Banknote Identification Methodology for Visually Impaired People

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***Abstract*—Around the world, there are many people with disabilities; it is estimated that 39 million people are blind and 246 million have limited vision, giving a total of 285 million visually impaired people. The use of information and communication technologies can help disabled people to achieve greater independence, quality of life and inclusion in social activities by increasing, maintaining or improving their functional capacities. In this context, this paper presents an automatic methodology for identifying banknotes that can be widely used by people with visual impairment. For this, we evaluated a set of four point-of-interest detectors, two descriptors, seven ways of generating the image signature, and six classification methodologies, which can be used as a basis for the development of applications for the identification of banknotes. Experiments performed on US Dollar (USD), Euro (EUR) and Brazilian Real Banknotes (BRL) obtained rates of accuracy of 99.78%, 99.12%, and 96.92%, respectively.**

I. Introduction

Visual impairment limits the viewing and identification of objects. According to the World Health Organization [1], there were about 285 million people in 2010 with vision problems, 39 million of whom declared themselves blind.

The emergence of new technologies has generated increasing numbers of mechanisms providing accessibility and inclusion for disabled people. The primary goals are to provide benefits such as higher independence and a better quality of life. The use of technological resources can help visually impaired people to perform tasks such as using computers to read newspapers, carry out academic research etc.

The recognition of banknotes is one of the most challenging issues faced by people with visual impairment, as it is an essential process in managing monetary transactions [2]. They have great difficulty in identifying the values of banknotes, making it difficult to perform everyday tasks such as the payment of bills, purchases and banking operations. Disabled people are also vulnerable to financial fraud.

In this paper, we propose an automatic banknote identification method that uses image processing, computer vision and pattern recognition techniques.

From this perspective, we carried out a literature review of the main techniques that are currently applied and evaluated a set of four local detectors and two descriptors, seven methods of generating the image signature, four individual classifiers, and two classifier committees. We performed tests using US Dollar, Euro and Brazilian Real Banknotes. We performed 336 experiments in total to identify the best set of algorithms.

This paper is organized as follows: in Section II, we discuss the main works related to the recognition of banknotes; in Section III, we describe the methodology for identification of banknotes, Point of Interest (PoI) detectors and descriptors, signature generation, classifiers, image database and evaluation metrics; Sections IV, V and VI present the experiments, results and a discussion, respectively; and finally, in Section VII, we present the conclusion to the study and discuss future work.

II. Related Work

We carried out a literature review with the aim of identifying the main techniques used in the recognition of banknotes. There are many papers related to this subject, and we considered papers using computer vision techniques to assist the visually impaired.

Hasanuzzaman et al. [3] proposed an approach for banknote recognition that used the Speeded Up Robust Features (SURF) descriptor [4]. They made manual cuts of several points on each banknote (front and back) to generate the reference regions. The method can recognize a banknote if at least two reference regions can be identified. In these experiments, the authors used 140 images of USD bills, containing 20 images in each class ($1, $2, $10, $20, $50 and $100), as a training set and 579 images for testing, achieving a 100% True Positive Rate (TPR).

Mulmule-Shirkhedkar and Dani [5] conducted a comparative study of SURF and Fast Retina Keypoint (FREAK) [6] descriptors for the identification of Indian banknotes. Their method used a model based on predetermined reference regions. For classification purposes, the authors compared the attributes of a new image with those of all previously stored examples. They used Indian Rupee (INR) banknotes of 5, 10, 20, 50, 100, 500 and 1000 denominations. In the experiment, they used 210 images (30 for each denomination), splitting the image sets as follows: 60% for training, 20% for testing and 20% for validation. The accuracies obtained were 95.15% for SURF and 92.85% for FREAK.

Costa et al. [7] developed an application for the recognition of EUR banknotes, using eight PoI detection and four descriptor algorithms. For classification, the authors evaluated

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the use of an extensive search and a heuristic approach called the Fast Library for Approximate Nearest Neighbours (FLANN) [8]. The authors evaluated the system using 80 images of banknotes. The best result was obtained using the Scale Invariant Feature Transform (SIFT) [9] algorithm as detector and descriptor, and classification based on an extensive search. The system successfully recognized all test images. However, the authors reported that the SURF detection and description algorithms were better suited for real-time use, even though they yielded lower-quality results.

