Digital Signal Processing 20 (2010) 769–779

Contents lists available at ScienceDirect

Digital Signal Processing

www.elsevier.com/locate/dsp

Robust poker image recognition scheme in playing card machine using Hotelling transform, DCT and run-length techniques

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ARTICLE INFO

Article history:
Available online 2 October 2009

Keywords:
Discrete cosine transform (DCT)
Discrete wavelet transform (DWT)
Hotelling transform
Poker game
Run-length (RL) technique

ABSTRACT

Poker is an interesting field for artificial intelligence research. It is a game of imperfect information and chance associated outcomes, where players deal with probability, risk assessment, and possible deception – just like real life decision-making. In our proposal, three strategies are used to organize a robust poker recognition scheme: (1) using Hotelling transform to place the object image in the correct position in poker pick-up stage; (2) a weighted compacted energy (WCE) of the image is used as the first feature in using DWT and DCT; and (3) calculating four orientation connectivity run-length values (FOCRLV) to distinguish different poker card images. There are two contributions in this article – one is the use of FOCRLV as a special feature to improve image recognition and the other is use of the compact energy band of an image as another feature to effectively identify the images. In order to demonstrate the effectiveness of the proposed scheme, simulations under various conditions were conducted. The experimental results show that our proposed scheme can exactly identify ranks and suits of the poker images 100% of the time, even when 40% noise is added, or when intensity level is increased or decreased 40%.

1. Introduction

There are numerous games which use playing cards to play, like "Bridge", "Spade Pig", "Blackjack" aka "21", "Fan-tan", "Solitaire", "13 cards" and "Red point select", etc., which many are familiar with and enjoy playing. However, there are few others less well-recognized or informal ways of poker playing. One example would be "pairing" – which is to try choosing 2 cards with the same rank from the pile of non-disclosed cards each time.

Poker is a card game with dozens of variants, most of which using one or more decks of 52 standard playing cards. In our study, we focus on the "stud" variation in which the players receive cards and then take turns to bet money or something else into a communal pot. At each turn, a player may either [1]: (a) fold: relinquishing all interest in the pot; (b) call: match the previous bet; or, (c) raise: make a bet that exceeds the previous bet. The aim of the game is to win as much of the bets as possible from the opposing players. Different numbers of betting rounds are used in different poker, interspersed with the replacement, receipt, or revelation of cards.

Billings et al. [2] proposed a poker program called "*Poki*" which uses learning techniques to construct statistical models of each opponent, and dynamically adapts to exploit observed patterns and tendencies. After simulation, along with the obtained results, the program is capable of playing reasonably strong poker.

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1051-2004/$ – see front matter
doi:10.1016/j.dsp.2009.09.008

Neumann and Morgensterm introduced Mathematical game theory in the 1940s [3] and used the game of poker as a basic model for 2-player zero-sum adversarial games, and proved the famous minimax theorem. An optimal solution provides a randomized mixed strategy which ensures that an agent will obtain at least the game-theoretic value of the game, regardless of the opponent's strategy. Unfortunately, finding exact optimal solutions is limited due to relatively small problem sizes, and not practical in most real domains. Billings et al. [4] explored the use of highly abstracted mathematical models that capture the most essential properties of the real domain, such that an exact solution to the small problem provides a useful approximation of the optimal strategy for the real domain.

Harn and Gong [5] proposed a bounded-to-unbounded Internet poker game. It provides both dealer and player distributed cards in a fair and secure condition. Additionally, the presented protocol assumes that the player is computationally bounded and the dealer is computationally unbounded.

As technology has gotten more advanced, technological products are now kind of taking control of people's lives in this e-generation. Since there is no categorical timetable for people's lives, inviting card-friends to get together to play cards to kill time is quite impossible and game machines are therefore very popular now. "Bridge", "Mah-jongg" and "Playing card" machines are produced for this reason. Those products solve the problems that satisfy people's need for entertainment and not having access to card-friends to play with. This paper focuses on the research of the essence of playing card machine technology, esp. "Playing card image recognition", and ways to get high veracity and highly robust recognition technology in as many different situations as possible.

There are many papers on object recognition using fuzzy, neural and feature-based identification systems [6–11]. Poker card recognition in this paper is based on feature-based [12,13] identification. In the current approach, Sobel edge detection is used as an assisting tool to extract the poker card from an input image first, and then the object image is rotated into correct orientation using Hotelling transform. Furthermore, the low frequency components and the connectivity of the poker card image were used as the features to identify exactly which poker card from the database. The remainder of this paper is organized as follows: Section 2 gives a presentation of the Hotelling transform. Section 3 illustrates the algorithm of the poker card image recognition. Section 4 presents the algorithm's experimental results. Section 5 concludes this paper.

