# Chessboard recognition system using signature, principal component analysis and color information

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# Chessboard Recognition System Using Signature, Principal Component Analysis and Color Information

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*Abstract*—**T This paper aims to implement a computer vision technique to translate an image into a description that can be read by computer programs to make decisions. The proposed system is applied to chessboard with a set of objects (pieces), and outputs the pieces names, locations, in addition to the pieces' colors. The signature feature has been used to distinguish the pieces types but when the signature comes to grief, the PCA (Principal Components Analysis) is used, and then the object color is obtained. The proposed system was trained and tested using Matlab, based on a set of collected samples using chessboard images. The simulation results show the effectiveness of the proposed method to recognize the pieces locations, types, and colors.**

***Keywords - Chess, Computer Vision, Signature Feature, PCA, Euclidean Distance.***

## I. INTRODUCTION

A picture is worth a thousand words, that is for human beings; the same thing can be said for machines, but machines need more than this, that of conversion of the pictures into a machine readable format by extracting features to discriminate and recognize objects, which is accomplished by comparing these features with a previously stored and known features of different objects.

There are many applications of object recognition systems, such as in the industry and assembly lines, robotics, object clustering, object tracking, face recognition and game playing [1,2,12]. All of these applications require a computer vision programs able to recognize different kinds of objects, for example as in [2,10,11], a computer vision is needed for robotics to automatically determine arbitrary chessboard location and identify chess pieces. A Chinese chessboard is reconstructed in [4] based on binarized Gabor filter and Hough transform; while in this work, only the signature feature is used and for some conditions a PCA (Principal Components Analysis) can be used to build a recognition system that is both computationally efficient and highly accurate.

The input to the system consists of a 2-D chessboard images, each image contains a set of objects (chess pieces); these pieces are arranged over the chessboard in different locations. In a chess game there are two opponents each of the opponents have a set of pieces that differ from the pieces of the other opponent only in color, here we have white and black pieces; the chessboard itself is a board that is divided into 8×8 squares (blocks), so we have 8 rows and 8 columns, the rows are numbered with decimal numbers 1,2,3,…,8 and the columns are labeled with alphabetical characters A,B,C, …,H, the squares are colored with two colors as a background for the board, each square is colored with a color that differ from the color of its adjacent, and with the same color of the square on its diagonal.

In this work a system that is capable of describing the type, the location, and the color of the pieces in the chessboard have been designed and built.

In this paper the operation of the recognition system will be described; including the description of the system architecture in Section II. The extracted features and the PCA method will be shown in Section III and Section IV respectively; in addition, these sections show how the system has been trained. Section V presents a method to determine the objects colors based on a threshold obtained from the set of samples. Finally, Section VI shows an experimental results and the discussion.

## II. SYSTEM ARCHITECTURE

The general block diagram that describes the operation of the online system is shown in Fig. (1), as it can be seen the input to the system is a chessboard image, and the output is a description of the chessboard's pieces, this description includes pieces' locations, pieces' types, and their colors.

The first step is image preprocessing, in this stage the undesired border have been removed and the image was resized, then, the image converted from RGB to gray scale image then to binary image. After that, the morphological operations like opening operation have been applied to make the image clear and remove the noises. Finally, in this step, each block is obtained (square in the chessboard).

In the second step, the features were extracted for all the objects that have been obtained from the previous stage, and then saved as a .mat file for future using.

In the third step, the gotten features are compared with the features of the objects that have been saved before. In order to do that, the Euclidean distances between the saved features and

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the obtained features have been calculated and used to decide whether the object is recognized or not.

Finally, in the fourth step, the system classifies the objects and put a description including piece location, piece type, and piece color. The details of the system can be seen in the flow chart depicted in Fig. (3), this flow chart shows a step by step execution of recognition system program.

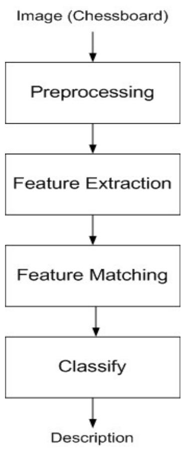


Fig 1: A general block diagram of the system.

## III. SIGNATURE FEATURE

In order to discriminate chessboard objects, good features or a set of features are needed. The signature feature was one of the most powerful features used for chessboard recognition system, it can be used alone to recognize the chessmen (chess pieces).