Abburu et al. [10] proposed a system for automatic banknote recognition. The proposed method can recognize both the nationality and the value of the banknote. This method works by identifying the country of origin using certain predefined areas of interest and then extracting the denomination value using characteristics such as size, color, or text in the note, depending on how much the bills are within it. The 20 most traded currencies were considered, as well as their denominations. For demonstration purposes, the Canadian $ 20 banknotes were chosen. The proposed system obtained 93.3% accuracy in carrying out the experiments, adequately identifying the nationalities of the cells presented.

Mittal e Mittal [11] developed a method based on deep learning to identify Indian currency rupee note denominations from their color images. The structure uses the concept of transfer learning, in which a deep convolutional neural network (CNN) [12], already trained on a vast data set of natural images, is reused for the problem of classification of the denomination from banknote images. The INR (Indian Rupees) notes used were: Rs.10, Rs.50, Rs.100, and Rs.500. In the experiment, a total of 95 images were used for each denomination, being acquired under different conditions, totaling 380 images. The authors obtained an accuracy rate of 96.60%. However, there were no tests with partial occlusions.

It is important to note that none of the cited works describes how the image signature was created. Signature creation is an essential step, since PoI detection algorithms detect a different number of points for each image, while classifiers take as their input attribute vectors of equal length. Thus, one of the contributions of our work is a comparison of four different signature generation methods, defined as follows: mean, median, mode and Bag of Visual Words (BoVW) [13], with word sizes of 200, 300, 400 and 500. We also perform tests on three types of banknotes (US Dollar, Euro and Brazilian Real).

III. Extraction and Identification of the Features of Banknotes

In this work, we propose a methodology for automatic banknote identification using PoI detectors and descriptors to extract the image features. Figure 1 shows the phases of a banknote recognition system.

The input to the system is an image of a banknote. Recognition is the most critical phase of the system, in which the image is analysed to extract the monetary value of the note. PoI detection is the initial step of recognition in which key interesting points for matching are identified in the image and its reference points.

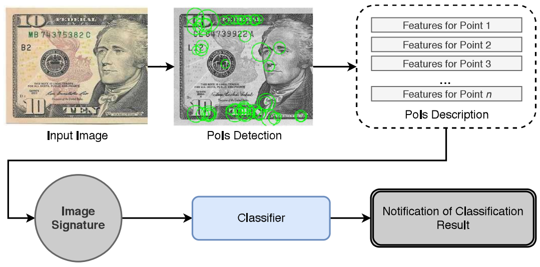

Fig. 1. Overview of the main processing stages of the banknote recognition system.

Following this, the descriptor, which provides parameters that describe each shape point, generates a vector of attributes that can later be compared and associated with the points of other signatures. In order to detect instances with different perspective views, these descriptors must be invariant to scale, rotation and different lighting conditions.

The descriptors detect numerous points in each image and generate an array of attributes. However, the generation of a signature uses only a single attribute vector. The image signature is a set of detected visual characteristics that describes a particular scene or an element of the scene.

The classification stage is composed only of the classifier training process, the objective of which is to divide the attribute space into decision regions. In this way, attribute vectors that are contained in the same decision region share the same class. In the present work, the input to the classifier is the signature of the image, and the output is the class to which the banknote belongs.

A. *Detection and Description of PoIs Evaluated*

To detect PoIs and describe their characteristics, we use several state-of-the-art algorithms. A good PoI detection algorithm must be able to identify and obtain regions that can be identified under several changes of perspective.

1) Detectors Evaluated: **Maximally Stable External Regions (MSER)**: Matas et al. [14] proposed an algorithm that would be robust to changes in perspective. The algorithm finds extreme points in the image and identifies related regions based on the brightness intensity of the pixels. It applies different threshold values and detects border regions with significant variations in intensity.

