Image Identification Scheme for Dice Game

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***Abstract*—In this paper, based on the features of dice images and the least distance criterion (LDC) method, we developed an auto-recognition scheme for dice games. First, we use R plane to replace gray-scale image to speed up processing. Next, we use O'stu method to convert the R plane into binary. Furthermore, image pre-processing steps are used to filter out the noise, and a non-circular object discard stage eliminates the bigger noise blocks. Finally, the LDC, the dice score calculation, and the score exception processing is used to accomplish the automatic identification scheme of the dice.**

***Keywords*— dice games, least distance criterion, segmentation, image processing**

1. INTRODUCTION

In fact, dice have been part of the way that humans play games for many centuries. It is probably about as long as man has been playing games at all. Six-sided dice had been developed near Rome dating back to 900 B.C. [1]. Recently, dice are most often associated with gambling games and strategy war games; they are used dice in highly abstract ways in both. Similarly, liar dice games [2] are a kind of interesting and popular game that can be found in almost every pub in China and Hong Kong.

Dice are thrown to provide uniformly distributed random numbers. It is necessary that fair dice be symmetrically shaped and have a center of gravity in the exact middle. The methodology that dice manufacturers apply to achieve fair dice is to make near-perfect smoothness and symmetrical cubes of a homogeneous material. It is a highly accurate technique.

Nowadays, electronic gambling machines have become increasingly popular. The first such machines employing electromechanical principles were slot machines. For increasing interest, electronic gambling machines have emerged using mechanical motion of various types to produce random numbers. Typically, these kinds of games are electronic roulette and electronic dice machines. In their structure, the important module of electronic dice machines is the detection of dice location and throwing manner. Such machines are extremely attractive to users. Simultaneously, they provide results visually giving no room for fraudulently acquired numbers.

Machine vision is a powerful tool which is widely employed in automatic monitoring and detecting processes. Many applications [3]-[4] using machine vision have been proposed for dice gambling machines. Correia et al. [4] proposed a technique which can automatically detect and classify the dice scores on the playing tables in casinos. They extract the dice pips based on the online analysis of images captured by a monochrome CCD camera. As machine vision was not provided during the recognition process, the suspicion of cheating cannot be eliminated. Huang [5] used machine vision technique to present a method which can estimate the location of each die and accurately and effectively calculate the score of dice in the games. Meanwhile, the modified unsupervised gray clustering algorithm is used to establish an auto-recognition system for several dice in the games. Other papers about dice can in found in [6]-[8].

In casinos, the score of dice is generally obtained by visual inspection because of suspicions about the potential for cheating with electronic devices. Here we use image processing techniques [9]-[12] to develop an automatic detection system with machine vision. The remainder of this paper is organized as follows. In Section II, the analysis of dice features are described. In Section III, we present the detection algorithm. The empirical tests are shown in Section IV. Finally, a conclusion of this paper is shown in Section V.

2. THE DETECTION ALGORITHM

Under analysis, there are several features which exist in a dice image; the color, the size and the distance between each pip. For the color, there are two colors of pips. The one-pt. face and four-pt. face are colored red; others are colored black. The next feature is the size. In fact, only the one-pt. face is a bigger size; others are small size. Finally, the third feature is the regular distance existing between each pip. In image zoom, we found that the distance existing between each pip is regular; this means the distance between each pip is invariant no matter whether the image is zoomed in or zoomed out.

In this paper, we focus on developing a simple and effective scheme for automatically identifying the score of dice images. Fig.1 shows the flow chart of our detection algorithm. At the beginning, we take the R plane as a reference plane for image processing. Next, an image pre-processing step is used to filter out the noise and discard the objects that are not dice pips. Because there are several dice in the dice game, a dice segmentation step used to distinguish the cluster of dice is necessary. In our approach, we use the least distance criterion method for accurate dice segmentation. Finally, we implement a dice score computation with an exception processing hired to calculate the score of each die. After all the scores are obtained, the image auto-recognition of the dice is accomplished. The details are described in the following.