2. Hotelling transform

The Hotelling transform is a principal component transform that diagonalizes the covariance matrix of a discrete random real sequence, and was originally introduced by H. Hotelling to process psychological data [14–16]. It also serves as an efficient tool in image processing.

The Hotelling transform is constructed on statistical properties of data represented in vector form. For a population of vectors $X = (x_1, x_2, x_3, \dots, x_n)^T$, the mean vector of a sample of Nvectors from the random vector population is the expectation of the vector population is given by

$$\bar{X} = E\{X\} = \frac{1}{N}\sum_{k=1}^{N} X_k \tag{1}$$

The covariance matrix of the vector population is defined as

$$C_X = E\{(X-\bar{X})(X-\bar{X})^T\} = \frac{1}{N}\sum_{k=1}^{N} X_k X_k^T - \bar{X}(\bar{X})^T \tag{2}$$

The entry $c_{i,i}$ of C_X is the variance of the ith component of vector X. The entry $c_{i,j}$ is the covariance between vector X_i and vector X_j.

Since C_X is symmetric and real, according to the theory of linear algebra, it will always find a set of N orthonormal eigenvectors of the matrix C_X. And matrix C_X can be orthogonally diagonalized into a full ranked diagonal matrix. Let H be a matrix whose rows are the orthonormal eigenvectors of C_X, ordered so that the first row is the orthonormal eigenvector corresponding to the largest eigenvalue of C_X and the last row is the eigenvector corresponding to the smallest eigenvalue; the Hotelling transform is expressed as $Y = H(X - \bar{X})$. It is possible to prove that the mean of Y vector is zero, that is

$$\bar{Y} = E\{Y\} = \frac{1}{N}\sum_{k=1}^{N} Y_k = 0 \tag{3}$$

And covariance matrix of the Y vector population is a diagonal matrix whose elements on the main diagonal are the eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_n$ of C_X, that is

$$C_Y = E\{(Y-\bar{Y})(Y-\bar{Y})^T\} = \frac{1}{N}\sum_{k=1}^{N} Y_k \bar{Y}_k^T - Y(\bar{Y})^T = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix} \tag{4}$$

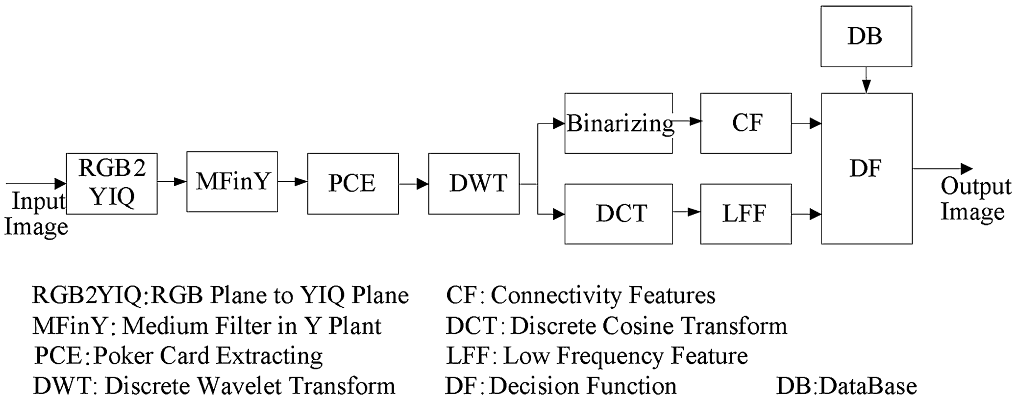

Fig. 1. The algorithm of the poker card image recognition.

3. Poker image recognition

A robust poker image recognition scheme can identify the input image exactly under some interference. In order to construct a superior poker image recognition scheme, several skills were used in this paper. The overall recognition process of our proposed scheme is shown in Fig. 1. First, an input color image was mapped into grayscale image by RGB2YIQ transform. Then, a median filter is used to reduce the noise. Successively, a poker card extracting stage is called to segment the poker card from an image. We compact the energy of the grayscale image (Y plane), and reduced its redundancy by discrete wavelet transform (DWT). After DWT, the LL band image was transferred by DCT to obtain a compact energy band feature. On the other hand, the LL band image was binarized for the connectivity feature calculation. In connectivity computing, we divided the binary image into two parts; one is the global-area that is the full range of a poker image. It contributed four features. The other part is the core-area, the upper-left area with size 35×70. It contributed two features. The core-area is useful in distinguishing complicate images such as the Ace, King, Queen, and Jack cards. After all of the features are extracted, a decision function is used as a criterion to decide whether the input image is exactly the image of the card while the features of the image were compared with the database. The details of the poker image recognition algorithm are described in the following.