Features from Accelerated Segment Test (FAST) [15]: The basic idea of this approach is to reduce the number of calculations required per pixel to decide whether or not a critical point is detected in the pixel. This is accomplished using a circle consisting of 16 pixels that is centred on the pixel under investigation. For the corner test, the algorithm evaluates only the differences in gray values between each of the 16 pixels of the circle and the centre pixel.

Speed-Up Robust Features (SURF): This algorithm identifies the location of PoIs and then generates a feature vector.

As this information is extracted based on the orientation of the Regions of Interest (RoI), the same pattern remains if the image is rotated.

Binary Robust Invariant Scalable Keypoints (BRISK): This is based on a circular sample, from which it calculates the brightness variations to form a chain of binary descriptors [16]. This method takes into account the rotation of a PoI, which can be described with the use of a scale-space theory to adapt the sampling pattern.

2) Descriptors Evaluated: **SURF**: The SURF descriptor is extracted in two steps. The first is assignment and orientation based on information from a circular region around the PoIs detected. The orientation is then computed using Haar wavelet responses. We used the creation of a vector of 64 features.

BRISK: The BRISK descriptor use of a pattern to sample the vicinity of the detected key point. The algorithm estimates the orientation of the key point and rotates the sampling pattern by summing the local gradients between all long pairs. We used the creation of a vector of 64 features and the orientation was computed.

B. Signature Generation

For each image in a database, the PoI detection algorithms return different numbers of points (n). Each point generates a vector of characteristics, thus forming an array of characteristics. However, the input to the classifiers must be a one-dimensional matrix (1x64 in this case, since 64 is the number of characteristics generated by the descriptor). Thus, we must use suitable techniques to represent the information in the matrix as a single feature vector, called the image signature. In this paper, we evaluate four signature generation techniques: mean, median, mode, and BoVW.

We follow the methodology presented in Figure 2 to generate signatures based on the mean, median and mode. Where PoIs are detected in an image, these are described and only a features vector is generated.

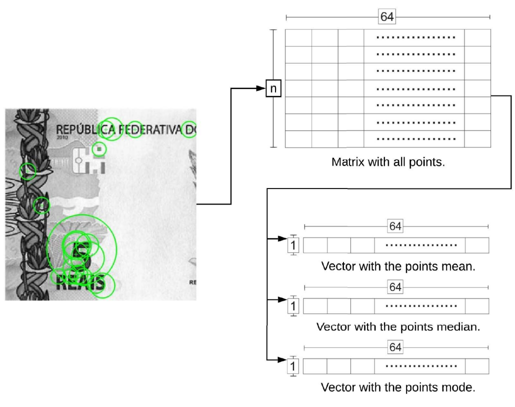

Fig. 2. Flowchart for signatures using mean, median and mode techniques.

In this work, we use the BoVW approach to change the feature representation generated by the PoI descriptors. The BoVW method rearranges the obtained features into vectors of the same size. The flowchart shown in Figure 3 details the methodology for generating image signatures using the BoVW.

The first step in the BoVW technique is the construction of a visual dictionary of words. We first split the database into training and test sets. All images in the training set are subjected to the detection and description of PoIs to generate the words that make up the dictionary. The resulting feature vectors are concatenated into a single matrix, which is clustered using the C-means algorithm, in which descriptors representing similar characteristics are grouped in the same cluster. The dictionary is then generated by the C centroids of C-means.

Following generation of the dictionary, all images in the training and test sets undergo the detection and description of PoIs. A quantisation step is then performed, in which each vector of each image is labelled with the nearest word, using a normalised histogram with the total word count. At the end of this step, each image is represented by a vector (image signature) containing the number of each of the words in the image. Finally, the C centroids represent all groups of characteristics formed and are considered the visual words of the dictionary.