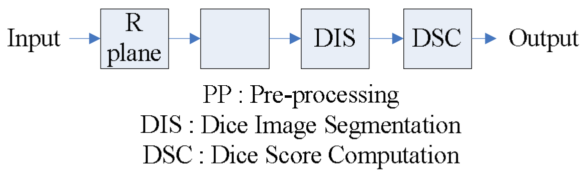


Fig. 1 The flow chart of the dice game auto-recognition

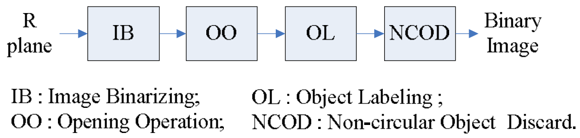


Fig. 2 The flow chart of pre-processing stage

2.1. Image Pre-processing

For improving identification accuracy, a pre-processing step is necessary. Fig. 2 shows the flow chart of pre-processing. First, the R plane is used as the input grayscale image. Next, an image binarizing (IB) step converts the gray-scale image into binary for speeding processing. In the IB step, the O'sthu method is adopted. For eliminating noise, the opening operation (OO) is used to reach our target. The object labeling (OL) process is used to mark and count the number of objects in the image. After objects are obtained, a non-circular object discard (NCOD) stage is implemented to reject those objects that are larger noise. Finally, the binary objects belonging to the dice pips are extracted.

2.1.1. Non-Circular Object Discard

It is well known that the pips of dice are usually circle shaped. If an object's shape is not circular, then we say the object is noise which can be deleted.

2.2. Dice Cluster Segmentation

In general, a dice game is composed of several dice, usually of four dice. The goal of this research is auto-recognizing the score of a dice game by image processing technique. Because of the dice touching problem, how to design an effective dice segmentation scheme became the primary concern. Fig. 3 shows the segmentation flow chart of our approach. When the binary object image is fed in, the objects size calculation (OSC) is used to record the size of the dice pips. Next, we check the size. If size is greater than the threshold then it is a one-pt. face, otherwise it is another dice face and the segmentation stage begins.

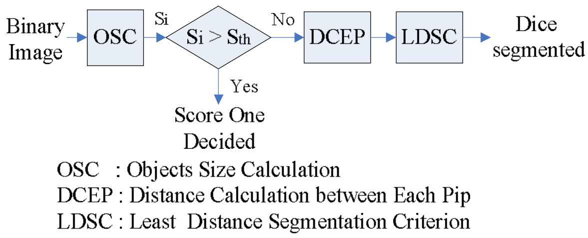
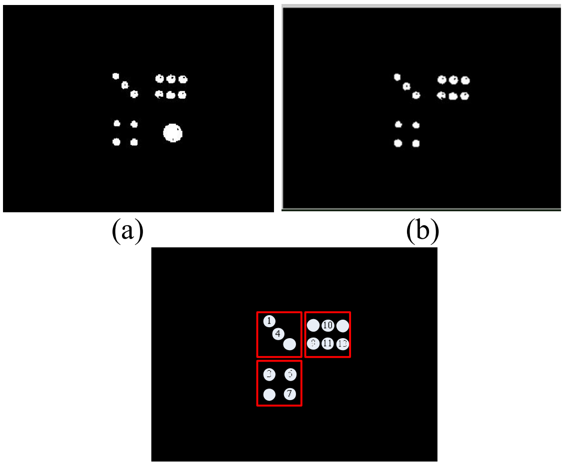


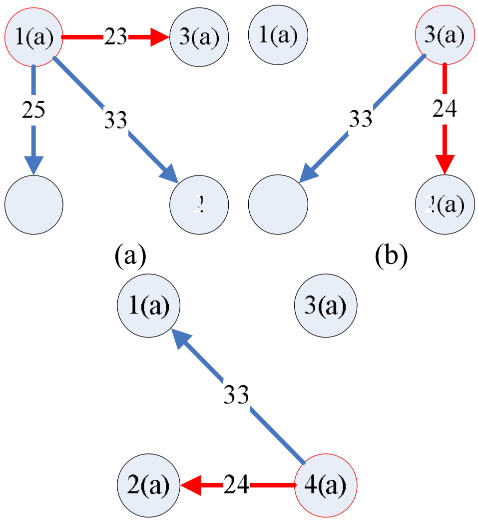
Fig. 3 The flow chart of dice segmentation