3.1. Image preprocessing

3.1.1. Median filter

The median filter is a nonlinear spatial filter, and a powerful tool at removing outlier type noise. It is thus well suited for preserving edges of an image. The filter mask simply defines what pixels must be included in the median calculation. The computation of the median filter starts by passing those n pixels defined by the filter mask, in the order from minimum to maximum value of the pixels as given in Eq. (5).

$$F_0 \leqslant F_1 \leqslant F_2 \cdots \leqslant F_{n-2} \leqslant F_{n-1} \tag{5}$$

where F_0 denotes the minimum and F_{n-1} is the maximum of all the pixels in the filter calculation. The output of the median filter is the median of these values and is given by

$$F_{med} = \begin{cases} \frac{F_{n/2}+F_{n/2-1}}{2} & \text{for } n \text{ even} \\ F_{n/2} & \text{for } n \text{ odd} \end{cases} \tag{6}$$

Typically, an odd number of filter elements are chosen, to avoid the additional step in averaging the middle two pixels of the order set when the number of elements is even.

Playing cards may get dirty after extended use. This may cause the cards images to be interfered by noise. So, a filter is needed to reduce noise and get rid of misjudgment in image recognition. The median filter has the suitable filter property that we need, so, we implement it as a processor in our poker card image recognition system to reduce the noise and increase the identification ratio.

3.1.2. Poker card extracting

Poker card extracting as shown in Fig. 2 is used to extract the object of a card's image from the input image that state in non-regular orientation. In the beginning stage of poker card extracting, an image thresholding technique binarizes the gray-scale image. Then an object segmentation processing is employed to find out the object from the binary image. In the object segmentation stage, a Sobel gradient mask as shown in Fig. 3 is used to get the edge information of the object, and a binary closing operation is used to fill the object within the interior region of the edge contour. After mapping the location

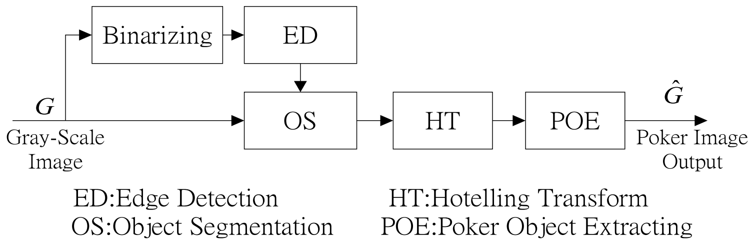

Fig. 2. The flow chart of the poker card extracting.

(a)

-1	0	1
-2	0	2
-1	0	1

(b)

-1	-2	-1
0	0	0
1	2	1

Fig. 3. The Sobel gradient mask: (a) $f_x(x, y)$ and (b) $f_y(x, y)$.

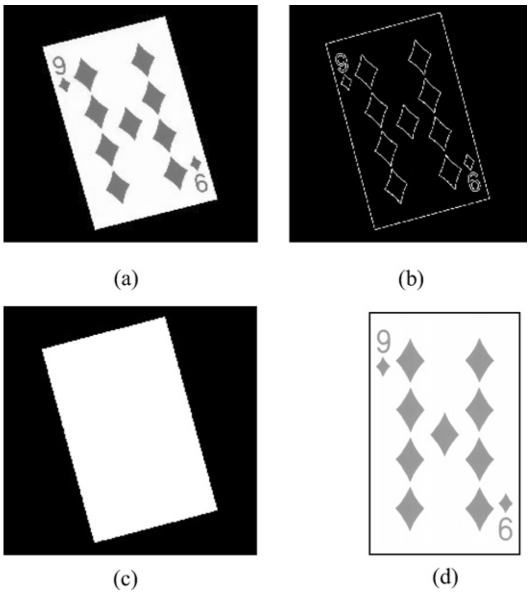

Fig. 4. The corresponding image through the procedure of poker extracting: (a) the gray-scale original captured image; (b) the edge image obtained from (a) by Sobel operation; (c) the image after closing operation; and (d) the extracted image of the poker object after Hotelling transform.

of the object back into the original gray-scale image, the object location was found and the poker card image was extracted exactly. Furthermore, we adopted Hotelling transform in poker pick-up (HTPP) stage to rotate the object image into upright orientation. In the HTPP stage, the standard format of poker image was obtained by rotating the object image's principal axes to coincide with coordinate axes by Hotelling transform. Fig. 4 shows the corresponding images after the individual process procedure of card extracting. Where Fig. 4(a) is the gray-scale image of the 9 of diamonds, and Fig. 4(b) is the edge image after Sobel operation on Fig. 4(a). In addition, Fig. 4(c) is the image after closing operation and Fig. 4(d) is the standard format of the playing card image after Hotelling transform.

