

Golf Ball Detection from Multi-Exposure Images under Heavy Occlusion

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Abstract— In this paper, we propose an automatic technique for detecting golf balls from multi-exposure images under heavy occlusion. The proposed technique consists of two processes. First, an automatic region-of-interest detection process based on image thresholding and labelling techniques is employed to separate regions of interest of golf ball from each multi-exposure image. Then, a novel adaptive ball detection and selection process based on circular Hough transform and circular shape correlation is applied to each region of interest for determining the location and radius of each golf ball with high-accuracy irrespective of occlusion. Experimental results show that the proposed technique is capable of automatic golf ball detection under heavy occlusion.

Keywords— Golf ball detection, multi-exposure image, heavy occlusion, virtual golf

I. INTRODUCTION

Virtual golf is an indoor golf simulation game that is played on a virtual golf course with real golf clubs and a ball. For reality, virtual golf is based on the physics simulation with actual initial conditions, such as the speed and spin of a golf ball. Therefore, the initial condition measurement is a critical issue for virtual golf. A variety of sensors, such as infrared LEDs, radars, and high-speed cameras, have been utilized to detect golf balls for measuring the initial conditions [1, 2, 3]. Most commercial systems adopt infrared LEDs due to the cost problem, but some professional systems utilize high-speed cameras for golf ball detection with great high accuracy [4, 5]. However, such professional systems are not popular due to the high cost of high-speed cameras. For this reason, some recent systems use multi-exposure cameras instead of using high-speed cameras [6]. Multi-exposure cameras have been originated to capture high-speed motion images [7]. In the literature, multi-exposure cameras have been used to detecting the high-speed motion of sports balls or to analyse the motion of human body parts [8, 9]. Although detecting golf balls with multi-exposure cameras is very cost-efficient, it brings out some technical issues. For example, multi-exposure cameras should use additional lighting equipment to highlight target objects against background. In addition, multi-exposure cameras overwrite multiple shots of high-speed motion into a single image, which can cause serious occlusion problems.

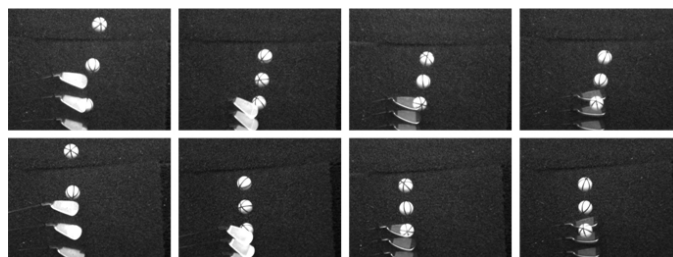


Figure 1. Multi-exposure images of real golf shots for our virtual golf game

In this paper, we propose an automatic technique for detecting golf balls from multi-exposure images under heavy occlusion. A multi-exposure camera module with two area-scan cameras, one line-scan camera, and four high-intensity lamps, developed for our virtual golf system, is used to capture high-speed motion images of real golf shots. The area-scan cameras are set to be exposed three times per capture and the line-scan camera is used to trigger the area-scan ones whenever golf balls pass the capture area. Samples of multi-exposure images of real golf shots for our virtual golf game are shown in Fig. 1. As shown in that figure, golf balls are occluded with golf clubs. To detect golf balls from those multi-exposure images under heavy occlusion, the proposed technique consists of two processes. First, an automatic region-of-interest detection process based on image thresholding and labelling techniques [10, 11] is employed to separate regions of interest of golf ball from each multi-exposure image. Then, a novel adaptive ball detection and selection process based on circular Hough transform [12] and circular shape correlation is applied to each region of interest of golf ball for determining the location and radius of each golf ball with high accuracy irrespective of the existence of occlusion. The effectiveness and efficiency of the proposed technique was verified with real multi-exposure images of golf shots for virtual golf. Experimental results show that the proposed technique is capable of automatic golf ball detection under heavy occlusion.

II. AUTOMATIC GOLF BALL DETECTION

The proposed technique has two processes. First, an automatic region-of-interest detection process is employed to separate regions of interest of golf ball from multi-exposure images. Next, an adaptive circle detection and selection process is used to determine the centroid and radius of each golf ball.

