Counterfeit Detection and Value Recognition of Euro Banknotes

Sebastiano Battiato, Giovanni Maria Farinella, Arcangelo Bruna and Giuseppe Claudio Guarnera
Image Processing Laboratory, University of Catania, Catania, Italy

Keywords: Banknote Recognition, Counterfeit Detection, Image Forgery.

Abstract: This paper describes both hardware and software components to detect counterfeits of Euro banknotes. The system is also able to recognize the banknote values. The proposed method makes use of images acquired with near infrared camera and works without mechanical parts. This makes the overall system low-cost. The effectiveness of the proposed solution has been properly tested on a dataset composed by genuine and fake Euro banknotes provided by Italy's central bank.

1 INTRODUCTION

The detection of counterfeit banknotes is one of the most important task in billing machines. Unfortunately these systems are very expensive and are used only for ATM machines (i.e., fully unsupervised by humans) where a high degree of reliability is required. In the last years, cheaper systems for validation and classification of banknotes have been commercialized. They are usually based on motor actuators aimed to let the banknote passing through light emitters and sensors in a dark area. On the other hand, the motors are expensive and the mechanical parts may frazzle in few years.

In this paper we present both hardware and software components useful to detect counterfeit of Euro banknotes and to recognize their currency values. This is obtained by exploiting a low cost system without motor actuators or other moving parts. A prototype of the proposed system has been built and tested on a dataset composed by genuine and fake Euro banknotes provided by the Bank of Italy. The system is composed mainly by an infrared camera, a microprocessor and a control flow that implements a robust decision system. A glass is placed in the focal plane of the camera in order to acquire a sharp image. The acquired image is then processed through the designed algorithms. The user should just lean a banknote on the glass and the system provides the information on the validity and the related value.

The remainder of the paper is organized as follows: Section 2 reviews the state of the art algorithms in the field. Section 3 summarizes the proposed algorithms for counterfeit detection and currency value recognition of Euro banknotes. In Section 4 the designed hardware prototype is described, whereas experimental results are presented in Section 5. Finally, conclusions are given in Section 6.

2 STATE OF THE ART

It is well known that, in order to avoid forgeries, the security systems of money are typically encoded in the banknotes (in several ways in the different currencies). This fact induced researchers to develop different counterfeit detection and value recognition algorithms taking into account the different currencies.

In (Hinwood et al., 2006) authors make use of light transmittance and pattern recognition techniques to recognize the value of banknotes. The proposed solution requires the banknote to pass through light emitters (LED) and receivers (photo transistors) placed in opposite side. Hence, the system requires a motor or a moving part. Moreover, the method can be simply deceived by counterfeit banknotes (not handled by the authors).

In the approach proposed in (He et al., 2004) the banknotes are segmented into different regions and a classifier for each segmented region is employed. A consensus on the classification results obtained on the different segmented regions provide the final decision. Specifically, genetic algorithms were used for classification of both, the segmented regions and fusion blocks.

A neural network and genetic algorithms has been exploited in (Takeda et al., 1999; Takeda et al., 2003) to address the problem of banknote recognition,

Battiato S., Farinella G., Bruna A. and Guarnera G..
Counterfeit Detection and Value Recognition of Euro Banknotes.
DOI: 10.5220/0004205100630066
In *Proceedings of the International Conference on Computer Vision Theory and Applications* (VISAPP-2013), pages 63-66
ISBN: 978-989-8565-48-8

whereas in (Khashman and Sekeroglu, 2005) the authors proposed an Intelligent Banknote Identification System (IBIS) based on neural networks technique. The system is designed for Turkish Lira and Cyprus Pounds identification.

