

Rupiah Classification System using Segmented Fractal Texture Analysis and HSV Color Features

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Abstract

The crime of forgery of rupiah currency can be anticipated by examining the rupiah banknotes based on traits or features contained on the original paper money. Features that are not owned by the rupiah banknote counterfeit is an ultraviolet sign that are owned by the original paper money. Rupiah banknotes feature extraction consists of a combination of color and texture feature extraction. The proposed method is the HSV color histogram for color feature extraction and Segmented Fractal Texture Analysis (SFTA) for texture feature extraction. The combination of HSV and SFTA is expected to improve the performance of rupiah banknotes feature extraction. Moreover this paper will analyze feature redundancy in Two Threshold Decomposition Algorithm in SFTA Algorithm. Experimental results show the proposed method can reach 100% accuracy. Experiment results also show that redundant features can be removed without affecting the accuracy of the system so that it can reduce the computational cost.

Keywords : feature extraction, segmented fractal texture analysis, HSV, rupiah, banknotes

1. INTRODUCTION

The rupiah is the currency used for daily transaction activity by citizen of Indonesia. Rupiah has some distinctive characteristics to distinguish between one and another nominal [1]. These traits include a watermark (watermark), thread safety (security thread), intaglio, rectoverso, optically variable ink, micro (micro text), hidden picture (latent image) and invisible mold (invisible ink).

Watermark is a picture found on the rupiah banknote that only can be seen toward the light. Security thread is a thread that woven on the banknotes of the rupiah so it looks horizontal from top to bottom and can be illuminated when viewed with ultraviolet lighting. Intaglio is a printings in rupiah banknote that feels rough when touched. Pictures of mutual contents (rectoverso) is the image on the face and back of rupiah banknote and co-exist one another. Optically variable ink is the mold on the rupiah banknote that will change the color when viewed from different viewpoints. The writings of micro (microtext) is the writing on the paper money of the rupiah that is very small so that it can only be seen using a magnifying glass. Latent image is an image that can only be viewed with a certain point of view. The invisible ink is the mold on the rupiah banknotes hidden which can only be seen with the help of ultraviolet lighting.

Color is powerful descriptor that can be used to differentiate the type of images in rupiah images classification. There are some of color space representation that used in image processing. The most common color space that used in image processing is RGB (Red, Green, Blue). Also other color space that used in image processing are LUV, YcrCb, LAB and HSV (Hue, Saturation, Value) which is close to human perception about color [2].

Besides color, features that frequent used in image processing is texture feature. Previous researches about image feature extraction use texture features as descriptor to differentiate the type of images. Most of previous researches use texture feature because texture can represent the images very well. Feature texture extraction can be done based on fractal dimensions approach. One of the texture extraction based on fractal approach is Segmented Fractal Texture Analysis (SFTA) [3]. Also texture feature extraction method can be done based on spectral or statistical approach. One of the texture extraction based on spectral approach is Wavelet Transform [4]. While the most common texture extraction based on statistical approach is Gray Level Co-occurrence Matrix (GLCM) [5],[6],[7],[8].

Previous research has proven that a combination of multi features can improve the accuracy of image classification system [9][10]. These features combined can produce a unique feature which can be used to present that image. The unique feature will be able to distinguish one image with another image because of the characteristics of each image are more different that can improve the process of classification.

In this paper only the color of the rupiah and the invisible ink traits will be used for rupiah feature extraction. The color of rupiah will be extracted by color feature extraction and the invisible ink traits will be extracted by using texture feature extraction. Previous research [2] have been proved that HSV color space is more like human perception better than RGB color space thus in this paper HSV will be used as color feature extraction. A texture extraction method can be done by using fractal approach. SFTA is the texture feature extraction that based on fractal approach.

In this study, proposed system is consist of HSV color feature extraction and SFTA texture feature extraction. This system will be used for classifying rupiah based on its nominal. The combinations of color and texture can distinguish between fake and original money. It also can represent rupiah features.

Datasets that will be used in this study are the rupiah images that consist of two kind of images. First image is the image that captured using normal lighting. Color feature extraction will be performed in this image. Second image is the image that captured using ultraviolet lightning. Texture feature extraction will be performed in ultraviolet image.

