Counting Turkish Coins with a Calibrated Camera

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4 authors, including:

Halil İbrahim ÇAKIR
Anadolu University

Cuneyt Akinlar
Eskisehir Osmangazi University

Counting Turkish Coins with a Calibrated Camera

Burak Benligiray[1(✉)], Halil Ibrahim Cakir[2], Cihan Topal[1], and Cuneyt Akinlar[3]

[1] Department of Electrical and Electronics Engineering, Anadolu University, Eskisehir, Turkey
{burakbenligiray,cihant}@anadolu.edu.tr
[2] Department of Computer Engineering, Dumlupinar University, Kutahya, Turkey
cakirhal@dpu.edu.tr
[3] Department of Computer Engineering, Anadolu University, Eskisehir, Turkey
cakinlar@anadolu.edu.tr

Abstract. We present a computer vision application that detects all coins in a test image, classifies each detected coin and computes the total amount. Coins to be counted are assumed to be lying on a flat surface. The application starts by estimating the extrinsic parameters of the input camera relative to this flat surface ($[\mathbf{R} \,|\, t]$), whose intrinsic parameters ($\mathbf{K}$) are assumed to be known beforehand. Then, a bilateral filter is applied to the image to remove textural details and noisy artifacts. Circles in the filtered image are detected and smaller concentric circles are eliminated. Finally, the geometric parameters (the center and the diameter) of the remaining circles are computed by back-projecting the reciprocal points from the circle contours using the estimated camera parameters. Having thus computed the diameter of each detected coin, the classification is performed by comparing the computed diameter with the actual coin diameters. The experiments performed with a dataset consisting of 50 images containing different combinations of Turkish coins show that the proposed method achieves 98% accuracy rate and works even when some coins are partially occluded, as the method does not use any texture information.

Keywords: Coin detection · Circle detection · Bilateral filtering · Pose estimation · Camera calibration

1 Introduction

The detection and recognition of coins in digital images is an important problem with many applications. Vending machines and mass coin classification machines are among the many real-world applications areas where coin identification is required. In these kinds of machines, the problem is usually solved by means of a mechanical system that makes use of the diameter, weight or conductivity properties of the coins.

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In addition to such mechanical systems, there are applications that utilize image processing techniques for coin detection and recognition. Such applications usually aim to detect fraud coins, or coins that belong to a certain ancient period. The goal of these applications is not to detect all coins in a complex image containing many coins, but is rather to classify a single coin by utilizing different features extracted from the coin's texture.

Reisert et al. report a coin recognition system that utilizes the image gradient directions [1]. To determine the alignment of two coins, it is adequate to know that their gradient directions are aligned. After determining the alignment of the gradient directions, the recognition process is completed by a Fast Fourier Transform. The results are then classified using the nearest neighbor classification algorithm and false positive rate is reduced by employing different criteria.

Fuerst et al. developed a machine called Dagobert that can classify coins belonging to 100 different countries, and can count up to 10 coins per second [2]. The machine has a mechanism to capture the images of both sides of the coin, which are then processed by a vision application to recognize the coin type. Finally, the classified coin is placed into the appropriate machine bin by a mechanical key system.

Zaharieva et al. have tested their coin recognition algorithm on three different data sets, and measured the success of the their algorithm on classifying antique and modern coins [3]. They report that their algorithm can classify modern coins better, compared to antique coins. Modi and Bawa describe a coin recognition system based on artificial neural networks [4]. Their work tries to recognize coins of worth 1, 2, 5 and 10 rupis from both faces of a coin that did not go through rotation. For feature extraction, the authors use techniques such as Hough transform and pattern averaging. Finally, the obtained feature vector is fed into the artificial neural network for classification.

Shen et al. propose using local texture features for image-based coin recognition [5]. The authors use Gabor wavelets and local binary patterns (LBP) to generate a feature vector. The coin image is divided into small parts due to the concentric circular structure. Gabor coefficient statistics and LBP values are combined together to generate a feature vector representing the coin image. A circular shift operator is also proposed to make Gabor features more robust against rotation. For classification, the nearest neighbor classification method is used due to its speed. It is known that more complex classifiers such as artificial neural networks or decision support systems are slower compared to a nearest neighbor classifier. The proposed algorithm is measured to have a 74% accuracy based on the average and standard deviation of the Gabor features.