The signature is a one-dimensional function, that can be extracted by various ways, we have used a plot of the distance from the centroid to the boundary of the object as a function of angle [3]; this reduces the dimensionality of the boundary from 2-D to an easy 1-D signature function.

The signature feature is size variant and depends on scaling, so; the signature have been normalized by dividing the signature by its maximum value, then, the spline have been computed for the normalized signature, the spline is a built-in Matlab function that performs interpolation on rows of the input matrix and returns the piecewise polynomial form of the cubic spline interpolation. The reason of using spline function is to simplify getting the signature points from the polynomial function.

There is no need to obtain all the points of the signature, so, a point every 15 degrees only was obtained, yielding 23 points due to ignoring 0 and 360 degree points. These points were saved for each object as a feature that will be used in the following steps for recognition and matching.

For each block of the chessboard, it is checked whether contains a piece or not (i.e. noise), then for each piece, the signature is gotten. For example, the signature for the black pawn is as seen in Fig. (2)

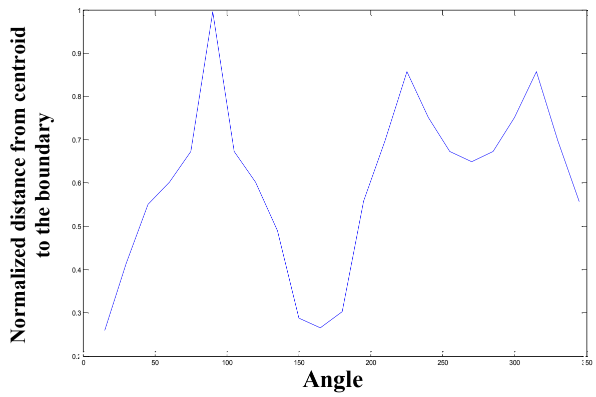


Fig 2: The signature for black pawn object.

## IV. PRINCIPAL COMPONENT ANALYSIS - PCA

When the signature comes to grief, the PCA (Principal Component Analysis) [7,8] is used; in this case PCA is considered as a replacement for the signature feature when it fails in recognizing the object with a high percentage of accuracy.

PCA involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components [5, 6]. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

PCA is the simplest of the true eigenvector-based multivariate analyses [6, 9, 12]. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA supplies the user with a lower-dimensional picture, a "shadow" of this object when viewed from its most informative viewpoint.

PCA Analysis has been used to determine the most discriminating features between images of components. To make PCA analysis, the system have been trained for 65 sample components, these components are collected from all the samples, then, the extracted Eigen values have been stored, the mean image of the training database, and the matrix of centered image vectors; as features in a (.mat) file; this was done, because we don't need to recomputed these features every time the system is run.

## V. OBJECT COLOR

After the object type is recognized by the signature feature or PCA, its color needs to be determined. Since the chessboard has only two colors namely black and white, it is easy to propose a technique to deal with this issue; the proposed technique is to compute the number of zeros and ones in each block in the chessboard. This process is viable due to the fact



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that the chessboard is already converted to binary image. The process of binarization is accomplished by obtaining the original RGB colored chessboard, then cutting the boarders and converting the board into gray scale image then into a binary resized image with a threshold of 25%, then the image was cropped into 64 blocks where each block represents a square of the chessboard.

By computing the number of 1's (white) and the number of 0's (black) as follows:

$$white = \sum_{r,c \in R} 1 \qquad (1)$$

$$black = \sum_{r,c \in R} 0 \qquad (2)$$

Where r and c are the rows and columns of image R, respectively.

A relation can be found to distinguish the color of the objects; the relation simply is the percentage of white pixels and the black pixels in each block f:

$$f = \frac{\#\text{ of white pixels}}{\#\text{ of black pixels}} \qquad (3)$$

This operation was calculated for all objects from all the training samples that were processed, and the following thresholds were concluded by observing the cutting edges between the black and the white objects.

$0 < f \leqslant 2.65$ the object is black,

$2.65 < f \leqslant 25$ the object is white,

$f > 25$ the object is noise (empty block),

$f < 0$ the object is noise.

