Tensor Voting, Hough Transform and SVM Integrated In Chess Playing Robot

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ABSTRACT
Robot which replaces and assumes the role of the human is becoming a common and popular problem. Also, game playing robot has challenges to researchers as well as people being interested in this field. In this paper, we want to introduce a new method to detect and recognize chess pieces of Janggi Chess game. Paper is a uniform approach from input image receiving to chess piece recognition. Besides, some new algorithms are used to get the highest performance of system and can apply for real robot system. The first, Tensor Voting is applied to find four corners of chessboard which can extract the full chessboard from background and noise for both simple and complex cases, which other methods are difficult to overcome. Secondly, Circle Hough Transform can detect the chess pieces' size and position correctly regardless of the effects of light, capture angle, the quality of images, etc. Furthermore, the piece recognition step is implemented using SVM (Support Vector Machine), a popular algorithm for classifying with highest performance. The promising results have confirmed the effectiveness of the proposed method.

Categories and Subject Descriptors
I.5.2 [Computing Methodologies]: Pattern Recognition – Design Methodology

General Terms
Algorithms.

Keywords
Tensor Voting, Chessboard Extraction, Piece Detection, Piece Recognition.

1. INTRODUCTION
Robot System is more popular and applied in many areas of normal life. In which, Chess Playing Robot is a system that can replace the role of human to play chess. Therefore, this system needs to have perception and behavior about all states of chess board like human. To do this, Chess playing Robot not only does need to analysis and gather information and calculate for each state of chess board, each step that pieces on the board change the position, but this system also has to remove all corruptions (noise, hand, light) that can exist in the images that it captures before processing these.

For many years, there are many researches about this system but almost researches focus on a part of this system such as piece detection [1-8] and there exist constraints and conditions to achieve high accuracy (no include noise, distort) beside, all methods applied on western chessboards or do not consider the pieces, which chess pieces are located inside squares and do not touch on the border of squares, moreover with Chinese and Janggi chessboard, the corners are occluded by pieces, so all method based on x-corner are not appropriate, and if pieces locate on a wrong position, all method based on line are not good, or piece recognition [14] using distance between center of pieces with contours for 360 degree but if the input images are affected by light (images include faded chess pieces) and with the effects of rotation and the size of pieces, the performance of piece recognition is not high as aspect.

To resolve problems on this system comprehensively: image processing module for detecting the board and localizing pieces, pattern recognition module for recognizing the piece type, and approach all requirements as close as possible we use some algorithms together and process step by step to extract the chess board from input images (include noise, distort), transform it to locate the pieces' position with the most accuracy, determine which positions on the chess board exist pieces, which ones do not then recognizing them into two groups and seven classes for each group.

To achieve the chess board from input images (images which camera assigned into Robot system captures from chess board in fact), our proposed method extracts the border of the chess board by determining four corners of it with Tensor Voting – a popular method for locating junctions, edges . This is one of the difficult steps of system because the degree of accuracy depends on the way we remove the background and noise from original images, include both simply and complex cases. Besides, we also confirm that we remove all information inside the chess board shape, only the border of chess board is remained before we determine the position for four corners of it. With four-corner being determined, we cannot only reconstruct a full chessboard fast and accuracy, but we can also be easy to eliminate cases of wrong piece position detection (outside of chessboard). Once we have four corners of chess board, the deformation of image to achieve the complete chess board will be easy by using homography transformation. The detection of pieces on the board will be implemented with high accuracy with circle hough detection because in image, we achieve only chess board with no background and any noise. The final stage is to recognize pieces. In fact, pieces on the chess board can rotate; change the size due to the way people hold them

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and the different positions of camera. Besides, these pieces are also sharp or fade due to the effect of light, capture angle and the quality of image. So we cannot use mapping method [14] to recognize. In our proposed method, we extract feature of pieces then using SVM for training and recognition with a large sample of database. By practicing, we achieve recognition results from input images with much better performance than previous methods and more detail will be described next sections.

The rest of paper is organized as follows, in section 2, we present all related works about chess playing robot. Section 3 describes our proposed methods in details. All experiments we achieve after using our proposed method will be found out in Section 4. Section 5 draws out the conclusion and future researches.