Kim and Pavlovic developed a method for automatic recognition of antique Roman coins [6]. The actual work is to recognize the Roman empire engraved on the face of the coin. The authors achieve this by concentrating on the dimensions of the coin rather than looking at the textural information. They report that using the coins' dimensions improves the recognition accuracy. The authors have also generated an antique Rome coin collection data set consisting of high quality images.

The proposed algorithms found in the literature mostly assume that the coins have already been detected and segmented from within the image either manually or by some segmentation method, and concentrate on the recognition of such segmented coins using textural features. In this paper, we concentrate on both the detection and the recognition of coins in a complex image containing an arbitrary number of coins regardless of which face of the coin is visible, and to compute the total amount of money. Although there is not a lot of work that target this problem in the literature, the authors in [7] attempt a heuristic approach by thresholding the image and counting the number of pixels above the threshold.

The obverse of all Turkish coins have the same picture of Ataturk, the founder of modern Turkey (see Table 1). Therefore, a method that makes use of textural features for coin recognition can only make use of the symbols present on the reverse of the coins. Since our goal is to design a system that detects and recognizes all coins that can be arbitrarily placed on a flat surface regardless of the side facing the camera, we aimed at determining the diameters of the coins and comparing them with the actual coin diameters. Since only geometric features are used for recognition, the proposed method works even in cases where the coins are partially occluded. Given that the textural features are not used, the proposed method is not useful for the detection of counterfeit coins.

2 The Proposed Coin Detection and Recognition Method

The proposed method concentrates on the geometric features of the coins to be detected rather than their textural features. The flow of the algorithm is presented briefly in Fig. 1. Since the difference between the diameters of different Turkish coins may be as small as 1 millimeter, the accuracy of the camera calibration will be critical (refer to Table 1). A small error in the diameter computation can easily lead to an incorrect classification. Therefore, it is important that the camera which the images are taken by is calibrated accurately.

When the application starts, the pose of the camera ($[\mathbf{R} \mid t]$) with respect to the plane where the coins will be placed is estimated. It is assumed that the intrinsic parameters of the camera have already been computed beforehand, and

Table 1. Turkish coins and their diameters [8].

Coin	1kr	5kr	10kr	25kr	50kr	1 TL
Diameter (mm)	16.5	17.5	18.5	20.5	23.85	26.15
Obverse (Heads)						
Reverse (Tails)						

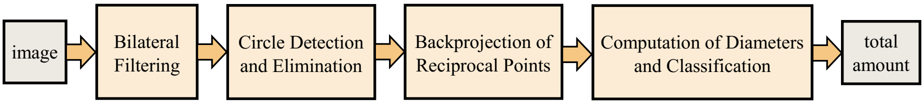


Fig. 1. The block diagram of the proposed method.

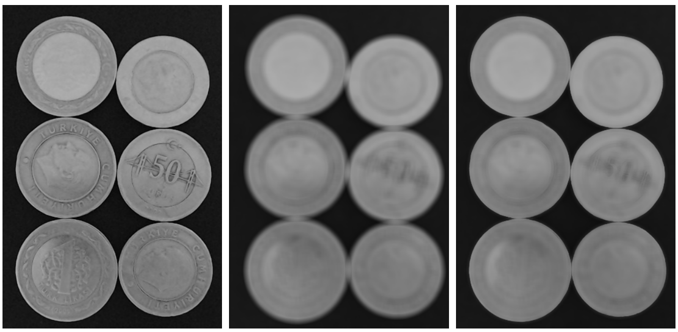
is available to the application. The pose computation is performed once at the start of the application using a marker pattern, and is not repeated every frame because the camera is fixed throughout the application.