2. RESEARCH METHODOLOGY

Rupiah classification system structure is shown in Figure 1. There are two feature extraction i.e. color feature extraction and texture feature extraction. Color and texture feature is extracted from rupiah images by using combinational method i.e. SFTA and HSV. Rupiah images with normal lightning will be extracted by using HSV color feature extraction. While rupiah images with ultraviolet lightning will be extracted by using SFTA texture feature extraction. Feature Vectors that acquired from both HSV color and SFTA texture are joined and become input for to the training phase of classification system. Thereby classification model will be used in testing phase to recognize rupiah feature vector. In this study Naive Bayes classifier is employed to classify rupiah feature vectors.

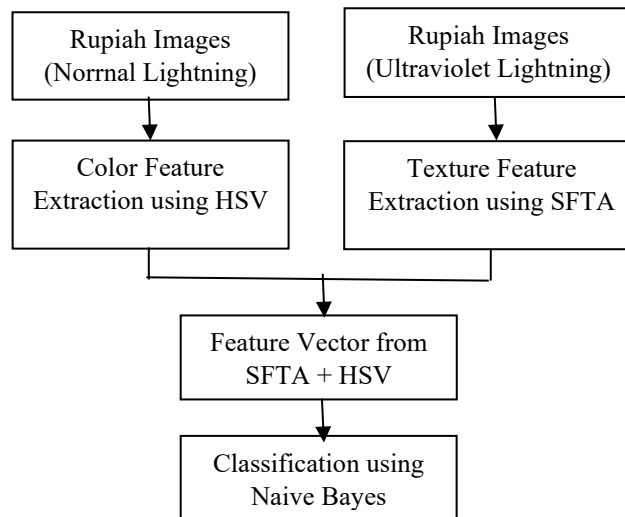


Figure 1. Structure of rupiah classification system

2.1 Hue Saturation Value (HSV)

HSV color space is more like human perception better than RGB color space [2]. HSV components are consist of Hue, Saturation and Value. Hue component represents variety of color, saturation component represent the range of color intensity (bright and pale) and value component represent the range of light (light and dark). Hue component start from red at 0o and then green at 120 o and then blue 240 o and then back to red at 360 o. Saturation component range is between 0 to 1. Value component range is between 0 to 1. Color quantization is a method to reduce color feature vector without reduce quality of images. This method is splitting color histogram into number of bins. In HSV good configuration that achieve optimum performance and computational cost is splitting color histogram into 72 bins (8 bins of Hue component, 3 bins of Saturation component and 3 bins of Value component). The division and establishment of color histogram into range in the bins which produce 72 feature vector of color feature is using the following equation:

$$H = \begin{cases} 0 & \text{if } h \in [316, 20] \\ 1 & \text{if } h \in [21, 40] \\ 2 & \text{if } h \in [41, 75] \\ 3 & \text{if } h \in [76, 155] \\ 4 & \text{if } h \in [156, 190] \\ 5 & \text{if } h \in [191, 270] \\ 6 & \text{if } h \in [271, 295] \\ 7 & \text{if } h \in [296, 315] \end{cases} \quad S = \begin{cases} 0 & \text{if } s \in [0, 0.2] \\ 1 & \text{if } s \in [0.2, 0.7] \\ 2 & \text{if } s \in [0.7, 1] \end{cases} \quad V = \begin{cases} 0 & \text{if } v \in [0, 0.2] \\ 1 & \text{if } v \in [0.2, 0.7] \\ 2 & \text{if } v \in [0.7, 1] \end{cases} \quad (1)$$

2.2 Segmented Fractal Texture Analysis (SFTA)

The texture was a feature of low-level image that is very important because it is closely related to human perception. In looking at an image, people tend to see and perceive the texture in it, so that identification based on texture form is the best way. One method is to use a texture feature extraction analysis of fractal. On the SFTA method used to use fractal analysis for the extraction of base texture of an image [3]. SFTA method has a two-stage process i.e. Two Threshold Binary Decomposition (TTBD) which is used to calculate the threshold of a multi image and SFTA extraction algorithm which generates the vector feature SFTA built from the resulting binary image size, measurements of the fractal used to depict the complexity of the structure of the object and limits of segmented on the image as shown in Figure 2.