2. RELATED WORKS

There are many earlier approaches to detect and recognize pieces from chess board images captured from the camera but they are separate approaches , focus on a particular part of the chess playing robot system such as pieces detection or pieces recognition. We can divide the methods for board detection into two categories: corner based and line-based detection. X corner-base detection [1-5] using SUSAN or Harris corner detection with post processing steps to find out all x shaped corner in the input images and remove fake corners and Line-base detection [6-8] using intersection between lines to find out the corner points). But both of methods exist problems and inaccuracy in some cases when the input images includes noise, distort and when chess pieces overlay on the corners on the board, the former will be fail, when chess pieces cover a line on the board, the latter will be fail. Moreover, all methods are applied for western chessboard which chess pieces are located inside of squares on the board, so if applying these methods for Chinese and Janggi chess which chess pieces are located on the corner of lines on the board, the formers are not appropriate. A part of this system is piece recognition, [14] using mapping method for graph of distance between center of piece's letter with the contours of it, this method can be achieve a good result if all pieces have the same size, same resolution, letter of pieces are intact after processing, vice versa, the map is difficult for recognition, and [2] mentioned but not clearly.

In our proposed method, we introduce all steps from receiving an input image to recognize pieces on the board to belong which class. The first we use Tensor Voting to find out four corner of the board based on the junction detection of Tensor Voting, after that, Homography Transform and Circle Hough Transform use to determine piece position, SVM learns training data and recognize piece. With the above methods and some noise removing procedures, our proposed method can be eliminated all issues mentioned above and can be applied idea for all type of chessboard. Moreover, the system entire processing (detect, recognition) create the unity of data and processing method, reduce the time for map data if using separate stage together.

3. PROPOSED METHOD

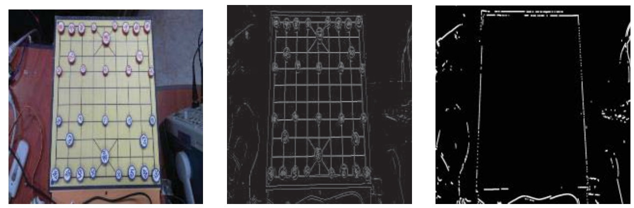
3.1 Determine Four Corners of Chess Board

The target of this stage is to specify the border of chessboard with the information of four corners from an input image. That we determine the borders of chessboard helps us extract completely only the chess board image, we can remove all background as well as noise, unfavorable information. This step is very important because this will decide the accuracy level of the rest step. If this step is good, piece detection and piece recognition steps will be interacted with only the chess board, they are not affected by noise and some other information.

To segment the border of chessboard, there are some main steps: raw border extraction, noise removal, tensor voting, and four-corner determination.

Raw border extraction

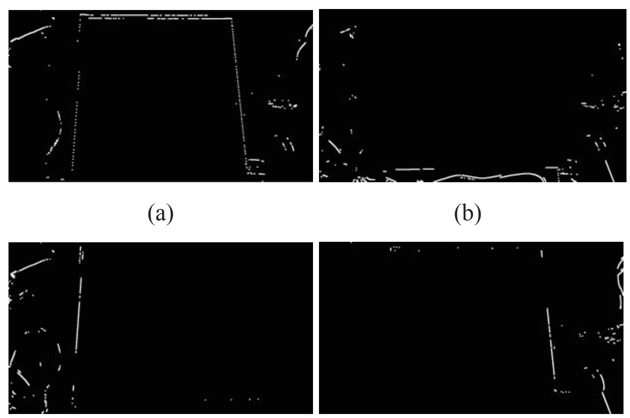
Raw border is an incomplete border and also includes noise, background. This border is extracted from binary image which is result of Sobel edge detectors by scan four sides of image from border of image to the first pixel met.



(a) (b) (c)

Figure 1. Sobel edge detector and extract raw border for a Janggi chessboard (a) original image (b) Sobel edge detector (c) raw border extracted from (b).

To achieve the raw border in Fig.1c from a binary image, a scan and remove procedure is applied on the binary image with four sides (up, down, left, right). We suggest that the size of image is(h, w), we will scan binary image in turn to get four side images:



(a) (b)

(c) (d)

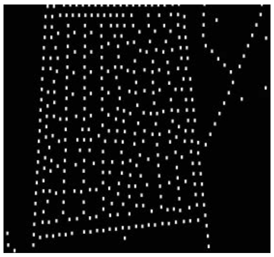
Figure 2. The raw border of four side of binary image (a) up side (b) down side (c) left side (d) right side.