3.2. The connectivity feature calculation

In judging the connectivity of the image, calculating the run-length value of the binary image is a fast and efficient technique. Chan and Chang proposed an algorithm using run-length encoding to calculate the difference between the LOGO and database. All the pixels of the poker image after binarization are two levels, 0 or 1. This is convenient in connectivity calculation by using run-length encoding because the 52 cards in a poker are all different in suit or rank from each other, therefore, the connectivity of each card's image must also differ. In order to enhance the connectivity effect, a four-

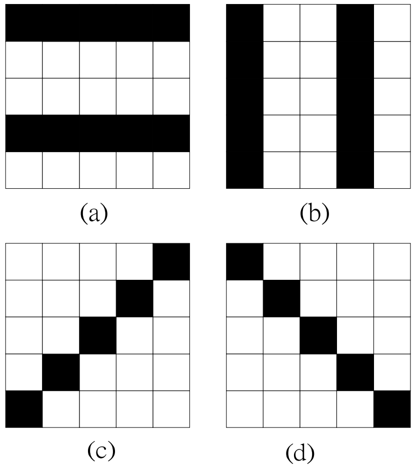

Fig. 5. The connectivity of the binary images in the: (a) horizontal, (b) vertical, (c) 45-degree, and (d) 135-degree orientations.

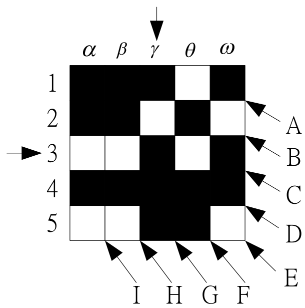

Fig. 6. The schematic figure for the run-length computation: (1–5) stand for the horizontal orientation; (α–ω) stand for the vertical orientation; and (A–I) stand for the 135-degree orientation.

orientation connectivity run-length value (FOCRLV) was used in this paper. In FOCRLV, the connectivity in the horizontal, in the vertical, in the 45-degree and in the 135-degree orientation were computed by run-length encoding. Meanwhile, the upper-left area (x range from 1 to 35, y range from 15 to 85) of the image was used as a core image because it was easily distinguished from the complicated areas of the A, K, Q and J card images.

The oriented connectivity of the image adopted in our scheme is shown in Fig. 5, where (a)–(d) are the connectivity of the horizontal, of the vertical, of the 45-degree and of the 135-degree orientations, respectively. Furthermore, Fig. 6 is the schematic figure for the run-length computation. Where, (1–5), (α–ω) and (A–I) denote the direction of the horizontal, of the vertical and of the 135-degree orientations while calculating the run-length value. For example, row 1 denotes the horizontal connectivity, and its run-length value is 10 ($3+3+3+0+1=10$). Another example, the mark E is the connectivity in the orientation of 135-degrees, its run-length value is 16 ($0+4+4+4+4=16$).

3.3. *The energy band features calculation*

3.3.1. *Discrete wavelet transform*

"Wavelet" is the term applied to a large class of orthonormal transforms that feature subsampling. The wavelet transform decomposes a signal into many bands of energy, which are sampled at different rates. Their rates are determined so as to maximally preserve the information content of the signal while minimizing the sample rate or resolution of each subband. Furthermore, wavelet attempts to maximize the precision of representation in both the time and frequency domains.

The discrete wavelet transform (DWT) is used to hierarchically decompose an image into a lower resolution reference image LL and their associated detail images LH, HL, HH. At each level, the LL image and the LH, HL, HH images contain the information needed to reconstruct the reference image at the next higher resolution level. In applications, the host image is usually transformed by DWT to obtain a multiresolution representation as shown in Fig. 7.

3.3.2. *Discrete cosine transform*

Discrete cosine transform is used to transfer the image from the spatial domain into the frequency domain. The coefficients of the DCT block with size 8×8 are the values corresponding to the DCT block foundation. In the coefficients of the DCT block as shown in Fig. 8, the upper-left corner is the DC value, varies by illumination, and is not suitable for use as a

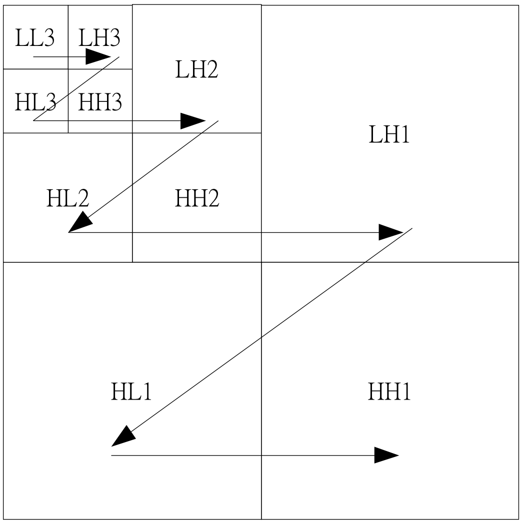

Fig. 7. Three level DWT hierarchical decomposition of an image.