2.1 Bilateral Filtering

The first step in processing a captured image is to apply a filter to remove noise and unwanted artifacts. The goal here is to remove, if possible, the small internal circles resident inside 50kr and 1 TL coins, and to also remove unwanted textural details engraved over some coins so that the following circle detection algorithm works more robustly. The traditional approach to perform this is to apply a Linear Gaussian Filter with a high standard deviation. Although this would remove the unwanted details present inside the coins, it would also deteriorate the actual edges of the coins; thus affecting the accuracy of the detected coin boundary and its diameter. Therefore, to remove unwanted details present over the coins while preserving edges, we use bilateral filtering [9]. Fig. 2 shows a test image and the results of applying linear Gaussian and bilateral filters respectively. It should be clear from Fig. 2.c that the result obtained by a bilateral filter contains less texture while preserving the coin edges better compared to the result obtained by a linear Gaussian filter in Fig. 2.b.

2.2 Circle Detection and Elimination

After bilateral filter is applied to the captured image, the filtered image is fed into the recently-proposed, real-time parameter-free circle detection algorithm,



(a) (b) (c)

Fig. 2. (a) Test image, (b) Image after linear Gaussian filtering, (c) Image after bilateral filtering.

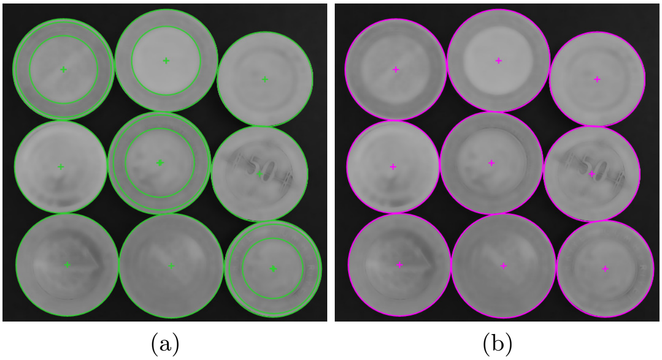


Fig. 3. (a) All detected circles, (b) Remaining circles after smaller concentric circles have been eliminated.

EDCircles [10], and a set of detected circles are obtained each in the form of center coordinates (x_m, y_m) and radii (r). Although bilateral filter removes most textural details from the coin surfaces, it is possible to detect inner circles, especially over 50kr and 1 TL coins since these coins consist of two different metallic parts having different colors. Additionally, it is possible to find double circles around the coin boundaries due to ridges, reliefs and shadows. Therefore, we go over the detected circles and eliminate the ones that have smaller radii among the set of concentric circles. Fig. 3.a shows all detected circles, and Fig. 3.b shows the remaining circles after elimination for a sample image.

2.3 Diameter Computation and Coin Classification

After the detection of the coin boundaries in the image and the computation of the coin center and radius, the next step is to compute the coordinates of this circle in the world coordinate system by means of the pre-computed camera pose. To perform this task, we compute $n = 2\pi/\alpha$ many reciprocal point pairs located over the circle's circumference as shown in Fig. 4, where α is the angular resolution of the points to be sampled. Then, for each point in the image coordinate system, its corresponding world coordinates are computed by back-projection using the camera pose $([\mathbf{R} \mid t])$ [11].

According to the pinhole camera model, the projection of point in the world coordinate system onto the image plane is performed by:

$$p_i = \mathbf{K}[\mathbf{R} \mid t]P_i \tag{1}$$

where P_i is a 3D point in the world coordinate system, and p_i is its projection onto the image coordinate system. To compute the real diameter of a coin, we need to compute the 3D coordinates of the reciprocal point pairs from the coin's boundary, and take the distance between them as the coin's diameter. For this purpose, we first compute the 3D coordinates of the camera center as follows:

$$P_k = -\mathbf{R}^{-1}t \tag{2}$$

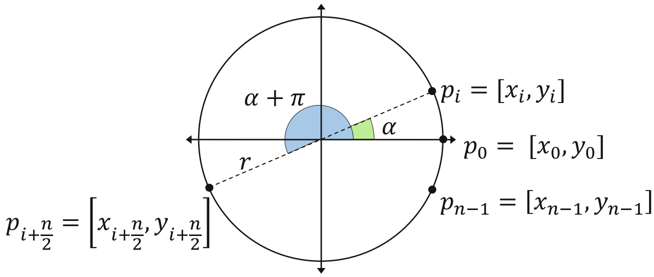


Fig. 4. Reciprocal point pairs used to estimate the diameter of a detected circle.