C. Classification

After the PoIs have been detected and described, it is necessary to classify them, i.e. to identify the images by analysing the features defined by the descriptors. For this task, we used individual classifiers and committees to evaluate the performance of the proposed methodology. We used the following individual classifiers: a Radial Basis Function (RBF) [17] with a hidden layer, used in an unsupervised way; a Random Tree (RT) [18] with 100 nodes; a MultiLayer Perceptron (MLP) [19] with 500 epochs; and Sequential Minimal Optimisation (SMO) [20], [21] with a polykernel function.

To evaluate the methodology using ensembles of classifiers, we selected two existing state-of-the-art algorithms. The first was the Random Forest (RF) [22], which can generate a set of classification trees in which each tree has one vote indicating its decision on the class of object, and the class with the highest number of votes is chosen for the object. We used a RF with 100 trees of unlimited depth. The second was a hybrid ensemble formed of the SMO, MLP and RBF classifiers (the three individual classifiers that obtained the best results), in which classification by majority vote was used. Each algorithm classifies the instance, and the label with the highest probability receives one vote. If multiple labels have the same expectation, each of these labels will receive one vote. After all classifiers have performed the tests, the label with the most votes is selected as the result of the test instance.

IV. Experiments

A. Images Database

To evaluate the results, we created a database for each banknote, by generating 1,008 images for each banknote. In total, the USD and EUR image databases contained 7,056 images, while the BRL database contained 6,048 images. We

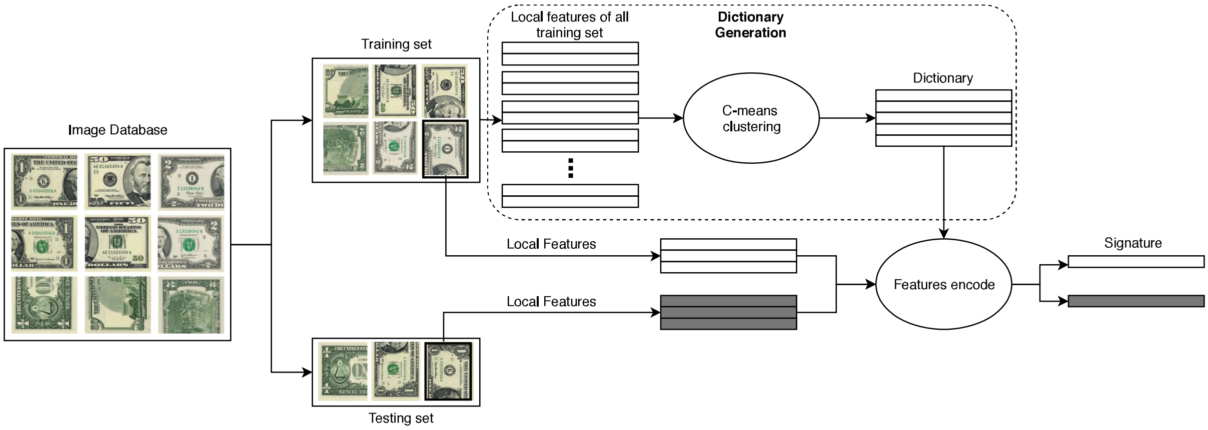

Fig. 3. Flowchart for signatures using BoVW.

obtained images of USD bills from Internet searches, images of EUR banknotes from the work of Costa et al. [7], and images of BRL notes from the webpage of the Central Bank of Brazil. The methodology for creation of the database followed four steps. Initially, we used front and back images, varying the position from horizontal to vertical, rotating them through 90º to the right, 90º to the left and 180º, giving a total of eight images for each note value, for each whole banknote.

In day-to-day applications, it is difficult to analyse the entire banknote. Thus, we included notes in the test database that were divided in half and into quarters. In this way, we obtained a total of 56 images for each class. Figure IV-A shows examples of whole banknotes and the two divisions used.

We made changes to the images to simulate possible events that may arise when capturing images: a median filter with size window [5 5], mimicking a blurred image; the insertion of salt and pepper noise in a ratio of 0.05; and the application of a blurring effect in conjunction with the noise. Figure IV-A shows examples of these three classes of images. We also decreased the brightness of these banknotes by 30% to simulate an image acquired in a low-light environment, and increased the brightness by 30%.