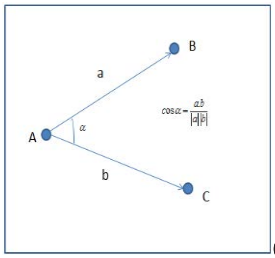
After extracting raw border, it is clear that we need to remove noise to get only border of chessboard. This step is called noise removal.

Noise Removal

As we can see, in the binary image, there are some features that can help us remove noise being separate lines and curves. The first feature is that chessboard object includes parallel lines and they are far apart a fixed interval, the second feature is that background and noise are separate lines and curves. Based on these feature, we propose a method to eliminate insignificant information by using the angle between pixels in sampled image.

The first, we will sample binary image with distance between pixels δ and this distance need to less than distance between lines in the chessboard. Then scanning entire sampled image, each pixel have value equal 1 will be interested in, we will find out its neighbors so that these neighbors belong to a circle with radian doubling δ (to ensure the neighbors of pixel belong to chessboard is more than 3 pixels). With pixels belong to background or noise, the number of neighbors will be less than or equal 3 pixels, the angle between 3 pixel will be calculated and remove all pixel with the number of neighbors being less than 3 pixels or equal 3 but angle is larger than 120 degree.


(a)



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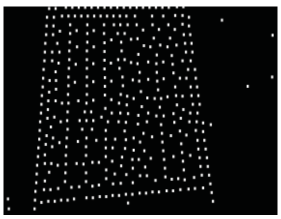
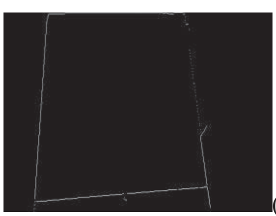

(c)

Figure 3. Remove noise and background from binary image (a) sampled image with distance δ (b) angle between three points (c) noise removed image

After achieving a raw border image and a noise removed sampled image, we combine two images to get only border of chessboard (Fig.4a). If we apply Hough circle detection algorithm on this image to find out lines, the results will be difficult for next processing, there are many virtual lines being insignificant and specially, we cannot extract four lines to create the border of chessboard.


(a)

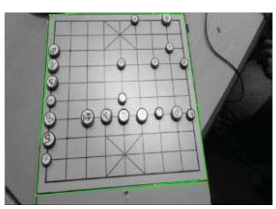

(b)

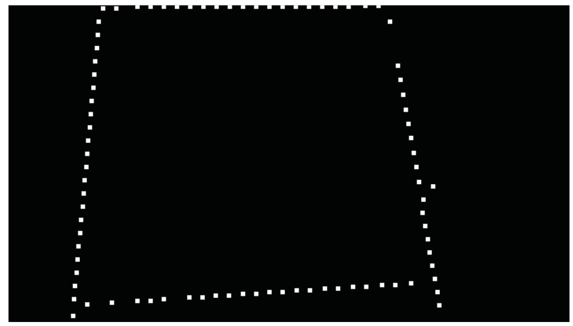
Figure 4. The border of the chessboard after remove noise (a) and the lines detect using Hough Circle Detection.

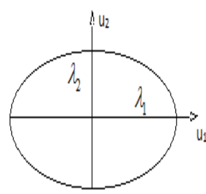
So there is a method to resolve this problem. As can be known, Tensor Voting is a method used for detect junction and edge very well thank to the voting process encoding data into tensor [15][16][17], voting according to the direction and information. After voting process, structure of data express very clearly then it is easy to find out four junctions corresponding to four corners of chessboard.

To simply and save time, we sample the border of chessboard image (Fig.5a) before applying Tensor Voting method. Each pixel with value being equal 1 will be encode into second order tensor (ball tensor)

The tensor voting process will be implemented for each feature vector (tensor) with the value sigma (δ) presenting the region that voter can vote to votee. Fig. 5a shows a tensor voting process from voter O to votee P, the region that P can receive vote information from O depend on the inscribed circle with center C determined by the value of sigma:

$$c = \frac{-16\log(0.1)x(\sigma-1)}{\pi^2} \tag{1}$$


(a)



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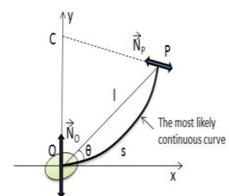


(c)

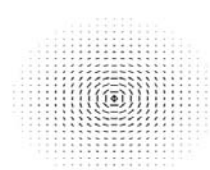
Figure 5. The sampled border image (1) tensor components (b) and voting process (c)

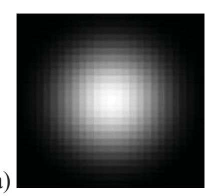
The sigma is the factor to measure the degree of smoothness, with a smaller value, the number of voting neighbors is small, fewer votes and inverse, this value can control the ability for remove noise form image.