Then using the ray equation that originates from the camera center and passes through point p_i, the 3D point that maps to p_i is computed with respect to the depth (λ):

$$L(\lambda) = P_k + \lambda \mathbf{R}^{-1}\mathbf{K}^{-1}p_i \tag{3}$$

For a known depth Z, it is possible to find the X and Y coordinates in 3-dimensions by computing λ:

$$\lambda = \frac{Z - Z_{P_s}}{v_3} \tag{4}$$

where Z_{P_s} is the Z component of the scene camera center and $(v_1, v_2, v_3)^T = \mathbf{R}^{-1}\mathbf{K}^{-1}p_g$. For convention, the plane which the coins lie on is defined to be $Z = 0$.

As seen from Fig. 4, we compute, from the circumference of each circle, n p_i points using angular resolution $\alpha = 2\pi/n$, which corresponds to $n/2$ reciprocal point pairs:

$$\begin{aligned} x_i &= x_m + r\ cos(n\alpha) \\ y_i &= y_m + r\ sin(n\alpha) \end{aligned} \tag{5}$$

In the next step, all these points are back-projected to the world coordinate system and their 3D coordinates are computed. From each reciprocal pair of 3D points, a diameter is computed by taking the distance between the points. The final diameter of the coin is assumed to be the average of the computed diameters:

$$\bar{R} = \frac{2}{n}\sum_{i}^{\frac{n}{2}} \parallel P_i - P_{i+\frac{n}{2}} \parallel \tag{6}$$

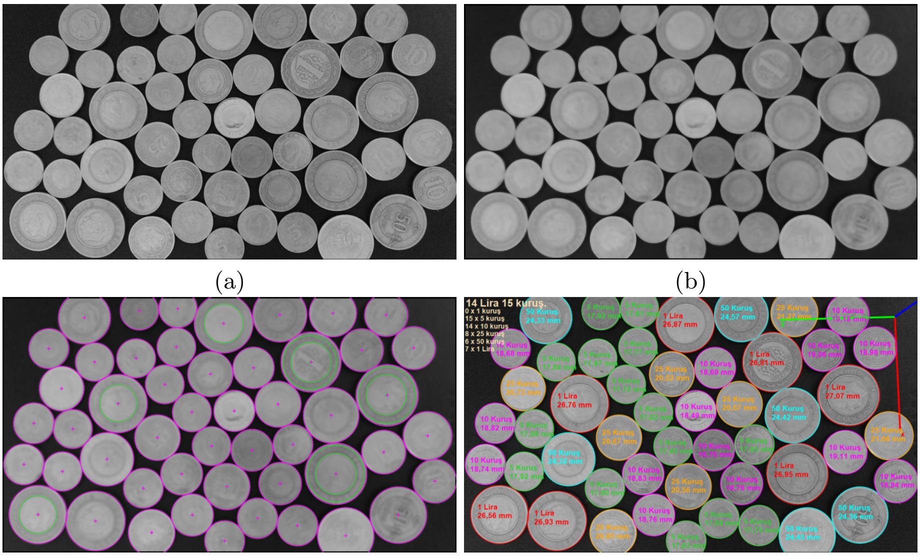
After the diameter of a coin is computed, it is compared with the real diameters of the Turkish coins given in Table 1, and the coin whose diameter is the closest is assumed to be the detection. Since the diameter difference between some coins is a mere millimeter, it is important that the computed diameter to be of high accuracy. To improve the system's performance and make it more robust, the number of reciprocal point pairs used to compute the coin's diameter may be increased.

Fig. 5. Experimental setup. The marker pattern used during initial camera calibration (left), the system in action (right).

3 Experimental Results

The experimental setup is shown in Fig. 5. A USB camera is attached to a tripod and is facing down a flat surface (a hardcover book in the figure) located at about 30 cm above the plane. We developed a vision application that receives real-time video feed from the camera at 1280×720 resolution.