Despite different approaches have been presented in literature, most of them do not take into account the Euro banknotes or the validation task. Moreover, some approaches have been tested only on simulated data. In the Euro banknotes there are several features which make challenging the forgery: the sheet, the watermarks, the particular inks with different behavior in visible, infrared and ultraviolet lights, etc. All the techniques above could be adapted to other currencies (e.g., Euro) for the recognition task, but their adaptation to counterfeit detection is not straightforward because, under visible light, the counterfeit banknotes usually are identical to the valid ones. Hence, a system designed for a specific currency (e.g., Euro) cannot be employed as it is for other currencies (e.g., Turkish Lira); each currency has its own specific features to be exploited for counterfeit detection and typically those features strongly differ from a currency to another.

Different than other approaches, in the proposed system the infrared (IR) technology has been exploited since it can provide good and robust features for counterfeit detection of Euro banknotes.

3 SOFTWARE COMPONENTS

The proposed software consists of three main blocks: Calibration, Training and Use Module.

3.1 Calibration

Since in our setup the LED illumination is not spatially uniform, and taking into account its changes from prototype to prototype, a calibration phase is required to remove illuminations variability. Specifically, in this phase a brightness map is computed and a compressed version of it is stored inside the flash memory. The brightness map is obtained by acquiring several images of a white sheet of paper in different environments (i.e., lighting conditions), and then considering the average of all the acquired frames. This process allows also to reduce noise (usually zero mean Gaussian noise). The map is then used during the Training and Use Modules to normalize the input banknote images.

The Training block is used to learn optimal features of the banknotes (i.e., patches), which will be used to determine the validity and the value of each banknote. The parameters are learned using a large data set of both genuine and counterfeit banknotes, which come in several face values.

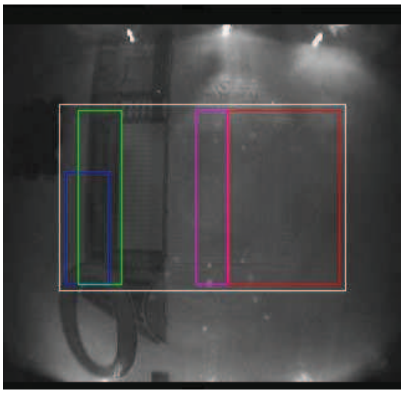

Figure 1: A banknote of 50 Euro as acquired by the IR camera of the system, and the set of regions used to test its genuineness. White: Overall ROI. Blue: the threshold to binarize the image is calculated in this area. Green: this area must be dark under infrared light. Red: when seen under infrared light, this area must be bright and without noticeable patterns. Magenta: additional area used to check the genuineness of some denominations.

In our tests we have used both genuine and real counterfeit banknotes collected, only for testing purposes, at the Bank of Italy. A training dataset of 1000 images has been acquired taking into account typical contexts of use of the apparatus, in which there are very different lighting conditions (e.g., neon, sunlight, incandescent and fluorescent lamps, etc.) and a high degree of misalignment with respect to the proscenium (the system must be robust to slightly translated and or rotated banknotes).

Genuine Euro banknotes are made such that only specific visual features are visible under infrared lighting. In particular banknotes must show darker areas in different zones depending on their value. Those areas always show characteristic patterns. However, there are overlap among all banknote values, for both dark and bright areas, which can be used as validity check.

The aim of learning stage was hence to find the best area to check banknote validity by using a training dataset composed by genuine and fake Euro banknotes.

Given the set of all genuine banknotes $G = \{G_1, G_2, \ldots, G_n\}$, the training block is devoted to search for the largest common dark area F_g, and the largest common bright area T_g of genuine banknotes.

3.2 Training

Let $F_{g,i} = IRSignal(G_i)$ be the infrared highlighted dark area of each G_i , then $F_g = \bigcap_i F_{g,i}$.

Let $T_{g,i} = G_i \setminus F_{g,i}$ be the unresponsive bright area of each G_i , then $T_g = \bigcap_i T_{g,i}$.

The regions T_g and F_g need to be refined in order to be robust to counterfeit banknotes, which in some case might show a slightly similar infrared response. In a similar way, given the set $C = \{C_1, C_2, \ldots, C_n\}$ of all counterfeit banknotes in our data set, we define $F_{c,j} = IRSignal(C_j)$ and $T_{c,j} = C_j \setminus F_{c,j}$.