Information that P catch from O is calculated by following formula:

$$DK(s,\kappa,\sigma) = e^{-(\frac{s^2 + c\kappa^2}{\sigma^2})} \tag{2}$$

The voting field applies for each tensor (each pixel in the border image Fig.6a):


(a)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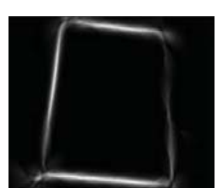
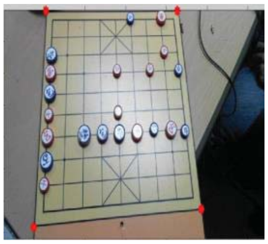

(c)


(d)

Figure 6. The voting field of ball tensor (a) (b), the edge after voting (curve saliency) (c) and Junction Saliency (d)

As can be seen in Fig.6d, after voting, that the positions are the intersection of two lines express very clearly and with the algorithm to find out extreme locations we can be easy to retrieve the position of four corners in the Fig.7


(a)

(b)

Figure 7. The original image after finding out four corners of chessboard, the position of four corners (a) and add lines connect four corners (b).

3.2 Homography Transform and Pieces Detections

With the information of four corners that we have achieved from Tensor Voting, in this stage, we base on the position of four corners to transform image and get the completely image of chessboard (there only includes the chessboard, all background and noise are out now). Next step is to discover whether which position on the chessboard has pieces existing.

The first step, we achieve the complete chessboard image using Homography Transform. A homography is an invertible transformation from a projective space to itself that maps straight lines to straight lines. Synonyms are co-lineation, projective transformation, and projection, though "co-lineation" is also used more generally. In the complex plane, a Mobius transformation is frequently called a homography. These linear-fractional transformations are expressions of projective transformations on the complex projective line, an extension of the complex plane. In higher dimensions Homogeneous coordinates are used to represent projective transformations by means of matrix multiplications. With Cartesian coordinates matrix multiplication cannot perform the division required for perspective projection. In other words, with Cartesian coordinates a perspective projection is a non-linear transformation

Given:

$$p_a = \begin{bmatrix} x_a \\ y_a \\ 1 \end{bmatrix}, p_b^{'} = \begin{bmatrix} \mathrm{w}^{'} x_b \\ \mathrm{w}^{'} y_b \\ w^{'} \end{bmatrix}, H_{ab} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \quad (3)$$

Then:

$$p_b^{'} = H_{ab} p_a \quad (4)$$

where

$$H_{ab} = H_{ab}^{-1} \quad (5)$$

Also:

$$p_b = p_b^{'} / \mathrm{w}^{'} = \begin{bmatrix} x_b \\ y_b \\ 1 \end{bmatrix} \quad (6)$$

So after applying original image and the information of four corners of chessboard, comprehensive chessboard image is reconstructed (Fig.8a).

Circle Hough Transform

This algorithm is used to determine the position on the chessboard that pieces exist. By extracting only chessboard in the previous stage, the application of this algorithm is not affected by noise, background so the result will be better than others. This technique is similar to the standard Hough transform, after an image is transform into hough transform, the parameters which define the circles will be applied to extract circle in this image.

A circle can be described completely with three pieces of information: the centre (a, b) and the radius. (The centre consists of two parts, hence a total of three)

$$x = a + R\cos\theta$$
$$y = b + R\sin\theta \quad (7)$$

When the θ varies from 0 to 360, a complete circle of radius R is generated.

So with the Circle Hough Transform, we expect to find triplets of (x, y, R) that are highly probably circles in the image.

Every point in the xy space will be equivalent to a circle in the ab space (R isn't a parameter, we already know it). This is because on rearranging the equations, we get:

$$a = x1 - R\cos\theta$$
$$b = y1 - R\sin\theta \quad (8)$$

For a particular point $(x1, y1)$. And θ sweeps from 0 to 360 degrees.R will be passed into this algorithm so that all size of pieces can be detected by it.