DC	1	5	6	14	15	27	28
2	4	7	13	16	26	29	42
3	8	12	17	25	30	41	43
9	11	18	24	31	40	44	53
10	19	23	32	39	45	52	54
20	22	33	38	46	51	55	60
21	34	37	47	50	56	59	61
35	36	48	49	57	58	62	63

Fig. 8. The coefficients of the DCT block.

feature for poker image recognition. The coefficients in the upper-left area are the low frequency band, energy concentrated, have good features of the image, and are suitable for poker image recognition. The low frequency band coefficients denoted by 1–9 of the DCT block in Fig. 8 are suitable features to be used in our scheme by weighting something.

3.3.3. *Compact energy band features calculation*

The DCT transfers the image from the spatial domain into the frequency domain. Where the coefficients in the upper-left corner are the low frequency band, are energy concentrated, and have good features of the image. Thus, we used the nine coefficients of the low frequency band as the first feature of the poker image recognition. Because poker card size is 640×400, the number of DCT blocks are $(320 \times 200)/(8 \times 8) = 1000$. Furthermore, we add all of the coefficients that were weighted as the first feature and shown in Eqs. (7)–(8).

$$\begin{aligned}\mathrm{sum}(k) = {} & \mathrm{dct}(1,3) \times 1.2 + \mathrm{dct}(2,2) \times 2 + \mathrm{dct}(3,1) \times 1.2 + \mathrm{dct}(2,1) + \mathrm{dct}(1,2) \\ & + \mathrm{dct}(3,2) \times 2.5 + \mathrm{dct}(2,3) \times 2.5 + \mathrm{dct}(4,1) \times 4 + \mathrm{dct}(1,4) \times 2 \end{aligned} \tag{7}$$

$$\mathrm{fea} = \frac{\sum_{k=1}^{1000} \mathrm{sum}(k)}{1000} \tag{8}$$

where sum(k) is the feature of block k, and k is the block number. dct(a, b) denotes the coefficient of the DCT block and a, b are the indexes of the DCT block.

The connectivity of the image is a feature usually used to identify different images. In general, the connectivity on the vertical, the horizontal, 45-degree and 135-degree orientations of the image are the most popular adopted to judge the image. In our approach, a run-length technique was employed to compute the connectivity at the four aforementioned orientations denoted fry, frx, fr45 and fr135. In addition, we denote the connectivity features prx and pry of the core-area (the upper-left rectangular area; $1 \leqslant x \leqslant 35$, $15 \leqslant y \leqslant 85$) computed by run-length techniques respectively. However, the calculated features' values are spread about broad range, and the large value could depress which it is small, so that we use a normalizing operation to balance all of the features.

3.4. Decision functions

In order to identify the input image against the database, we developed a decision function to calculate the total error of the features between the input image and database. When the value of the decision function is at its smallest and less than the range-threshold ε compared to the entire database, the rank and suit of corresponding database is exactly the rank and suit of the input playing card. Once the identification algorithm starts, the database will first be established. It includes the features of the fifty-two standard poker cards. Then before the decision function gets going, all kinds of feature errors between the input image and database are computed using Eqs. (9)–(16). The feature errors are expressed as the following: $e1(i)$ is the error of the first feature between low frequency components of the image and fea of the database. Errors $e2(i)$, $e3(i)$, $e4(i)$, and $e5(i)$ are the errors of the four orientation connectivity features between the database and image feature values in vertical, horizontal, 45-degree and 135-degree orientations, respectively. In addition, errors $e6(i)$ and $e7(i)$ are the errors of the connectivity features between the database and the core-area image feature values in vertical and horizontal orientation, respectively. Finally, a decision function as the sum of all feature errors with weighting, is given in Eq. (16).