Let C^* be the set of all C_j such that $(F_{c,j} \bigcap F_g \neq \varnothing) \wedge (T_{c,j} \bigcap T_g \neq \varnothing)$. We can finally define T and F considering C^* as follows: $T = T_g \setminus \bigcup_j T_{c,j}$ and $F = F_g \setminus \bigcup_j F_{c,j}$

For each banknote B_k in $G \bigcup C$, for each possible threshold $s \in [0, 255]$, we computed the percentage $percB_{k,s}$ of pixels above s in region T_k and the percentage $percD_{k,s}$ of pixels below s in regions F_k. Using those values we computed optimum $percB^*$ and $percD^*$ thresholds to separate genuine and counterfeit classes.

To classify the banknote value, during training phase we learn the most discriminant patterns P_i for each possible banknote value $D_i \in D = \{5, 10, 20, 50, 100, 200, 500\}$, such that the intra-class distance is minimized whereas the inter-class distance is maximized. This process is very tricky for some banknote values which share similar patterns (e.g., 5 *Euro* and 20 *Euro*). The final output is a set of patches, with the corresponding position, related to the different banknote values. To take into account slightly translated and/or rotated images, the search area of each patch has the same shape and center coordinates of the patch itself, but it is wider: approximately the search area is 2.5 times the corresponding patch area.

Once the training phase is performed, the selected banknote features (i.e., the learned patches, locations and thresholds) are stored in the flash memory and used to infer validity and value of input banknote images.

3.3 Banknote Authentication

Once the image has been corrected for the non-uniform led illumination (see Section 3.1), a proper threshold needs to be found according to the actual input data. In our experiments we have noticed that the average gray value (indicated as $MeanRef$) of the blue region shown in Fig. 1 can be robustly used for this purpose.

To check the genuineness, the percentage of pixels inside the green region with a gray value below $MeanRef$ $(i.e., percLT)$ is computed, together with the percentage of pixels inside the magenta and red regions with a grey value above $MeanRef$ $(i.e., percGT)$. If $((percLT > percD^*) AND (percGT > percB^*))$ the banknote is classified as genuine.

To identify the face value, the system makes use of patches learned during the training stage (i.e., templates related to the different banknotes values) and the corresponding search areas coordinates. Search areas are wider than the patches in order to be robust to small misalignments. Each template patch is placed at the center of its search area and a correlation measure between the pattern itself and the corresponding pixels on the search area is used for comparison. The procedure then search if a translation around the neighborhood of the current position could increase the correlation. This is performed by moving the pattern position. This step is then repeated until the correlation reaches a local maximum. The pattern with the highest correlation determines the final value to be assigned to the input banknote. Information about genuineness and face value are then sent to the display, in order to inform the user about the results of the banknote analysis. The overall computational speed is of about 1 second for validity and 2 seconds for value recognition using the architecture described in the Section 4.

4 HW PROTOTYPE

The hardware prototype has been designed to demonstrate the effectiveness of the proposed framework.

The Infrared LEDs (IR leds block) illuminate the scene. It is composed by 6 LEDs placed around the proscenium (the area where the banknote is placed). The illumination is not uniform in the real system. Hence, a calibration is needed to take into account the non uniformity and the performances decay during the system life (see Section 3.1). An optical filter is inserted to avoid the external light source to influence the image acquisition system. It is placed on top of the infrared camera (IR camera block) that acquires the image. The camera is a common low cost camera with CCTV output. Since the output is analog, an analog to digital converter (A/D converter block) is used to obtain a digital standardized format (i.e., $CCIR-656$). The digital image is acquired by the microprocessor. In the prototype we have used an $ATMEL\ AT91SAM9XE256$, containing a $ARM926EJ-S^{TM}$ processor, 200MHz with 256KB internal high-speed flash memory to store the program instructions. It contains also an Image Sensor Interface (ISI) port able to capture video sequences compliant with the standard ITU-R BT 601/656. The software contains, beside the control logic for the entire

Table 1: Genuine/Counterfeit classification.