To simulate images captured in different environments, we added backgrounds to banknotes with good quality, that contained noise, that were blurry, and that were blurry with noise. Figure IV-A shows samples of images in the three background colours used (i.e. white, black and gray).

B. Metrics for Performance Evaluation

From the data achieved at the feature extraction stage, we can evaluate the classifiers using an evaluation methodology. To obtain the values of the confusion matrix, we divided the dataset randomly to give a training set containing 90% of the data. The other 10% were used in the validation step. This procedure was performed 10 times to obtain an average for the evaluation metrics. The results in this work were analysed using three metrics from the literature: accuracy (A) [23], sensitivity (S) [24] and kappa (κ) [25].

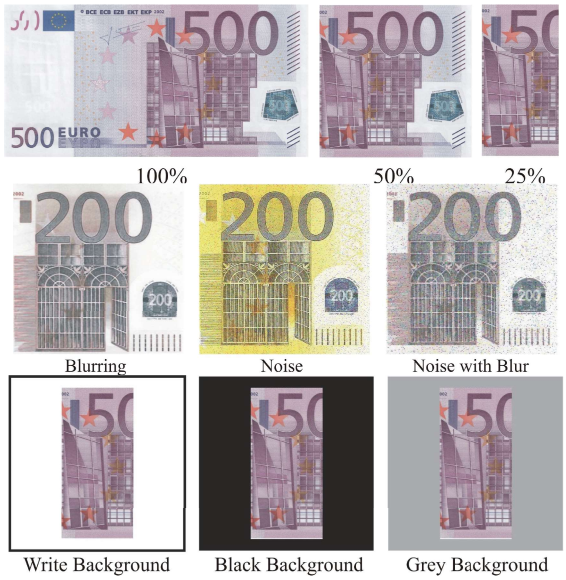

Fig. 4. Samples of images of banknotes, from our database.

The kappa rate is based on the number of concordant responses, and can be calculated based on Equation 1. In this case, "observed" is the overall value for the correct percentage and "expected" are the calculated values using the totals of each row and column of the confusion matrix. According to Landis and Koch [26] the value of κ assumes values between 0 (zero) and 100 (one hundred). The result is qualified according to the value of κ as follows: $\kappa \leq 20\%$: Bad; $20\% < \kappa \leq 40\%$: Fair; $40\% < \kappa \leq 60\%$: Good; $60\% < K \leq 80\%$: Very Good e $\kappa > 80\%$: Excellent.

$$\kappa = \frac{(observed - expected)}{1 - expected} X \ 100 \qquad (1)$$

Following the simulation, WEKA software was used to compile a table containing all the results listed by class, i.e. showing the results based on the note value. In this experiment, we calculated the average of the recognition for all the classes, to obtain a value for the general description of the classification.

V. Results

We tested 336 different system configurations for each currency, varying the algorithms for PoI detection [4], PoI description [2], generation of signatures [7] and classification [6]. For each currency, the best results were obtained by different combinations of PoI detector, descriptor, signature and classifier. We performed a Z-test [27] to statistically compare the results at a significance level of 5% to assess whether one configuration was significantly different from another.

A. Results for Dollar Banknotes

Table I presents the best results achieved for all classifiers for the USD images, as well as the combination of detector, descriptor and signature that gave this result.

The BoVW approach with a word size of 500 was used as an image signature. The SURF detector combined with the SURF descriptor and the SMO classifier achieved the best result, with an accuracy rate of 99.78% and a sensitivity rate of 99.77%. The kappa rate ranked the result as excellent, with a rate of 99.73%.

The Z-test showed that another configuration using a word length of 400 and the same combination of PoI detector, PoI description and classifier exhibited equivalent performance.