We could not compare the proposed method with other state of the art methods, because our problem can not be defined as recognizing ancient coins [3,6] or classifying different coins individually [1,2,4,5]. Our method uses an



(a) (b) (c) (d)

Fig. 6. (a) Test image, (b) The resulting image after bilateral filter is applied. (c) All detected circles are marked in green, the circles remaining after elimination are marked in pink. (d) Classified and marked coins.

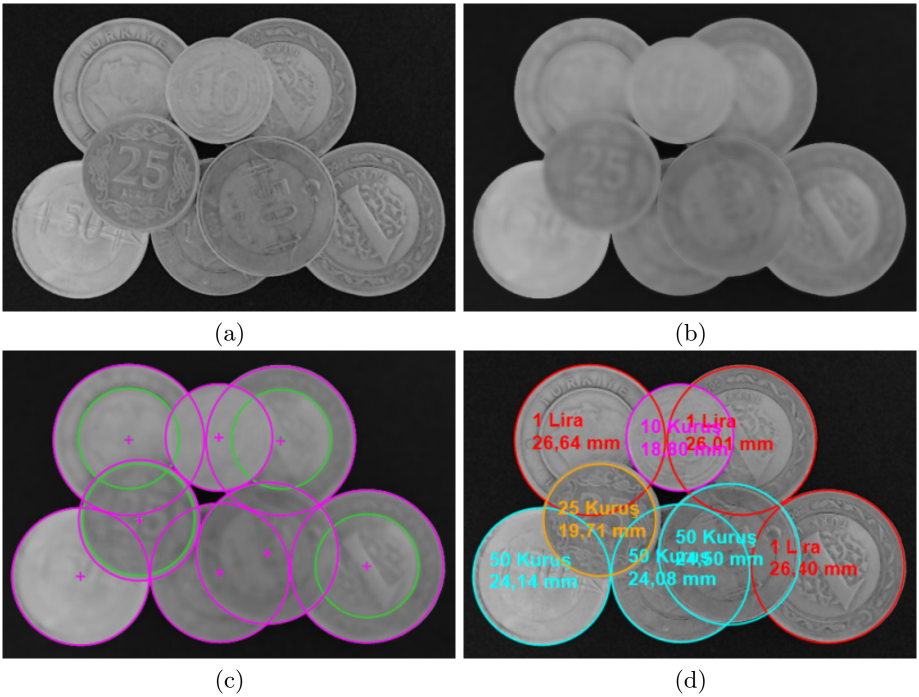


Fig. 7. (a) An image with partially occluded coins, (b) the image after bilateral filtering, (c) detected (green) and selected (pink) circles, (d) marked coins after classification.

image with multiple coins and results in a set of classificaitons, which can also be interpreted as a total amount of money.

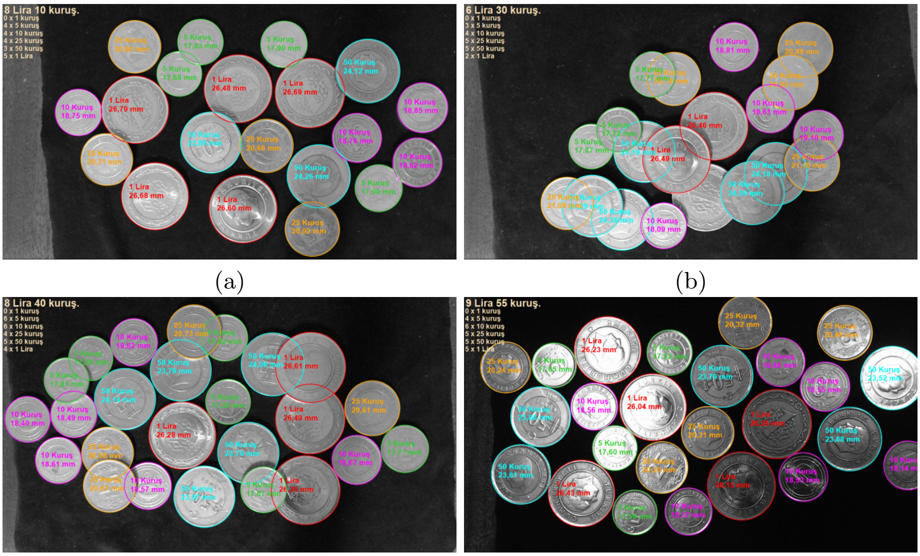
Fig. 6 shows the performance of the proposed method for an image containing a certain number of coins placed arbitrarily over the plane. It is notable that although some coins are only partially visible in the image, they are still correctly detected and classified.