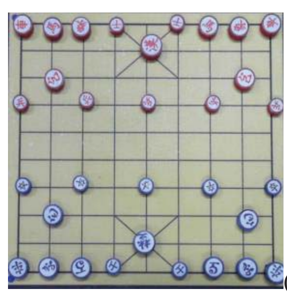
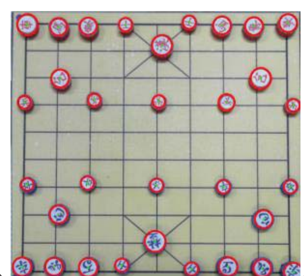

(a)

(b)

Figure 8. The full chessboard extract from original image using Homography Transform based on the four corners from previous step (a) and the chessboard with pieces detected based on the Circle Hough Transform (b).

3.3 Extract Pieces' Features and Recognition

Correct piece recognition is the most important task of Chess playing robot system. All above steps and methods are implemented to serve for this step to recognize chess pieces completely and accuracy. With this system, although there are many steps and complex processing methods but the evaluation belongs to this stage, so if these above steps are good but this step is not very good, all system will be not appreciated. As can be mentioned in [14], the piece recognition was implemented by using mapping the graph of 360 distance between center to the contour of piece's letter, but this does not get the good result if the pieces achieved have difference size, not intact letter, shaded letter and in [2] is not clear and cannot apply for all cases and specially, for Chinese and Janggi chessboard. So in this paper, we introduce a method using SVM for training data to learn and recognize. Thank to the large training data collected from a lot of chessboards in fact and there takes care of all special case (shaded pieces, noise, not intact) and some intermediate processing steps, the achieved recognition result is very good and corrects in almost case.

Extract Pieces' Features

Based on the result of the piece detection, we storage the position of pieces on the chessboard with their radius to extract pieces image with the standard size 100x100. Because of normalization and the pieces have size very small on the original image, we sharp these images (Fig.9 (a1-e1)) before using Canny to detect edges (Fig.9 (a2-e2)). The scale parameter we put into the Canny algorithm need to ensure that all segments of piece's letter are intact (by experience, the value of 0.14 satisfies). To achieve only letter of pieces (remove all noise and circle around letter), we remove all pixel having value of 1 that gather into arcs with radius from 35 to 40, then using the connected object detection method in binary image to remove all redundant characters. After all above step, we collect letter image 100x100 including only letter (Fig.9 (a3-e3)).

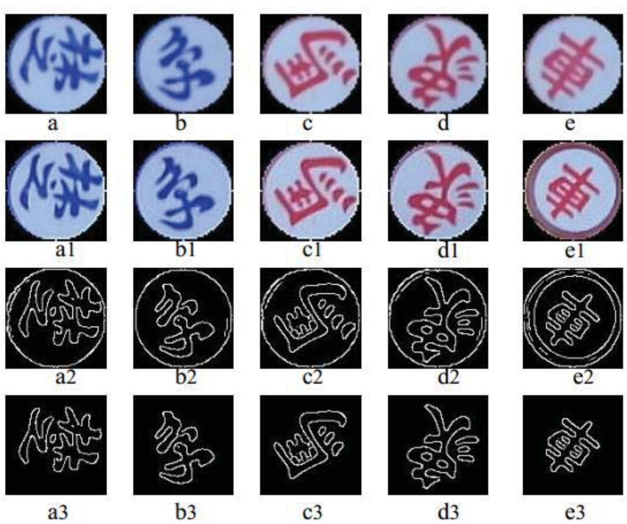


Figure 9. Original pieces which are extracted from the chessboard (a-e), Un-sharp piece images see clearly (a1-e1),binary image of these piece using Canny (a2-e2) and piece images after removing all backgrounds (a3 – e3).

With the separate letter images achieved above, the distances between the center and the contour of them are calculated to create feature vectors of the letters. In details, as can be seen in the Fig. 10, each letter is divided into 360 small parts corresponding to 360 degrees of a circle. So, 360 distances from the center of letter and the contour of 360 small parts are considered as a feature vector of that letter. Moreover, to increase the robustness of the proposed method, each letter is scaled in the range of [0, 100] to get a set of feature vectors to use as training data.

Recognition

Support vector machines [18] (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, a SVM training algorithm builds a model that assigns new examples into one category or the other. A SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. And this algorithm was improved to apply for multi classes of recognition [19], all features of SVM satisfy and are appropriate to use in this robot system to recognize chess pieces.