B. Results for Euro Banknotes

Table II shows the combination of detector, descriptor and signature type that gave the best result for each classifier tested. The best results for the identification of EUR images were given when the image signature was generated by BoVW with a word size of 300. The random forest used in conjunction with the MSER detector and the SURF descriptor obtained the best accuracy rate of 99.12%, a sensitivity of 99.10% and Kappa rate of 98.97%, which is considered excellent.

A Z-test showed that a configuration with word lengths of 200, 400 and 500 with the same combination of PoI detector, PoI description, and classifier exhibited equivalent performance.

C. Results Using Real Banknotes

Table III shows the combination of detector, descriptor and signature type that improved the result for each classifier. The BoVW approach was used as the image signature with a word size of 400. The MSER detector combined with the SURF descriptor and random forest obtained the best classification for the BRL banknotes, with an accuracy rate of 96.92%, a sensitivity of 96.92% and a kappa rate of 96.31%, which represents an excellent result.

A Z-test showed that configurations with word lengths of 300 and 500 with the same combination of PoI detector, PoI description, and classifier exhibited equivalent performance. An equivalent performance was also achieved with a combination of SURF as a detector and descriptor, BoVW as a 300-image signature, and the random forest classifier. We applied this combination in tests with images obtained with a smartphone camera (next to use in everyday life), to validate our proposal and verify recognition using notes different from those contained in the generated image database.

Figure 5 shows captured images examples. We tested in whole images and folded in half, with bright and dark backgrounds. Table IV illustrates the classification results.

Fig. 5. Samples of real banknotes images.

In the whole banknotes, an accuracy rate of 91.66% and a Kappa index of 90.00% were obtained, which represents an excellent result. The folded notes achieved an accuracy rate of 80.55% and a Kappa index of 76.67%, representing a very good result.

VI. Discussion

Table V shows the average of the PoIs detected in the banknote images. It can be observed that although the MSER and SURF detectors returned fewer points, the characteristics returned were more robust and precise, giving a better classification rate.

This result demonstrates that the MSER and SURF algorithms are more robust to variations in illumination, scale, transformation, rotation and noise from sensor variations during image acquisition. Since they extract features with fewer points than the others, they are also computationally faster.

According to [16], BRISK offers a markedly faster alternative and a performance that is comparable to that of SIFT and SURF. In the tests performed here, the SURF descriptor was superior to BRISK. For the USD bills, there were no results for the BRISK descriptor among the best results. For the EUR and BRL notes, there was only one instance, as we can see from Tables I, II and III.

For the EUR and BRL banknotes, there were combinations that were statistically the same, i.e. the BoVW with word sizes of 300, 400 and 500 with the MSER detector, the SURF descriptor and the random forest classifier. For the USD bills, there was no combination among the best results where the EUR and BRL banknotes were statistically the same.

VII. Conclusion

This paper has presented a classification system for banknotes of some of the world's major currencies. We have evaluated the use of several PoIs and classifier algorithms.

TABLE I
COMBINATIONS FOR THE BEST CLASSIFICATION OF DOLLAR BANKNOTES.

Classifier	A (%)	S (%)	κ (%)	Detector	Descriptor	Signature
MLP	98.68 ±0.63	98.69 ±0.64	98.46 ±0.74	MSER	SURF	Mean
RBF	92.51 ±0.77	92.50 ±0.78	91.26 ±0.90	MSER	SURF	BoVW (500)
Random Tree	61.88 ±2.80	61.86 ±2.79	55.53 ±3.27	MSER	SURF	BoVW (400)
SMO	**99.78 ±0.11**	**99.77 ±0.12**	**99.73 ±0.13**	**SURF**	**SURF**	**BoVW (500)**
Ensemble	95.09 ±1.09	95.09 ±1.10	94.26 ±1.27	MSER	SURF	Mean
Random Forest	98.50 ±0.34	98.48 ±0.36	98.25 ±0.40	MSER	SURF	BoVW (500)

TABLE II
COMBINATIONS FOR THE BEST CLASSIFICATION OF EURO BANKNOTES.