$$e1(i) = \left|\left(\mathrm{fea} - \mathrm{dbase}(i,1)\right)/\max\left(\mathrm{dabse}(i,1)\right)\right| \tag{9}$$

$$e2(i) = \left|\left(\mathrm{frx} - \mathrm{dbase}(i,2)\right)/\max\left(\mathrm{dbase}(i,2)\right)\right| \tag{10}$$

$$e3(i) = \left|\left(\mathrm{fry} - \mathrm{dbase}(i,3)\right)/\max\left(\mathrm{dbase}(i,3)\right)\right| \tag{11}$$

$$e4(i) = \left|\left(\mathrm{fr45} - \mathrm{dbase}(i,4)\right)/\max\left(\mathrm{dbase}(i,4)\right)\right| \tag{12}$$

$$e5(i) = \left|\left(\mathrm{fr145} - \mathrm{dbase}(i,5)\right)/\max\left(\mathrm{dbase}(i,5)\right)\right| \tag{13}$$

$$e6(i) = \left|\left(\mathrm{prx} - \mathrm{dbase}(i,6)\right)/\max\left(\mathrm{dbase}(i,6)\right)\right| \tag{14}$$

$$e7(i) = \left|\left(\mathrm{pry} - \mathrm{dbase}(i,7)\right)/\max\left(\mathrm{dbase}(i,7)\right)\right| \tag{15}$$

$$\mathrm{err}(i) = 35 \times e1(i) + 0.3 \times \left(e2(i) + e3(i) + e4(i) + e5(i) + e6(i) + e7(i)\right) \tag{16}$$

where i denotes the sequence number of the poker card.

4. Empirical results

Fifty-two poker card images with size 640×400 were used in simulation for demonstrating the performance of the proposed scheme. To commence, the features of the playing cards were computed and stored in database, dbase(i, j), for $i = 1, 2, 3, \ldots, 52$ and $j = 1, 2, 3, \ldots, 7$. The order of the cards stored in the database is in the sequence of: Ace of hearts, Ace of spades, Ace of diamonds, Ace of clubs, 2 of hearts, 2 of spades, 2 of diamonds, 2 of clubs ... King of hearts, k of spades, King of diamonds, King of clubs. In simulation, the image was divided into non-overlapping blocks with size 8×8, and the total number of blocks is $(320 \times 200)/(8 \times 8) = 1000$. On the other hand, we used the value 190 as the threshold to transfer the gray-scale image into binary by using the thresholding technique, and took $\varepsilon = 6.0$ empirically. In simulation, all of the test images were used to add noise, increase intensity and decrease intensity under PhotoShop version 6.0. The experimental results show that our proposed scheme can exactly identify ranks and suits of the poker card images 100% of the time, even with +40% noise, +40% intensity, or −40% intensity.

Figs. 9 and 10 present the test images states, where Figs. 9(a) and 10(a) are the original input images. Figs. 9(b) and 10(b) denote the input images with 40% noise added. Figs. 9(c) and 10(c) indicate the input images with 40% intensity levels increased. The input images with 40% intensity levels decreased are shown in Figs. 9(d) and 10(d). Table 1 is the features of the standard database according to the order in summation of the weighted low frequency component, connectivity in the vertical, horizontal, 45-degree orientation and 135-degree orientation of the full image and the connectivity of the vertical and horizontal in the core-area. Table 2 holds the features of the four suits of rank Q in the standard database. Tables 3 through 6 host the Queen of hearts, Queen of spades, Queen of diamonds, and Queen of clubs with noise and intensity level interference, respectively. Finally, Fig. 11 shows the capability to resist all kinds of interference.

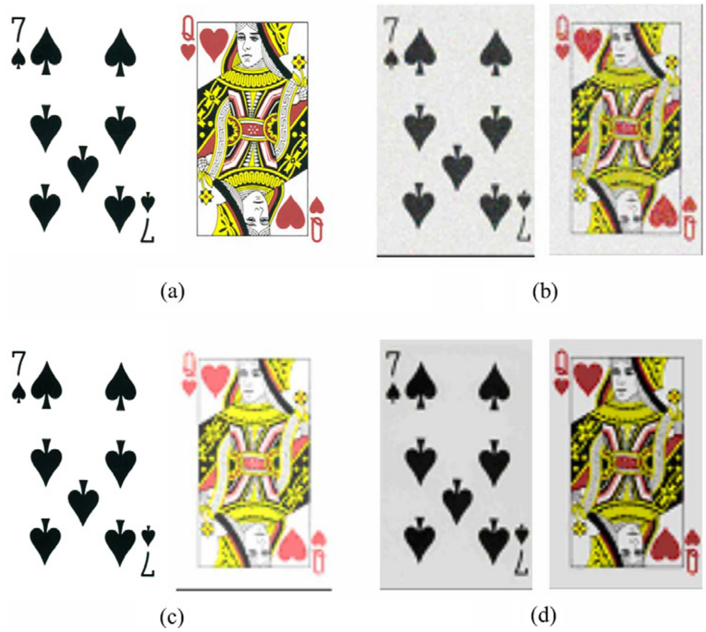

Fig. 9. The test image states: (a) original images; (b) the images with 40% noise added; (c) the images with 40% intensity level increased; and (d) the images with 40% intensity level decreased.

