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Playing Card Recognition Using Rotational Invariant Template Matching

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Abstract

A rotational invariant template matching method is proposed in this paper to enable accurate playing card recognition. Some prior approaches for card recognitions have been made, but they are all unsuccessful. Character segmentation algorithms and affine transformation are then used in the playing card recognition system which works well for low noise images. The proposed method is proved to be computationally efficient and sufficiently accurate for use in card games such as Baccarat.

Keywords: rotation, transformation, segmentation, template, playing card recognition

1 Introduction

The intention of this project is to build a playing card recognition system as an aid for card game. The system has the capability to recognise a standard deck of playing cards, with both ranks and suits uniquely recognised. Recognising playing cards involves character segmentation, affine transformation, edge detection and template matching. Rotation and scaling are considered for robust playing card recognition.

The accuracy of card rank recognition with proposed method is about 99.79 percent in low noise circumstance, and the accuracy of suit recognition is about 81.06 percent.

2 Background

In general, artificial neural networks have the capability for applications in pattern recognition problems. The prior knowledge in pattern recognition such as rotation and scaling are always taken into account. Widrow *et al.*[1] presented a pattern recognition system which is insensitive to rotation at every 90 degree of input pattern. Onodera *et al.* [2] proposed a three layer feed-forward network which can recognise rotated standard pattern. The centre of the pattern which is standard point is calculated for affine Transformations. The formula (1) (2) is used to calculate the coordinates of the standard point.

$$i_0 = INT\left[\frac{\left(\sum_{i=1}^{M}\sum_{j=1}^{M} i\cdot D(i,j)\right)}{\left(\sum_{i=1}^{M}\sum_{j=1}^{M} D(i,j)\right)}\right] \quad (1)$$

$$j_0 = INT\left[\frac{\left(\sum_{i=1}^{M}\sum_{j=1}^{M} j\cdot D(i,j)\right)}{\left(\sum_{i=1}^{M}\sum_{j=1}^{M} D(i,j)\right)}\right] \quad (2)$$

(i, j) is the coordinates of each pixel of the pattern. D is the number of the pixels of the pattern. i_0 is the centre of the x axis of the pattern, which is a total of weight in x axis divided the number of pixels the pattern contains. j_0 is the centre of the y axis of the pattern, which is a total of weight in y axis divided the number of pixels the pattern contains.

By using the method proposed by Onodera *et al* [2], the translation invariant pattern can be obtained by rearranging the elements of original patterns from its standard point.

Fukumi and Omatu [3] constructed a system which is efficient for use in rotated pattern recognition and also can estimate the rotation angle of input pattern.

The methods used in above systems are tested to be stable and reliable, but they are complicated to card recognition and somewhere have the weakness.

Hollinger and Ward [4] built a card recognition system using computer vision for card game blackjack. However, the results of their card recognition system are not stated clearly.

3 Prior Approach

In order to adjust the rank and suit images to be the same position as templates placed, an axis, which is formed by the centroid of rank or suit pattern image and a point on the contour of that pattern which is furthest from the centroid, is used as benchmark for rotating. The centroid is calculated as $\left(\frac{x_{\min}+x_{\max}}{2}, \frac{y_{\min}+y_{\max}}{2}\right)$ first. And then the system calculates the distance between the controid and each point in the contours of the pattern, in order to find the furthest point. After testing, this method of calculating controid is accurate for regular shapes such as rectangle, but is not good enough for irregular shapes such as the shape of 2.

Another method is then applied to calculate the contoid, which uses the formula (1) (2). This method performs well in the calculation of centre point for any shape. After the centre point is determined, the problem then appears which is difficult to find the furthest point to the centre point. More than one furthest point is found for some ranks, such as 8, 6 and 9. Therefore, there is no unique benchmark can be used for rotation. This problem could be solved by generating much more templates for certain cards. However, more templates mean more comparison for matching, which can lead to slow processing speed and low accuracy. This approach fails consequently.

Moving on to another attempt for card recognition, each pattern in a card image is compared with template. There are several patterns in a card image, especially for Jack, Queen and King where many patterns exist. Therefore, the recognition time is extremely long and this approach has been eliminated.

