assigned to two classes and thus were just inappropriate for the authentication process, we call it a 100% detection rate.

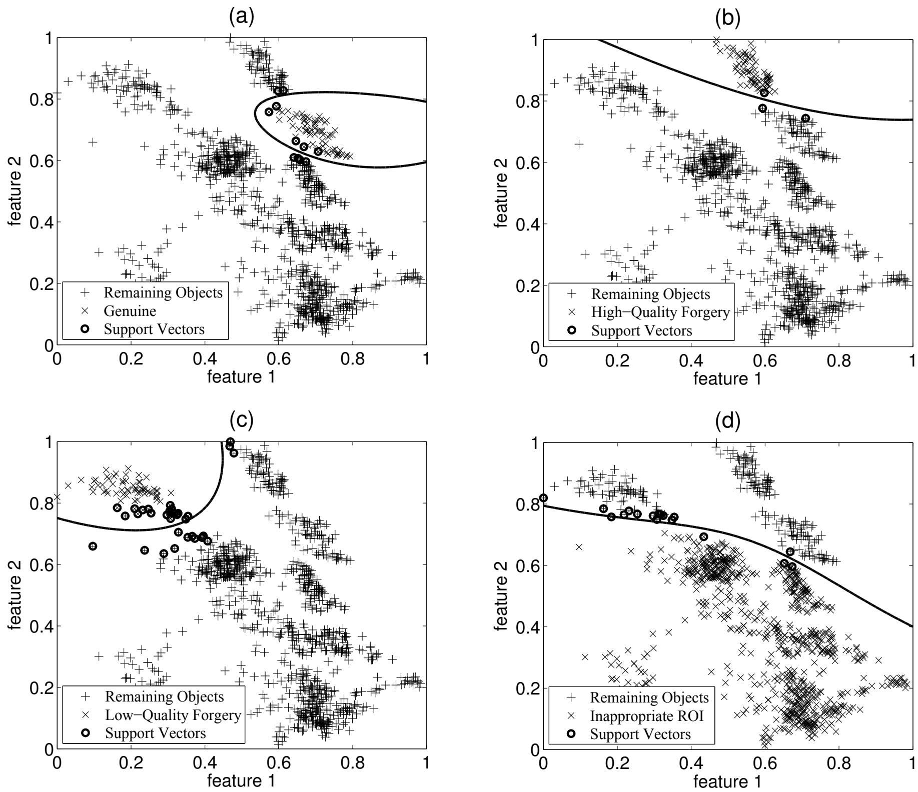

Fig. 6. Separation of the object classes by a SVM with polynomial kernel with degree q: (a) class "Genuine" with $q = 13$; (b) class "High-Quality Forgery" with $q = 10$; (c) class "Low-Quality Forgery" with $q = 8$; (d) class "Inappropriate ROI" with $q = 13$.

5 Conclusion and Outlook

In this paper, we looked into a new authentication concept for security prints. Our approach is to use a special redundant form of the Fast Wavelet Transform to get the spectral components of banknote representations, which are subsequently analyzed. We calculate features of the detail coefficients, which contain characteristics of the patterns and allow a class separation.

Our research shows that authentication of security prints by means of analysis of the spectral components of the print surface is possible when using a redundant WT and an SVM. By use of cluster border enhancement it is possible to widen the areas of validity of the classes, and therefore it is possible to extend the authentication process to unknown denominations.

When extending the process to a variety of different structures of a banknote, it is necessary to do a pre-segmentation based on expert knowledge. This is important because not every region on a banknote contains appropriate Intaglio printing structures, which are necessary for our authentication approach. Future work has to focus on automatic adaption of the redundant Wavelet Transform and classification. This is essential when you want to establish a dependable analytical authenticity method that is independent of currency or denomination.

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