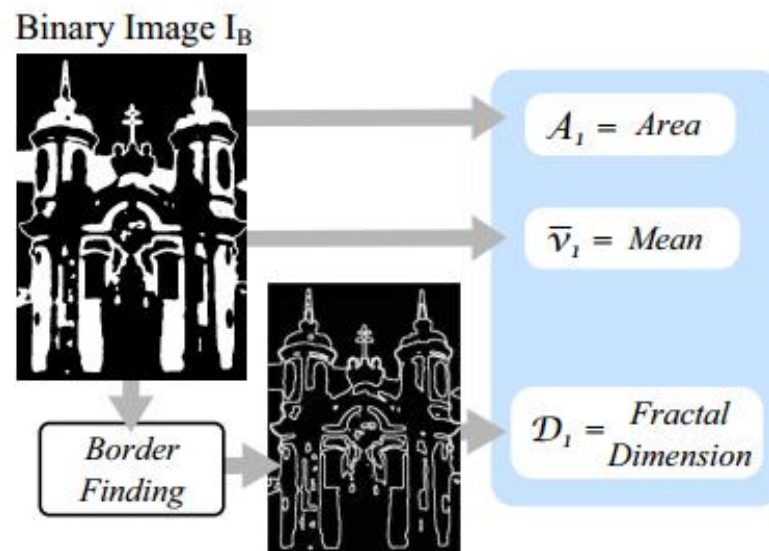


Figure 2. The result of SFTA Vector features

Analysis of fractal algorithm used on the SFTA is Hausdorff Fractal Dimension. As for the algorithm to find the Hausdorff Fractal Dimension is as follows :

1. Pad the image with pixel dimensions into the background so that its dimensions are power of 2.
2. Adjust the box size and notate it with the 'e' so it becomes the same size as the input image.
3. Count N (e) the present number of boxes containing at least one object in pixels.
4. If $e > 1$ then $e = e/2$ and repeat step 3.
5. calculate the $\log(N(e)) \times \log(1/e)$ and use the least square method to set up the line that generated the comply with points.
6. Hausdorff Fractal Dimension D obtained from the slope of the resulting line.

2.3 The Evaluation for Classification System

True positives, true negatives, false positives and false negatives will be used to examine the result of classification system with trusted external judgment. The terms positive and negative are used to refer the classification system prediction. While the terms true and false are used to refer the trusted external judgment. Relations between true positives, true negatives, false positives and false negatives are shown in Table I. In this study accuracy will be used to examine the classification system. Accuracy is obtained from number of classified images divided by total number of testing images. The formula to compute percentage of accuracy is shown in equation (2).

$$\text{Accuracy} = (\text{True Positive} + \text{True Negative}) / (\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}) \quad (2)$$

Table 1. Classification System Evaluation

True	Positive	Negative
True	True Positive	True Negative
False	False Positive	False Negative

2.4 Dataset

Rupiah images that is used in this research consists of 4 kind of classes ("sepuluh ribu", "dua puluh ribu", "lima puluh ribu", "palsu"). Each class has 10 images and each image has a size of 320x240 pixel. This dataset is divided by 66% for training data and 34% for testing data.

Figure 3. shows the sample of original rupiah images and their nominal and also shows the sample of fake money for each nominal.