Rather than obtaining the color of the object; this function can distinguish a noisy object (i.e. a block without chess piece), since, some samples are not clear enough from the preprocessing stage, and there still some noise from the heavy background samples, these blocks are misclassified, but when the color percentage were compared, it can be found that this percentage is high, because the major part of the block is white and there is some black lines and dots, so these blocks are ignored and considered as a noise.

In this system, the signature percent is matched firstly, if the signature percent > 1.02 we decided to use the PCA analysis feature because it is more accurate. See fig (3).

## VI. EXPERIMENTAL RESULTS & DISCUSSION

The proposed algorithm has been applied on many different images, for the sake of clarification; the result of one sample image is shown in a different stage of the system. First of all, the RGB image was read as seen in Fig. (4).

Then, the image is cropped to get the board, after that, it converted to gray level as shown in Fig. (5).

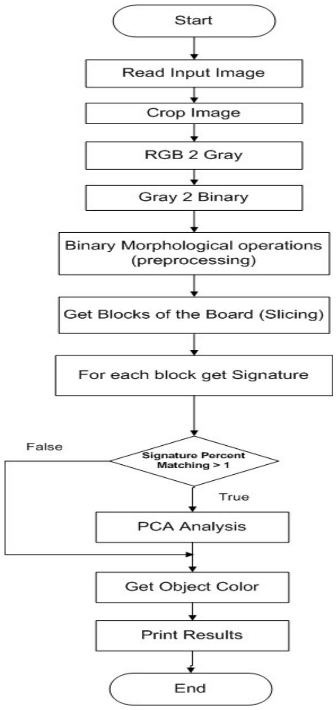


Fig 3 : Chessboard recognition system flow chart.

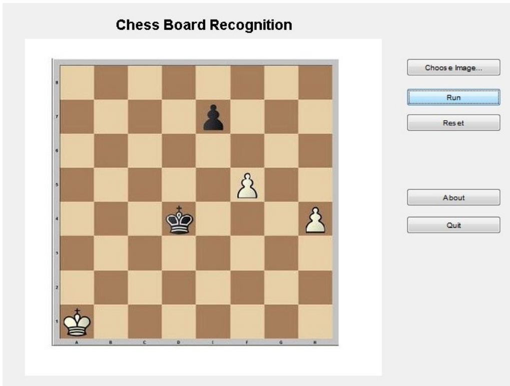


Fig 4 : The input RGB image.

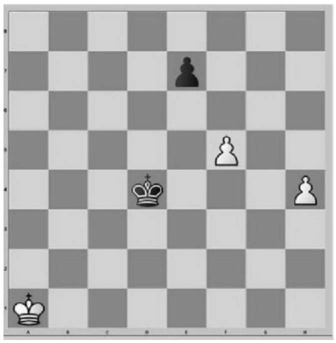

Fig 5 : The gray level of the input image.

Next, the gray level image was converted to a binary image; some preprocessing like opening operation was done. The result image is as seen in Fig. (6).



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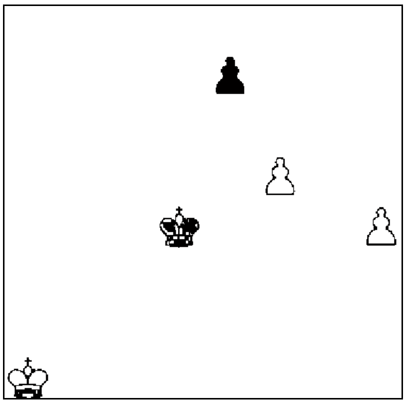

Fig 6 : The binary image.

Then, the board sliced into 64 blocks as shown in Fig. (7).

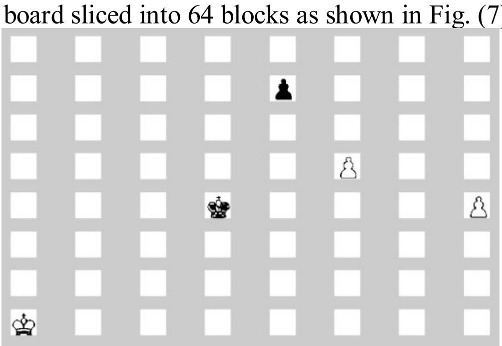

Fig 7: Slicing the board into 64 blocks.

For each block, we have checked whether it contains a piece or not (noise), then for each component the signature was gotten. Then, the Euclidean distance has been computed between this signature and the stored signatures for all the elements, and the minimum Euclidean distance was gotten which means the best match.