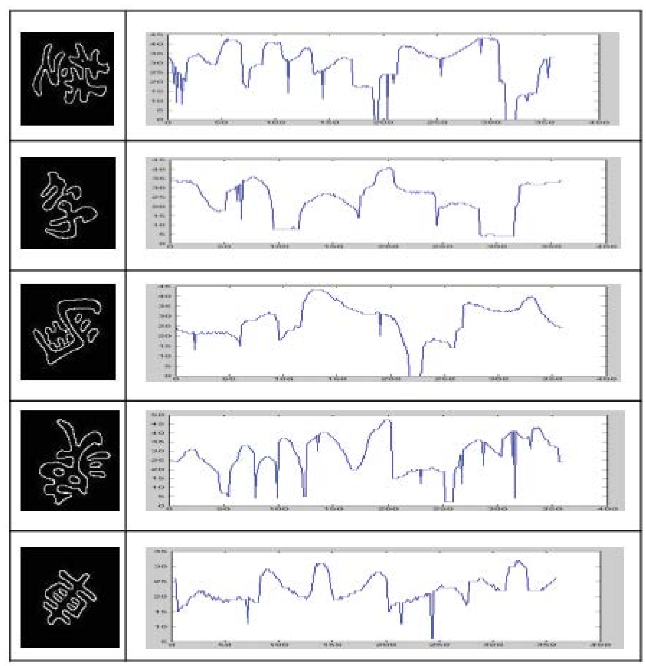


Figure 10. The graph of distance between the center of piece's letter with contour (a set of features includes 360 values).

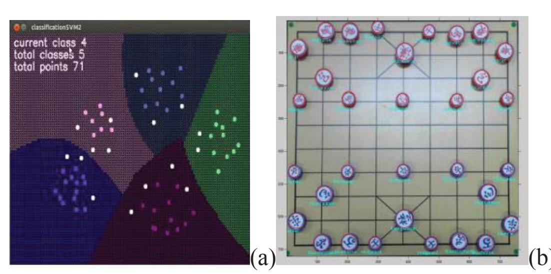


Figure 11. SVM for multi-class (a) and the recognition result after determine the position of piece on the chessboard (b)

After extracting pieces' features in all cases, we use SVM (Fig.11a) to learning training data with kernel function is linear to achieve the highest performance. The Fig.11b shows the recognition result of pieces on an optional chessboard preprocessed from an original image captured from camera. The achieved recognition successful rate is high (can up to 99%) and correct in almost special cases (noise, not intact letter, shaded letter) with the predefined training data, overcome backwards of previous papers.

4. EXPERIMENTAL RESULTS

To evaluate the performance and the accuracy of our proposal method, we collected almost cases which can appear in during of chess play. As mentioned above, the chess is a traditional game at many eastern countries (China, Japan) and more popular nowadays. A fact that this game is asked for two peoples and it takes a long time to end of this. So the development of this system to replace the role of human is necessary and have high economic. Besides, the instruments are required to play this game is simple: chess board and pieces. Therefore, it is undeniable that this game can be played in almost places; only a small space can be useful for playing this game. But this simple creates difficulties for processing of Robot system. It is clear that a game can be hold in almost places means images that camera captures chess board will always include difference background and noise. Therefore, our practice applies for many scenarios. We try to find out all cases can occur to show the accuracy of our method.

The first, we show the result of the four-corner chessboard determination step with many input images having the difference level of noise, background, the light effections.

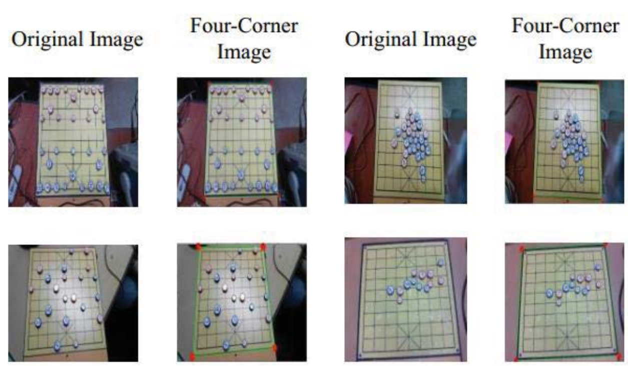


Figure 12. The original image and the image with four corner of the chessboard

As can be seen in the Fig.12, with backgrounds being very complex (two images in the first row), the result of chessboard extracting is excellent, four corners of chessboard are detected correctly. In the second row, the color and brightness of background change in the two images but the results are still perfect.