4 Implementation and Methods

4.1 Image Capture

A web camera used in the playing card detecting system acts as a sensor to scan playing cards. In the process of generating templates, the web camera captures 13 images, which contain 13 different ranks and four kinds of suits. The resolution of the camera is important. The higher resolution camera is used, the better result can be achieved. The web camera used in this playing card detection system needs to be placed close to the card.

4.2 Templates Determining

The rank and suit of playing cards need to be recognised. Therefore, 18 patterns with 13 ranks and 4 suits are generated as templates; rank 10 is separated into two patterns 1 and 0. Each template image is a smallest rectangle that contains a rank or a suit, which is then resized to 15 × 20 pixels. The templates are separated into two parts: the positive templates and the reverse templates. The positive templates contain ranks and suits patterns with zero degree rotation, and the reverse templates contain the reverse patterns of positive templates. The classification of the templates could help to reduce the memory cost in the future procedure of comparison.

Figure 1: Positive and reverse templates samples

4.3 Playing Card Selection

Playing card selection involves constructing binary image by thresholding grey image. Thresholding eliminates some noise to a certain extent [5] [6].

Next, edge detection is used to find contours of images. The contours of images are stored in the sequence of a tree. The contours of card are outside contours, which are obtained at the first level of the tree sequence. Contours of rank and suit are inside contours, which can be retrieved in the next level.

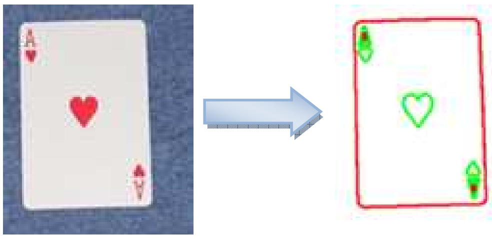

Figure 2: Finding contours

To distinguish playing cards from other objects, the system looks for the rectangle pattern which contains some inside contours. The polygonal curves of contours are approximated with low precision when doing the calculation to find rectangle shape.

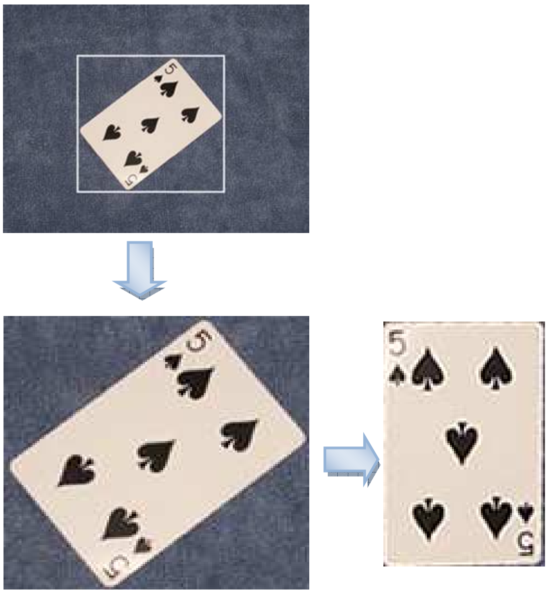

Figure 3: Flow chart of playing card segmentation

After finding the card image, the region of interest is set to a rectangle which contains the card only. The ROI is then enlarger by using bicubic interpolation. The image that only contains card is finally obtained after rotating.

4.4 Card Scaling

The system uses bicubic interpolation when enlarging the region of interest that contains card to enhance the accuracy of finding contours of pattern. For normalization, the enlarged card images are resized to 300 pixels in height, and the width of cards are also enlarged correspondingly.

4.5 Card Rotation

The captured image of a card can be in any position in the background. When doing the comparison with templates, cards are rotated to the same position as templates. Clockwise rotation is applied. As the coordinates of points in the images are known, the radian of rotating angle can be calculated.