Since we adopt the LDC method to distinguish dice, we thus calculate distant between each pip (CDEP) and least distant segment criterion (LDSC). CDEP is used to enhance segmentation speed and LDSC is used to segment the dice cluster. The overall dice segmentation procedure is shown in Fig. 4. The test image with one-pt. dice is shown in Fig. 4(a). Because the one-pt. face has a larger pip size, it will be picked out and ignored firstly. Therefore, the one-pt. face disappears as Fig. 4(b) shows. When all the dice clusters are segmented, all clusters will be marked off with red boxes squares as Fig. 4(c) shows.



(a) (b) (c)

Fig. 4 The dice segmentation procedure: (a) the original binary image; (b) the one-pt. face was discovered and later ignored; and (c) all the dice segmented and marked off with red boxes.



(a) (b) (c)

Fig. 5 The schematic of dice cluster segmentation: (a) initial state with the first pip index selected; (b) the second pip is found; and (c) the third pip has been decided.

2.2.1. The Distance Calculation between Each Pip (DCEP)

In the DCEP stage, the Euclidean distance equation is used to calculate the distance between each pip and records it as in Table I. According to Table I, the distance of pip 1 and pip 2 is 25, and the distance of pip 1 and pip 3 is 23 as row 1 lists. In another case, the distance of pip 3 and pip 2 is 33, and pip 3 and pip 4 is 24 as row 3 lists. Likewise, other cases are all listed in Table I. The purpose of DCEP is to help the following LDSC operation that clusters dice.

TABLE 1

THE RELATIVE DISTANCE BETWEEN EACH PIP

Pip index	1	2	3	4
1	-	25	23	33
2	25	-	33	24
3	23	33	-	24
4	33	24	24	-

2.2.2. Least Distant Segmentation Criterion (LDSC)

How to segment the dice clusters is a crucial issue of dice game automatic recognition schemes using a camera mechanism. In dice clustering, several dice may touch each other and increase the difficulty of image segmentation. Especially, in camera zoom in or zoom out, the pip size became irregular. Therefore, developing an effective dice cluster segmentation technique is necessary. In this paper, we use the LDSC method to achieve accurate dice clustering. The following describes the steps of LDSC.

Step 1: mark each pip and giving it a pip index.

Step 2: compute the distance between each pip in the image.

Step 3: search for least distance pip from an initial pip index (initial pip index like pip number 1) to others as Fig. 5(a) shows.

Step 4: search least distance pip from next pip index to others as Fig. 5(b) and Fig. 5(c) show.

Step 5: repeat step 4 until the least distance pip index encounters the initial pip index. The paths of the least distance pips in the process are constructed as a same face cluster.

Step 6: repeat step 3 - step 5 to segment other dice clusters until all dice clusters are done.

2.3. Dice Score Calculation and Exception Processing

Obtaining the dice score is the final target in this paper. In general, the dice score can easily be obtained from calculating the number of pips in a die cluster when it is segmented. Because the six-pt. face is composed on two three-pt. faces in image processing under the LDSC method, therefore, an exception is needed to process this problem in this approach. Fig. 6 shows a six-pt. face composed of two three-pt. faces in dual inline permutations which could be misjudged as two three-pt. faces. In order to eliminate errors, an exception processing is offered and described in the following.

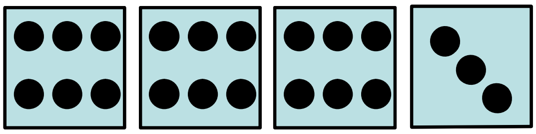


Fig. 6 Causing a misjudged case; a six-pt. face is composed of two three-pt. faces in dual inline permutations under the LDSC method.

Step 1: let sum denote the sum of all three-pt. clusters, and $m = \mathrm{mod}(sum/6)$, where the mod is a modular operation, and $q = (sum - m)/6$, if $m = 0$ then $nb = q$, otherwise $nb = q + 1$, na denotes the cluster number of segmentation but ignoring three-pt. clusters. If (na + nb) is equal to 4 then the number of six-pt. clusters is q. If $m \neq 0$ then the number of three-pt. clusters is 1, else the number of three-pt. clusters is 0, otherwise go step 2.