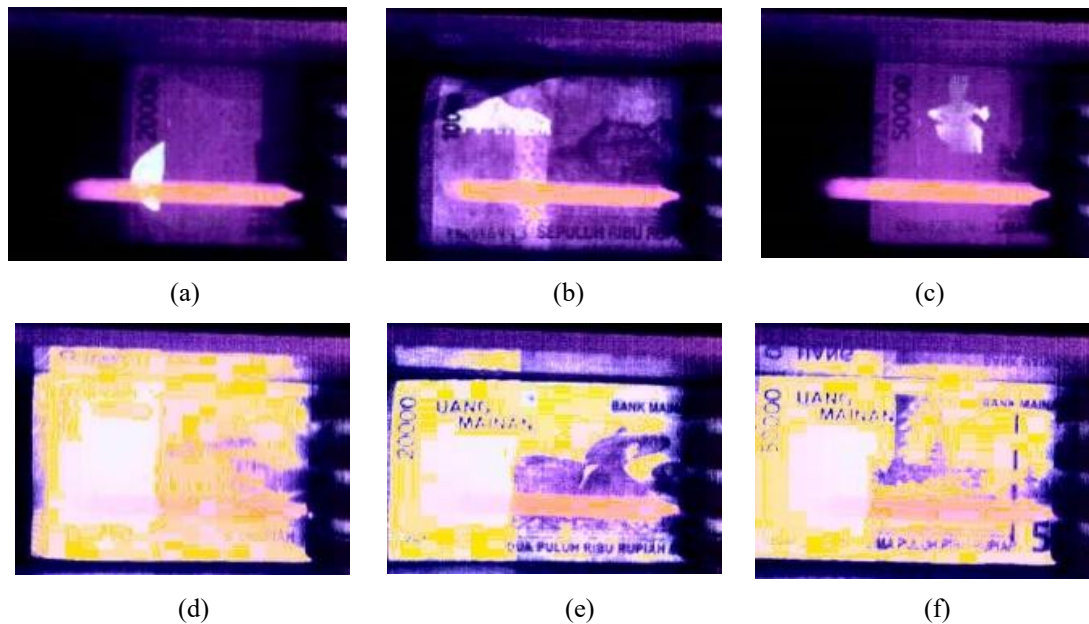


Figure 3. Example of (a) Original Sepuluh Ribu Rupiah (b) Original Dua Puluh Ribu Rupiah (c) Original Lima Puluh Ribu (d) Fake Sepuluh Ribu Rupiah (e) Fake Dua Puluh Ribu Rupiah (f) Fake Lima Puluh Ribu Rupiah

3. RESULTS AND DISCUSSION

The performance of rupiah classification system is measured by accuracy for each scenario. The scenarios in this study are as follows :

1. The first scenario is for testing feature redundancy in Two Threshold Binary Decomposition Algorithm that implemented in SFTA. This scenario to find out whether there is any decrease in accuracy if the redundant features removed.
2. The second scenario is to measure the performance of the accuracy of the classification system that uses only the extraction of texture feature SFTA.
3. The third scenario is to measure the performance of the accuracy of the classification system that uses a combination of feature extraction of color HSV and texture feature extraction SFTA.

The first phase of TTBD algorithm the image will be decomposed according to the number of threshold then each image will be thresholded with multi threshold otsu. Then in the second phase the image will be decomposed again according to the number of threshold then each each image will be thresholded with the equation (3).

$$I_b(x, y) = \begin{cases} 1 & \text{if } t_l < I(x, y) \leq t_u \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

Table 2. Experimental Results On Scenario 1

No.	Scenario 1	Accuracy
1.	Original SFTA	92.8571 %
2.	SFTA with redundant feature reduction	92.8571 %

Table 3. Experimental Results On Scenario 2 and 3

No.	Scenario	Accuracy
1.	SFTA	92.8571 %
2.	SFTA + HSV	100 %

But these two phases will produce the same binary image on the decomposition of the last image. So the TTBD will produce two identical binary image of the resulting produce exactly the same vector features. So as to avoid redundant features can be selected only one binary image on one phase decomposition in algorithms TTBD. The results of the evaluation scenario 1 on table II shows that there is no decrease in accuracy though vector feature has been reduced.

Experiments with using the features of textures and combinations of features are texture and color feature in scenario 2 and 3 shows the difference in the performance of a classification system. The results of the experiment indicated in table III shows the performance of a classification system that uses a combination of textures and colors fit is better compared to the classification system which uses texture only. The accuracy of the classification system is achieved using a combination of texture and color feature in scenario 3 achieves 100% accuracy. While the accuracy of the classification system is achieved using only of texture features in scenario 2 reached 92.85% accuracy.

4. CONCLUSION

In this study, a classification system was developed to distinguish between the nominal value and authenticity of rupiah banknotes. The system was implemented using the Naive Bayes classification model, which has been widely applied in currency authentication and other image-based classification problems due to its simplicity, computational efficiency, and strong performance on probabilistic classification tasks. Experimental evaluation demonstrated that the proposed approach achieved an accuracy rate of up to 100% in classifying and authenticating banknotes. The results indicated that the combination of texture and color features produced superior performance compared to the use of texture features alone. Texture features were extracted using statistical and fractal-based approaches, which have been proven effective in various image recognition and texture analysis tasks. Color features were processed in the HSV color space to improve robustness against illumination variation, leveraging the separation of chromatic and intensity components to better reflect human visual perception [11]. The integration of these complementary features provided a more discriminative representation of banknotes, resulting in higher classification accuracy. It was further observed that the reduction of redundant features did not result in any decline in classification accuracy, consistent with prior research on efficient feature selection and dimensionality reduction for high-dimensional datasets [12], [13]. This finding has significant implications for real-time or embedded systems, as it enables faster computation, reduced memory usage, and lower processing costs without sacrificing accuracy. Such efficiency is critical for applications requiring rapid and reliable classification in operational environments. The findings confirm that accurate and efficient rupiah classification can be achieved through the proposed methodology. Potential applications include automated cash handling systems, counterfeit detection devices, and point-of-sale authentication mechanisms. Future work will focus on incorporating rotation and scale invariance, as demonstrated in recent computer vision studies [14], [15], to enhance system robustness under varied presentation conditions.

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