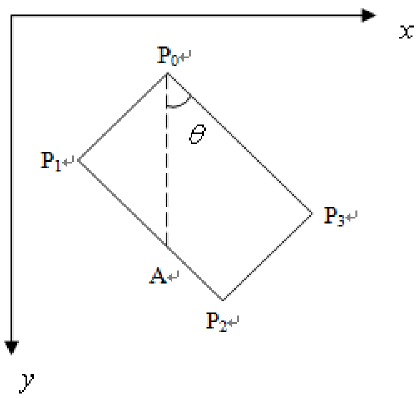

Figure 4: Rotation angle of a card

θ is the rotating angle when line P_0P_1 is shorter than line P_1P_2. $P_0(x_0, y_0)$, $P_1(x_1, y_1)$, $P_2(x_2, y_2)$ and $P_3(x_3, y_3)$ are the vertexes of a card, which are known. Point $A(Ax, Ay)$ lies on line P_1P_2, and AP_0 is vertical to x axis.

$$Ax = x_0 \tag{3}$$

$$Ay = \frac{(x_0 - x_1)\times y_2 + (x_2 - x_0)\times y_1}{x_2 - x_1} \tag{4}$$

By knowing the coordinates of three points P_0, P_1 and A, we can get the angle θ.

After rotating the image, the new width (w') and height (h') of the image is calculated by using formula (5) (6), w is the original width and h is the original height.

$$h' = |w \times \sin\theta| + |h \times \cos\theta| \tag{5}$$

$$w' = |h \times \sin\theta| + |w \times \cos\theta| \quad (6)$$

$$Matrix = \begin{vmatrix} \cos\theta & \sin\theta & 0.5w \\ -\sin\theta & \cos\theta & 0.5h \end{vmatrix} \quad (7)$$

Equation (7) is a rotation matrix. By multiplying this matrix, a new image determines. The rotated image does not have the same size as the original image and the values of pixels at non-integer coordinates are retrieved using bilinear interpolation. [8]

4.6 Character Segmentation

Character segmentation involves card rank and suit segmentation. For card rank segmentation, the region of interest is a rectangle which contains the top left corner or the bottom right corner of card, where contains up to three patterns. Three possible patterns in ROI are rank pattern, the part of the suit pattern and the part of inside picture pattern. Each possible obtained pattern is segmented for an image with the smallest rectangle that contains the contour of pattern. These obtained images are compared with templates to retrieve the rank pattern of card. For card suit segmentation, the system captures first ten patterns that are found in the card. Each of those patterns is segmented for image with the smallest rectangle that contains the contour of pattern and then compared with templates to retrieve the suit pattern of card.

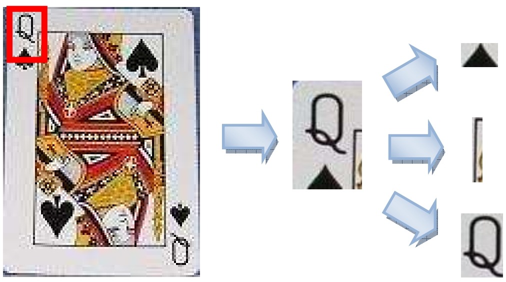

Figure 5: Character segmentation of Queen

4.7 Template Matching

The image that contains required pattern as mentioned in character segmentation is resized to 15 × 20 before the comparisons. Every pixel of the image is compared with template. There are several steps for comparing the resized images with templates to recognise rank and suit of card. First, the obtained patterns in the top left corner region of interest are compared with the positive templates which are mentioned in template determining section. If the rank pattern is not found, the obtained patterns in the right bottom region of interest are then compared with the reverse templates. The rank patterns should be likely found through these procedures. If the rank patterns are still not found, the system will try to find them in the procedure of finding the suit patterns. The suit patterns normally start to be found after the rank patterns are recognised. First ten patterns found in a card will be compared with templates to find the suit pattern of card. The card recognition system determines a card based on the degree of match.

5 Experiment and Results

The playing card recognition system can recognise the rank and suit of cards in a dark background. However, the system is only reliable when cards are separated from each other.

An experiment has been carried out to test the effectiveness of the proposed template matching algorithm. Templates of thirteen different ranks have been generated before doing the experiment. Also, 52 different cards have been captured by a camera with resolution of 1024 × 768 pixels at a distance of half a meter. The card size is then about 150×200 pixels, and the size of rank patterns is about 15×20 pixels.

In the experiment, the playing card recognition system is used for recognising the 52 images after every 10 degree rotation, from 0 degree to 180 degrees. Then, those images are scaled to 90%, 80%, 70%, 60%, 50% and 40% of the original image size. Those images will be recognised after every 10 degree rotation when the size of images is scaled every time. Therefore, each of those 52 cards is recognised for 108 times with 6 different sizes.