Step 2: let sum denote the sum of all three-pt. clusters, and $q = sum/3$, na is the cluster number of segmentation but excluding three-pt. clusters. If (na + q) is equal to 4 then the number of three-pt. clusters is q, otherwise go step 3.

Step 3: let sum denote the sum of all three-pt. clusters, and $q = (sum - 6)/3$, na is the cluster number of segmentation but for those three-pt. clusters. If (na + $q+1$) is equal to 4 then the number of six-pt. clusters is 1, and the number of three-pt. clusters is q, otherwise go step 4.

Step 4: let sum denote the sum of all three-pt. clusters, and $q = (sum - (6 \times 2))/3$, na is the cluster number of segmentation but not including those three-pt. clusters. If (na + $q+2$) is equal to 4 then the number of six-pt. clusters is 2, and the number of three-pt. clusters is q.

Example 1: there are three six-pt. dice and a three-pt. die as Fig. 6 shows. According to step 1, we have a sum of 21, $m = \mathrm{mod}(sum/6) = 3$, $q = (sum - m)/6 = 3$, $na = 0$, $nb = q + 1 = 4$, owing to $(na + nb) = 4$ then the number of six-pt. clusters is $q = 3$, and the number of three-pt. clusters is 1.

Example 2: there are four three-pt. dice as Fig. 7 shows. According to step 1, we have a sum of 12, $m = \mathrm{mod}(sum/6) = 0$, $q = (sum - m)/6 = 2$, $na = 0$, $nb = q = 2$, $(na + nb) = 2 \neq 4$, therefore go to step 2. In step 2, we have a sum of 12, $q = sum/3 = 4$, $na = 0$, $(na + q) = 4$ thus the number of three-pt. clusters is 4.

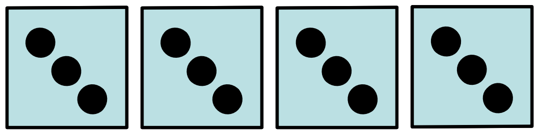


Fig. 7 The case of four three-pt. faces.

Example 3: there is a six-pt. face and three three-pt. faces as Fig. 8 shows. According to step 1, we have a sum of 15, $m = \mathrm{mod}(sum/6) = 3$, $q = (sum - m)/6 = 2$, $na = 0$, $nb = q + 1 = 3$, $(na + nb) = 3 \neq 4$ therefore go to step 2. In step 2, we have a sum of 15, $q = sum/3 = 5$, $na = 0$, $(na + q) = 5 \neq 4$ therefore go to step 3. We have a sum of 15, $q = (sum - 6)/3$ =3, $na = 0$, Since $(na + q + 1) = 4$, the number of six-pt. clusters is 1, and the number of three-pt. clusters is 3 .

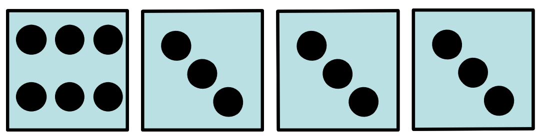


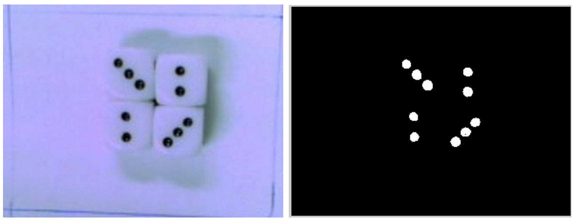
Fig. 8 The case of a six-pt. face and three three-pt. faces.

3. Experimental Results

In the experiment, many combinations of different dice with different scores are selected to test. Fig. 9 shows a regular dice line-up case. Fig. 9(a) is an original image; it is composed by double two-pt. and three-pt. dice in a regular line together. Fig. 9(b) is the binarized image of Fig. 9(a). According to Fig. 9(b), we have difficulty in identifying which ranges are a dice cluster. On the other hand, Table II shows the relative distance between each pip of the dice image in Fig. 9. Table III is the dice score and clustering path obtained from Table II by least distance criterion.