If the minimum Euclidean distance exceeds a predetermined percentage (which is determined by trial in the previous section) then PCA analysis is used in the matching process as an alternative. As we have described; to make PCA analysis, the system has been trained for 65 sample components, and the extracted Eigen images have been stored as features. The training set is shown in Fig. (8).

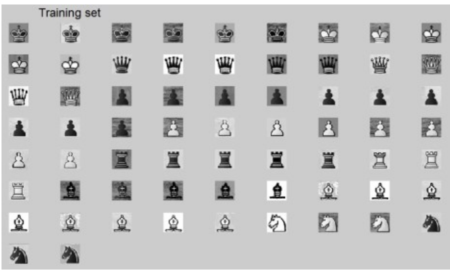


Fig 8: The training set of the PCA analysis.

The Eigen images are shown in Fig. (9).

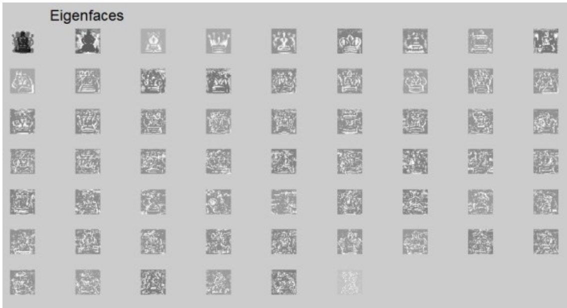


Fig 9: The Eigen images of the PCA analysis.

And finally the resulted mean image is shown in Fig. (10).

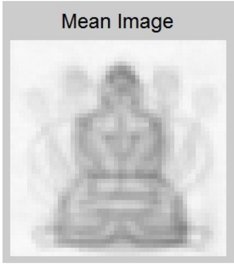


Fig 10: The mean image of the PCA analysis.

The input block image has been projected against the Eigen faces and the system reconstruct an image as shown in Fig.(11); this images is then used to recognize the object of the input image using the Euclidean distance between the reconstructed image and the saved known objects.

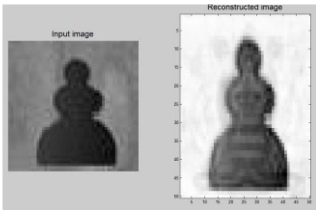


Fig 11: The input image (left) and the reconstructed image (right).

The block location is determined based on the index of the block in the blocks matrix that we have used. See fig (12) which shows an example of results.


Fig 12: The result for the taken input sample. See fig (4).

A testing set has been collected; which contains 107 samples; each sample is one of the expected objects listed in table (1), the system performance results show that the system recognized 101 samples correctly with an overall percentage of 94.4%.



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The results in table (1) show the type of the error for each sample. The errors resulted from the color algorithm is because of the usage of the threshold technique described in previous section. The errors resulted from the type method is often caused by noisy images of the knight and the white queen blocks. Finally, the signature technique comes to grief in 45 samples with a percentage of 42.1% of the overall samples.

Table 1: System performance results of 107 samples.

| Object | Correctly recognized samples / total samples | Percentage % | Type of error |
|---|---|---|---|
| Black King | 7/7 | 100 | - |
| White King | 6/6 | 100 | - |
| Black Knight | 10/11 | 90.9 | type |
| White Knight | 9/11 | 81.8 | color, type |
| Black Bishop | 9/9 | 100 | - |
| White Bishop | 9/10 | 90 | color |
| Black Queen | 7/7 | 100 | - |
| White Queen | 8/9 | 88.9 | type |
| Black Pawn | 12/12 | 100 | - |
| White Pawn | 10/10 | 100 | - |
| Black Rook | 7/7 | 100 | - |
| White Rook | 7/8 | 87.5 | color |
| Overall | 101/107 | 94.4 | 3 in color and 3 in type |

## VII. CONCLUSION

In this work a system has been implemented to recognize a set of objects from an image, as in any computer vision system the input is an image and the output is a description. This system can recognize multiple objects based on the features extracted for each component. The simulation results give a satisfactory accuracy but with few errors. The errors can be eliminated by adding more discrimination features, the errors of the color algorithm can be eliminated by usage of the HSI (Hue, Saturation, Intensity) system.

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