The results of card rank recognition are shown in figure 6. The accuracy of rank recognition is ideal until the card images are scaled below 60% of original size. Figure 7 lists the accuracy of rank recognition against the reduction of image resolution for each rank. Rank 5 has relative low recognition accuracy, as it is always recognised as rank 6.

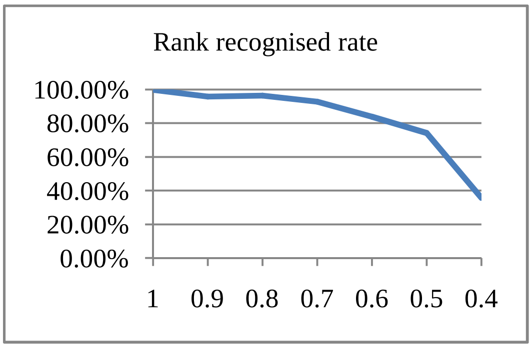

Figure 6: The percentage of accuracy for rank template matching against reduction of image resolution

	1	0.9	0.8	0.7
A	100.00%	91.67%	95.83%	93.06%
2	100.00%	100.00%	100.00%	100.00%
3	100.00%	100.00%	100.00%	100.00%
4	100.00%	100.00%	100.00%	100.00%
5	98.61%	79.17%	70.83%	56.95%
6	100.00%	100.00%	100.00%	100.00%
7	100.00%	100.00%	100.00%	93.06%
8	100.00%	100.00%	100.00%	100.00%
9	100.00%	100.00%	100.00%	100.00%
T	98.61%	100.00%	100.00%	98.61%
J	100.00%	87.50%	100.00%	95.83%
Q	100.00%	100.00%	95.83%	87.50%
K	100.00%	86.11%	90.28%	79.17%

	0.6	0.5	0.4
A	72.22%	75.00%	22.22%
2	97.22%	72.22%	34.72%
3	100.00%	98.61%	91.67%
4	100.00%	91.67%	61.11%
5	59.72%	48.61%	2.78%
6	97.22%	97.22%	66.67%
7	90.28%	94.44%	30.56%
8	97.22%	79.17%	33.34%
9	100.00%	100.00%	44.45%
T	77.78%	26.39%	11.11%
J	52.78%	51.39%	16.67%
Q	76.39%	76.39%	12.50%
K	69.44%	52.78%	37.50%

Figure 7: The percentage of accuracy for template matching against reduction of image resolution for each rank

The card suit recognition results are shown in Figure 8. There are three bars which represent the accuracy of suit recognition for thirteen ranks (left side bar), the accuracy of suit recognition for ranks excluding jack, queen, king (bar in the middle) and the accuracy of suit recognition for ranks jack, queen, king (right side bar). As jacks, queens and kings are traditionally represented by a variety of alternative standard patterns, they are more difficult to be recognised.

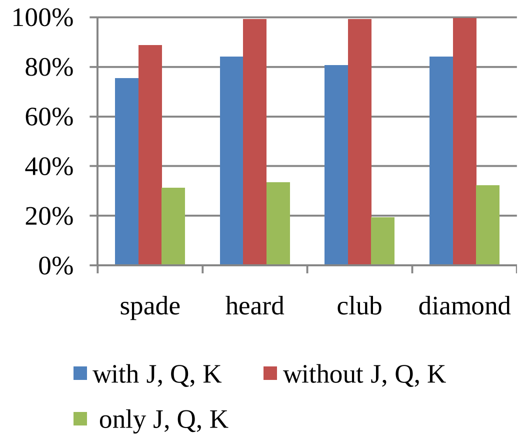

Figure 8: The accuracy rate for suit recognition

It is important to notice that the rotation does not affect the accuracy of recognition in proposed system.

According to the results, it is clear that the resolution of camera is important to the recognition accuracy in the proposed card recognition algorithm. However, the method is robust to rotation of playing cards.

6 Conclusion and Future Work

The rotational invariant template matching method proposed in this paper is proved to be computationally efficient and accurate for playing card recognition. However, noise significantly influences the accuracy of the recognition. Also, the same cards need to be used as the cards generating templates. The system cannot be generalized to the wide variety of playing card decks available.

More works can be done to increase the accuracy of suit recognition such as adding a colour differentiation method [9]. In addition, a generalized template and approach for more robust to noise [10] can be developed in the future research [11]. Moreover, a new version of this system could include rules for various card games.

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