Fig. 7 shows a more complex scenario where the coins are stacked on top of each other with the coins at the top occluding a significant portion of the coins at the bottom. Even in this though test case, all coins have been correctly detected and classified. The two factors that influence the success of the proposed method the most are the employed circle detection algorithm [10], and the accurate external calibration of the camera. A demo video that shows how the system operates can be found in [12]. To measure the overall performance of the proposed method, we created a dataset consisting of 50 images each containing different combinations of 1 TL, 50kr, 25kr, 10kr and 5kr Turkish coins. The number of coins in each image is either 5, 10, 15, 20 or 25. The coins are placed on the plane to create many different scenarios ranging from simple no occlusion cases to severe occlusion cases, where some coins are placed on top the others partially blocking the coins placed at the bottom.

Table 2. Confusion matrix of the proposed method on the dataset.

Coin	No. Coins	Missed	1 TL	50kr	25kr	10kr	5kr
1 TL	145	1	142	2	0	0	0
50kr	155	1	0	154	0	0	0
25kr	150	1	0	0	149	0	0
10kr	150	3	0	0	0	143	4
5kr	150	0	0	0	0	3	147

Table 2 shows the performance of the proposed method on the 50 image dataset. Of the 750 total coins present in the 50 images, 735 of them are detected and classified correctly, with an accuracy rate of 98%. 6 coins are totally missed with no detection. Specifically, one 1 TL, one 50kr, one 25kr and three 10kr are not detected at all. Missed detections are due to severe occlusions, where several coins are placed on top of each other. As also seen from Table 2, there are some false detections and classifications. For example, two 1 TL coins are detected as 50kr coins. This is due to the inner ring present on 1 TL coins. In rare occasions, when the outer ring of 1 TL coin is not detected, the inner ring is detected and classified as 50kr. The other common false detection occurs due to similarity between 5kr and 10kr coins. Since the diameter difference between these coins is just 1 millimeter, in the case of occlusions or imperfect detection of the coin boundary due to lighting conditions, it is possible to classify 5kr as 10kr, and



(a) (b) (c) (d)

Fig. 8. Experimental results under various conditions.

Table 3. Dissection of the running times of the proposed method in different steps on an image with 1280×720 resolution.

Algorithm Step	**Running Time**
External Calibration(performed only once)	57 ms
Bilateral Filtering (9×9 kernel)	307 ms
Circle Detection & Elimination (EDCircles [10])	30 ms
Classification by Diameter Computation	21 ms
Total	**358 (+57) ms**

vice versa. As seen from Table 2, four 10kr are classified as 5kr, and three 5kr are classified as 10kr. See Fig. 8 for results with additional test images.

The dissection of the running time of the proposed method in different stages for an image of size 1280×720 pixels on a 3.70 GHz computer is given in Table 3. As seen from the table, bilateral filtering is the part that takes the most amount of time. If we use linear Gaussian filter instead of the bilateral filter, then the filtering time goes down to about 10 ms, but the robustness of the system decreases. But even with bilateral filtering, the method takes about 350 ms in total, and can thus run at 3 frames per second.

4 Conclusions

We present a system that reliably detects and classifies Turkish coins in images captured by a calibrated camera. The proposed system differs from the systems found in the literature in that it only makes use of geometric features of the coins, disregarding their textural features. It works even in presence of partial occlusions, since the method does not make use of the texture information as other methods in the literature. Experiments show that the proposed method is sensitive to lighting conditions, as the shadows around the coin boundaries create difficulties in coin detection and contour localization.

We plan to extend this work by incorporating a texture based classification step. The coins classified using the textural information can then be used to estimate the pose of the camera, thus removing the need for the pre-calibration step proposed in this paper. Once the pose is estimated using the coins classified using textural information, the rest of the coins on the scene can be classified using the approach proposed in this paper. The resulting system will be able to work under arbitrary camera poses.

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