True Positive (counterfeit banknote correctly classified)	**False Positive (genuine banknote incorrectly classified)**
100%	4.3%
False Negative (counterfeit banknote incorrectly classified)	**True Negative (genuine banknotes correctly classified)**
0%	95.7%

Table 2: Banknote value classification.

	5E	10E	20E	50E	100E	200E	500E	Counterfeit
5E	88,00%	0,00%	0,00%	0%	0,00%	0,00%	0,00%	12,00%
10E	1,00%	91,00%	0,00%	0,00%	0,00%	0,00%	0,00%	8%
20E	0,00%	0,00%	98,00%	0,00%	0,00%	0,00%	0,00%	2%
50E	0,00%	0,00%	0,00%	99,00%	0,00%	0,00%	0,00%	1,00%
100E	0,00%	0,00%	0,00%	0,00%	93,00%	0,00%	0,00%	7,00%
200E	0,00%	0,00%	0,00%	0,00%	0,00%	98,00%	1,00%	1,00%
500E	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	95,00%	5,00%

subsystems (e.g., IR led, IR camera settings, Display, etc.), the related algorithms (for both validation and classification) described in Sections 3. The prototype has been also equipped with external SRAM memory, since the microprocessor contains only 32KB of internal SRAM.

5 EXPERIMENTAL RESULTS

To evaluate performances of the proposed technique we used our prototype to acquire a test set of 1750 banknote images, with the same criteria used for the training dataset (i.e., both counterfeit and genuine banknotes have been acquired under several environment lighting conditions, with different illuminants and brightness). In both cases, training and experimental phases, the banknotes samples have been provided by the Bank of Italy.

Acquired counterfeit banknotes include also specimens carefully calibrated to mislead digital counterfeit detectors. To deal with special cases (i.e., fake banknotes provided by the bank), additional procedures have been included. The overall processing time is very close to the base algorithm, since it includes a few average computations on very small areas. Table 1 reports the results of the validity assessment. Table 2 shows the results of the banknotes value classification.

6 CONCLUSIONS

In this paper we have proposed an effective system to detect counterfeit of Euro banknotes composed by both hardware and software modules. Conversely to the state of the art algorithms, the proposed solution makes use of infrared imaging and low-cost hardware. The proposed system allows recognizing not only the value, but also forgeries. The described algorithms are robust to changes in environment lighting, in terms of illuminant type and incident intensity. Thanks to a training phase it is also robust to non-uniformity of the infrared light. The experiments performed on genuine and fake banknotes provided by the Bank of Italy show good performances in both validity and value recognition.

ACKNOWLEDGEMENTS

The authors would like to thank Imperial Emporium Srl and the Bank of Italy for supporting this research activity.

REFERENCES

He, C., Girolami, M., and Ross, G. (2004). Employing optimized combinations of one-class classifiers for automated currency validation. *Pattern Recognition*, 37(6).

Hinwood, A., Preston, P., Suaning, G., and Lovell, N. (2006). Bank note recognition for the vision impaired. *Australian Physical and Engineering Sciences in Medicine*, 29(2).

Khashman, A. and Sekeroglu, B. (2005). Multi-banknote identification using a single neural network. In Blanc-Talon, J., Philips, W., Popescu, D., and Scheunders, P., editors, *Advanced Concepts for Intelligent Vision Systems*, volume 3708 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg.

Takeda, F., Nishikage, T., and Omatu, S. (1999). Banknote recognition by means of optimized masks, neural networks and genetic algorithms. *Engineering Applications of Artificial Intelligence*, 12(2).

Takeda, F., Sakoobunthu, L., and Satou, H. (2003). Thai banknote recognition using neural network and continues learning by dsp unit. In Palade, V., Howlett, R., and Jain, L., editors, *Knowledge-Based Intelligent Information and Engineering Systems*, volume 2773 of *Lecture Notes in Computer Science*. Springer Berlin - Heidelberg.