The second context, after determining the border of chessboard based on the tensor voting with the four corners of this, we will show the result of piece detection by using the circle hough detector, for all position of pieces with the difference size and located optionally.

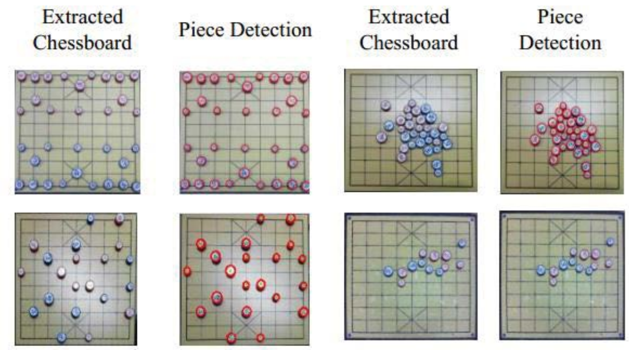


Figure 13. The full chessboard based on the Homography Transform and the results of piece's position detection.

In the Fig.13, there are two images in the first row with the high resolution (761x720) with the piece detection result being very good, the red circle boundaries around pieces equal to the size of pieces, so this is easy to extract piece image to recognize, but in the rest of image on the figure, the resolution equal a half of above ones (387x366) so the result is not very good, this is the cause of the wrong recognition result for recognition steps.

And the last, in the Fig. 14, we show the performance of piece recognition with the above step's results. Although affecting of many factors (light, rotation, size, resolution) but the recognition result are still good.

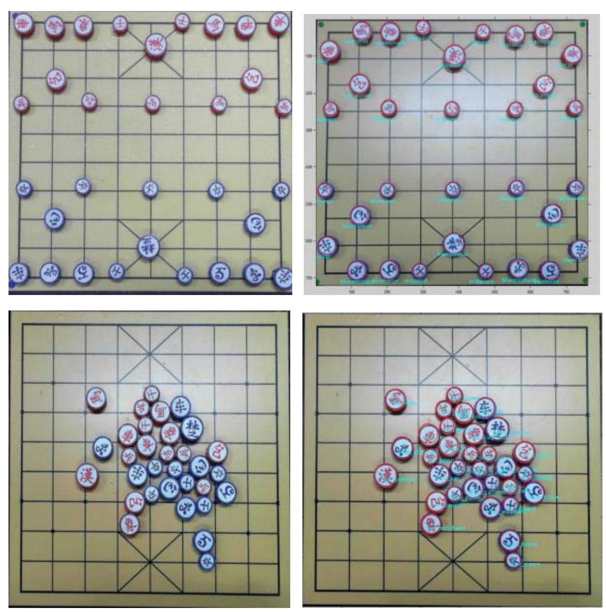


Figure 14. The result of piece recognition

And finally, the Fig. 15 shows the accuracy of the proposed method for 13 types of pieces including on the chess board. For the training data, we collect 30 different images of each piece type corresponding to 300 feature vectors. For testing, 100 chess board images are captured in different conditions of camera position, light and capture angle. The performance show the promising results of our proposed method with the lowest accuracy being at 95.05% for red_cannon piece and the highest one being at 99.01 for red_general. It is likely that the red_general is the most complex letter on the chess board, so the feature vectors of this piece contain the data being very different from the others.

Therefore, this type of piece can be easier to recognize. And the opposite is true with red_cannon piece.

Piece's Name	Image	Recognition Accuracy(%)	Piece's Name	Image	Recognition Accuracy(%)
red_horse		98.75	blue_cannon		98.75
red_pawn		98.99	blue_car		98.75
guard		97.59	blue_elephant		98.75
red_general		99.01	blue_general		99.01
red_elephant		96.83	blue_horse		96.83
red_car		98.75	blue_pawn		98.75
red_cannon		95.05			

Figure 15. The accuracy of each piece on the chessboard in the recognition step

5. CONCLUSIONS

In this paper, we introduced a new proposal method to determine four corners of chessboard to achieve a full and complete chessboard image from all optional input images, then using circle Hough transform to determine the position of chess pieces on the chessboard before recognizing which class pieces belong to. The fact that there are a lot of cases is difficult to recognize because noise, rotated pieces, difference size of piece letters, so using the training algorithm to recognize is necessary and SVM is considered as a good method for learning machine. For dataset, almost cases that we can meet in the fact are collected and processed so the accuracy of this system is very high and robust. In the next research, we want to continue to improve the performance of this system for all cases.

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