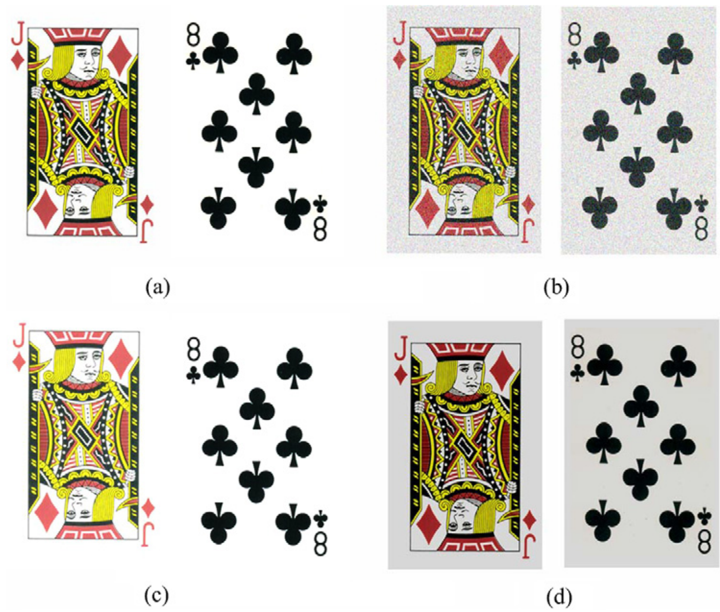

Fig. 10. The test image states: (a) original images; (b) the images with 40% noise added; (c) the images with 40% intensity level increased; and (d) the images with 40% intensity level decreased.

5. Conclusions

The energy of the image is concentrated in the low frequency band and the connectivity of the image is a good feature for pattern recognition. In this paper, a Hotelling transform sets the object image in correct orientation in the poker pick-up (HTPP) stage. Next, we used a four-orientation connectivity run-length value (FOCRLV) method to calculate connectivity features. Additionally, a weighted compacted energy band feature using DWT and DCT is used for improving poker image recognition.

This paper focuses on the research of the essence of playing card machine technology "Playing card image recognition", and achieves high veracity and highly robust recognition under a variety of conditions.

Table 1
The features of the standard database.

Item	fea	frx	fry	fr45	fr135	prx	pry
1	17.89	4774	4001	1813	1942	916	379
2	−6.78	16078	9425	7814	7002	969	367
3	1.16	15338	8036	6282	5735	971	380
4	−10.86	13168	8838	6435	6170	998	385
5	−16.41	10737	7458	5323	5161	983	388
6	−10.36	11782	6987	4914	4621	938	342
7	−7.13	9518	5830	4671	4302	1128	391
8	−18.56	8428	4758	4309	3970	949	343
9	−5.20	8884	4657	2802	2824	905	332
10	15.10	7982	4210	2468	2491	944	300
11	6.32	4669	2405	779	780	901	311
12	3.65	4653	2426	753	783	815	245
13	−57.5	4752	2538	833	878	773	249
14	2.33	16373	10590	8309	7908	904	362
15	−4.17	16400	9849	8203	7389	928	372
16	4.81	15475	8581	6662	6121	922	365
17	−1.44	13869	9372	6939	6473	874	369
18	4.87	11469	8116	5517	5304	921	371
19	−2.96	11915	7671	5172	4777	906	335
20	16.25	9819	6503	4915	4528	972	393
21	−2.75	8671	5225	4551	4095	920	335
22	13.56	8892	5401	3248	3179	828	338
23	4.70	7921	4802	2841	2785	838	298
24	−11.15	4817	2502	793	872	688	303
25	−24.16	4865	2548	828	861	765	259
26	−76.89	4790	2674	889	898	746	272
27	−3.35	16633	10488	8467	8041	929	360
28	−3.90	16286	9529	8101	7340	946	368
29	10.60	15572	8149	6720	6165	936	357
30	2.52	13731	8987	6881	6599	954	378
31	1.297	11387	7585	5705	5502	947	377
32	6.90	12151	7226	5481	5214	953	361
33	−0.71	10114	6123	5252	4869	1065	397
34	1.02	9086	5027	4988	4549	967	339
35	1.55	9575	5006	3383	3413	941	354
36	14.67	8489	4452	3050	3014	946	303
37	−61.42	4848	2429	763	811	808	309
38	−37.65	4850	2463	794	816	817	267
39	82.38	4979	2577	860	895	808	272
40	21.33	16105	10528	8299	7912	946	391
41	−8.28	15748	9638	7871	7125	978	404
42	5.83	14758	8300	6356	5866	949	398
43	−11.68	12571	9086	6547	6277	856	400
44	−15.39	9847	7820	5237	5164	867	402
45	17.30	10798	7303	4825	4590	783	367
46	−4.24	8277	6162	4747	4486	857	400
47	1.16	7094	4912	4403	4162	783	341
48	−4.81	7492	5056	2821	2851	782	363
49	−8.81	6563	4518	2531	2569	814	317
50	−51.19	4780	2407	746	753	750	308
51	33.72	4752	2463	788	837	671	256
52	99.36	4883	2739	936	897	660	272