Fig. 10 shows the dice spread in a scattered state; Fig. 10(a) is the original test image. Fig. 10(b) denotes the binarized image of (a). Table IV is the relative distance between each pip of dice in Fig. 10. Table V is the dice score and clustering path obtained from Table IV by least distance criterion.

Several test states wherein locations of dice are scattered or regular are included. We zoom in to and zoom out from the image for examining the algorithm's identification ability.



(a) (b)

Fig. 9 Close cluster of dice: (a) the original image; (b) the binarized image of (a).

TABLE II

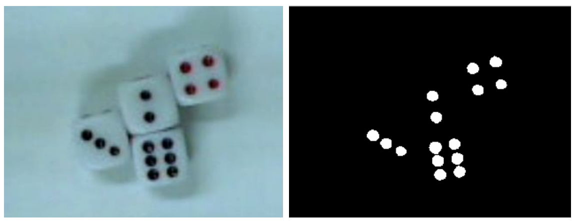
The relative distance between each pip of dice images in Fig. 9.

Pips index	1	2	3	4	5	6	7	8	9	10
1	-	60	83	16	33	105	103	70	76	103
2	60	-	23	48	39	56	62	80	68	71
3	83	23	-	71	60	47	59	95	79	71
4	16	48	71	-	16	88	86	58	61	86
5	33	39	60	16	-	72	69	48	46	69
6	105	56	47	88	72	-	16	81	58	31
7	103	62	59	86	69	16	-	69	46	15
8	70	80	95	58	48	81	69	-	23	58
9	76	68	79	61	46	58	46	23	-	36
10	103	71	71	86	69	31	15	58	36	-

TABLE III

THE DIE SCORE AND CLUSTERING PATH

Die score	Clustering path (number denotes pip index)
3	1 → 4 → 5 → 1
2	2 → 3 → 2
3	6 → 7 → 10 → 6
2	8 → 9 → 8



(a) (b)

Fig. 10 Scattered dice: (a) the original image; (b) the binarized image of (a).

TABLE IV
The relative distance between each pip of dice images in Fig.10.

Pips index	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	-	17	36	80	72	75	78	87	92	98	106	136	129	162	156
2	17	-	19	74	56	64	61	70	77	81	88	129	120	155	146
3	36	19	-	72	39	55	42	51	60	63	69	124	111	147	136
4	80	74	72	-	59	24	74	89	60	76	91	55	52	81	79
5	72	56	39	59	-	35	15	30	21	26	38	99	81	119	103
6	75	64	55	24	35	-	50	65	36	52	67	68	56	91	81
7	78	61	42	74	15	50	-	15	26	22	27	112	93	130	112
8	87	70	51	89	30	65	15	-	37	26	22	125	105	142	123
9	92	77	60	60	21	36	26	37	-	16	31	88	67	105	86
10	98	81	63	76	26	52	22	26	16	-	15	103	81	118	97
11	106	88	69	91	38	67	27	22	31	15	-	117	95	131	109
12	136	129	124	55	99	68	112	125	88	103	117	-	24	27	36
13	129	120	111	52	81	56	93	105	67	81	95	24	-	37	26
14	162	155	147	81	119	91	130	142	105	118	131	27	37	-	26
15	156	146	136	79	103	81	112	123	86	97	109	36	26	26	-

TABLE V
THE DIE SCORE AND CLUSTERING PATH

Die score	Clustering path (number denotes pip index)
3	1 → 2 → 3 →1
2	4 → 6 → 4
3	5 →7 → 8 →5
3	9 →10 → 11→9
4	12 → 13 → 15 →14 → 12

4. CONCLUSIONS

In this paper we study the features of dice and analysis their advantages and drawbacks. We give up using the color feature for recognition but we adopt the size feature and regular relative distance feature. Meanwhile, we implement the least distance criterion method to segment dice in a dice game image. The distance ratio between pips of a dice game image is relative distance, invariant of image zoom in or zoom out. Thus, the least distance criterion is very suitable for dice segmentation under camera captured image. Experimental results show our scheme can perfectly identify the dice score of the dice images in over 250 times simulations of different cases.

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