Classifier	A (%)	S (%)	κ (%)	Detector	Descriptor	Signature
MLP	97.85 ±0.50	97.85 ±0.48	97.48 ±0.59	MSER	SURF	Mean
RBF	89.67 ±0.27	89.69 ±0.29	87.95 ±0.32	MSER	SURF	BoVW (400)
Random Tree	78.37 ±1.21	78.38 ±1.20	74.77 ±1.42	MSER	BRISK	BoVW (400)
SMO	97.79 ±0.38	97.80 ±0.36	97.40 ±0.44	MSER	SURF	BoVW (400)
Ensemble	93.97 ±0.88	93.98 ±0.88	92.95 ±1.03	MSER	SURF	Mean
Random Forest	**99.12 ±0.11**	**99.10 ±0.11**	**98.97 ±0.13**	**MSER**	**SURF**	**BoVW (300)**

TABLE III
COMBINATIONS FOR THE BEST CLASSIFICATION OF REAL BANKNOTES.

Classifier	A (%)	S (%)	κ (%)	Detector	Descriptor	Signature
MLP	94.25 ±0.74	94.25 ±0.73	93.09 ±0.89	MSER	SURF	Mean
RBF	78.74 ±1.88	78.74 ±1.89	74.49 ±2.26	MSER	SURF	BoVW (400)
Random Tree	72.09 ±1.87	72.08 ±1.86	66.51 ±2.24	MSER	SURF	BoVW (400)
SMO	92.70 ±0.59	92.70 ±0.60	91.24 ±0.71	MSER	SURF	BoVW (400)
Ensemble	89.40 ±1.18	89.41 ±1.18	87.27 ±1.41	MSER	BRISK	Mean
Random Forest	**96.92 ±0.68**	**96.92 ±0.67**	**96.31 ±0.81**	**MSER**	**SURF**	**BoVW (400)**

TABLE IV
RESULT USING REAL BANKNOTES, OBTAINED WITH SMARTPHONE CAMERA.

Banknote	Background	Amount	A (%)	S (%)	κ
Whole	Dark	12	91.66	91.70	90.00
Whole and Half	Dark and Brigth	72	80.55	80.60	76.67

TABLE V
MEANS OF THE POINTS RETURNED BY THE DETECTORS.

Banknote	BRISK	FAST	MSER	SURF
dollar	2.012	1.520	481	510
euro	1.793	1.441	270	274
real	945	743	278	190

For the intermediate step of generating signatures, we used the BoVW approach.

This study stands out from other related works since it seeks to identify the best descriptor and classifier for the most widely used banknotes in the world. In an attempt to identify banknotes from different perspectives, orientations, and pieces of the image, we have also increased the power of recognition of notes in several different ways.

According to the tests conducted in this study, the best results were obtained using a signature image generated using the BoVW and classified with the random forest committee. For the classification of USD bills, the best result was obtained using the SURF descriptor, and for the EUR and BRL banknotes, the best results were obtained with the MSER descriptor.

In an automated system in which the type of banknote tested is unknown, the MSER descriptor, the BoVW approach and the random forest committee should be used, as these achieved the best results for two of the three databases tested and a kappa rate of excellent for all databases.

In future work, we aim to use the descriptors and classifiers analysed in this study as a basis for the creation of applications for mobile devices that can assist visually impaired people in the identification of banknote denominations. Tests using other descriptors in conjunction with classifiers should be used in an attempt to achieve better results. Another critical point is the classification step; since our primary objective was a description of the images, the evaluated classifiers were not tuned, and we believe that the results could be improved with fine parameter tuning.

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- SOUSA, L. P.; VERAS, R. M. S.; VOGADO, L. H. S.; BRITTO NETO, L. S.; SILVA, R. R. V.; ARAÚJO; F. H. D.; MEDEIROS, F. N. S. Banknote Identification Methodology for Visually Impaired People. International Conference on Systems, Signals and Image Processing. IEEE, 2020. p. 261 - 266. On-line version: https://drive.google.com/file/d/1vBPM5ThogQBOnPgLbR1qOzTcF6pRfFC1/view.

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