Table 2
The features of rank Q in the standard database.

Item	fea	frx	fry	fr45	fr135	prx	pry
Heart Q	−24.16	4865	2548	828	861	765	259
Spade Q	3.65	4653	2426	753	783	815	245
Diamond Q	−37.65	4850	2463	794	816	817	267
Club Q	33.72	4752	2463	788	837	671	256

The experimental results show that our proposed scheme can exactly identify ranks and suits of the poker card images 100% of the time, even when 40% noise is added, or when 40% intensity levels are increased or decreased.

Table 3
The features of the Queen of hearts under noise and intensity level interference.

Item	fea	frx	fry	fr45	fr135	prx	pxy
Original image	−24.16	4865	2548	828	861	765	259
40% noise added	−18.50	4839	2530	839	869	768	287
40% brightness increased	−25.50	5340	3149	1282	1213	898	365
40% brightness decreased	−27.21	4703	2438	752	776	720	248

Table 4
The features of the Queen of spades under noise and intensity level interference.

Item	fea	frx	fry	fr45	fr135	prx	pxy
Original image	3.65	4653	2426	753	783	815	245
40% noise added	2.58	4443	2320	697	726	715	230
40% brightness increased	10.48	4797	2605	863	916	828	251
40% brightness decreased	2.95	4347	2295	665	690	651	223

Table 5
The features of the Queen of diamonds under noise and intensity level interference.

Item	fea	frx	fry	fr45	fr135	prx	pry
Original image	−37.65	4850	2463	794	816	817	267
40% noise added	−38.40	4696	2372	744	776	766	255
40% brightness increased	−31.82	5026	2574	874	896	877	285
40% brightness decreased	−41.11	4636	2350	716	747	752	238

Table 6
The features of the Queen of clubs under noise and intensity level interference.

Item	fea	frx	fry	fr45	fr135	prx	pry
Original image	33.72	4752	2463	788	837	671	256
40% noise added	22.47	4565	2365	734	787	657	250
40% brightness increased	27.07	4990	2630	923	960	727	275
40% brightness decreased	33.88	4502	2303	689	732	632	236

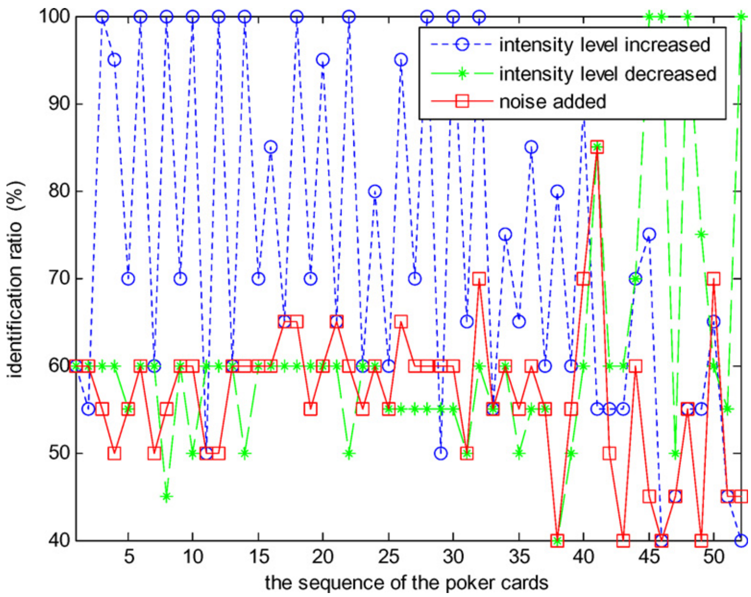

Fig. 11. The capability to resist all kinds of interference.

Acknowledgment

This work was partly supported by the National Science Council, Taiwan (ROC) under contract NSC 97-2221-E-167-019.

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