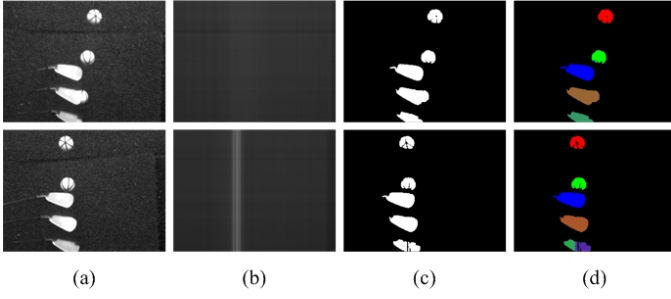


Figure 2. Automatic region-of-interest detection. (a) Input image. (b) Background model. (c) Regions of interest of golf ball. (d) Segmented regions of interest of golf ball

A. Automatic Region-of-Interest Detection

A multi-exposure image of golf shot for our virtual golf game can be separated into dark background and bright foreground regions. As shown in Fig. 1, golf balls belong to the foreground region. Therefore, the foreground region is the region of interest of golf ball. Usually, we can obtain the foreground region if we know the background model of the input image [13]. To obtain the foreground region, we make a background model as follows. Let us denote I a multi-exposure image of $U \times V$ pixels. By assuming that the background region dominates I , we can make a background model B with

$$B(u, v) = \frac{\text{med}[I(u, 1:V)] + \text{med}[I(1:U, v)]}{2}, \quad (1)$$

where $\text{med}[I(u, 1:V)]$ represents the median value of the u -th row of I and $\text{med}[I(1:U, v)]$ the median value of the v -th column of I . Then, the foreground region can be obtained by applying an image thresholding technique to the absolute difference D between the input image I and the background model B , which is defined by

$$D(u, v) = |I(u, v) - B(u, v)|. \quad (2)$$

An optimal threshold d_{opt} that maximizes the between-class variance of the absolute difference values of D is computed with

$$d_{\text{opt}} = \text{Arg} \left\{ \max_d \left(P_b P_f (q_b - q_f)^2 \right) \right\}, \quad (3)$$

where d is in $[0, 255]$, P_b the probability of pixel values below d , P_f the probability of pixel values above d , q_b the mean of pixel values below d , q_f the mean of pixel values above d . Then, the foreground region G is obtained with

$$G(u, v) = \begin{cases} 1 & \text{if } D(u, v) \geq d_{\text{opt}} \\ 0 & \text{otherwise} \end{cases}. \quad (4)$$

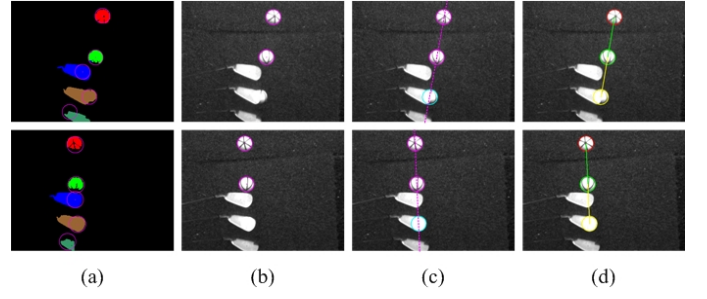


Figure 3. Adaptive ball detection and selection. (a) Golf ball candidates. (b) First and second locations of golf ball. (c) Third location of golf ball on the golf ball path. (d) Final locations of golf ball

An image labelling technique like the fast connected component labelling algorithm [11] is applied to the foreground region G to obtain segmented regions of interest of golf ball, $S = \{S_1, \dots, S_M\}$. Figure 2 demonstrates the above automatic region-of-interest detection process.

B. Adaptive Ball Detection and Selection

Golf ball candidates, $C = \{C_1, \dots, C_M\}$, are obtained by detecting a circular object from each region of interest of golf ball with the circular Hough transform [11]. Then, we compute a similarity score between each golf ball candidate C_m and its circular shape model H_m . The similarity score is defined by

$$\mathcal{Q}(C_m) = \sum_{u=u_m-1.25r_m}^{u=u_m+1.25r_m} \sum_{v=v_m-1.25r_m}^{v=v_m+1.25r_m} H_m(u, v)(1 - 2G(u, v)), \quad (5)$$

where (u_m, v_m) and r_m are the location and radius of C_m , respectively, and H_m is defined by

$$H_m(u, v) = \begin{cases} 1 & \text{if } \sqrt{(u - u_m)^2 + (v - v_m)^2} \geq r_m \\ 0 & \text{otherwise} \end{cases}. \quad (6)$$

We sort the golf ball candidates in the descending order of the similarity score and then select the locations of the first two ones, denoted by O_1 and O_2 , as the first and second locations of golf ball and the radius of the first one as the final radius r of golf ball. The n -th golf ball, O_n , is assumed to be located on the following path

$$L(t) = ((1-t)u_1 + tu_2, (1-t)v_1 + tv_2), \quad (7)$$

where (u_1, v_1) and (u_2, v_2) are the location of O_1 and O_2 , respectively, and t is a time parameter. On the path $L(t)$, we search the n -th location of golf ball O_n with a normalized cross correlation-based block matching algorithm like [14] such that O_n maximizes the following correlation score

$$W(O_1, O_n) = \sum_{u=-1.25r}^{u=+1.25r} \sum_{v=-1.25r}^{v=+1.25r} \frac{(I_1(u, v) - E_1)(I_n(u, v) - E_n)}{\sqrt{V_1 V_n}}, \quad (8)$$

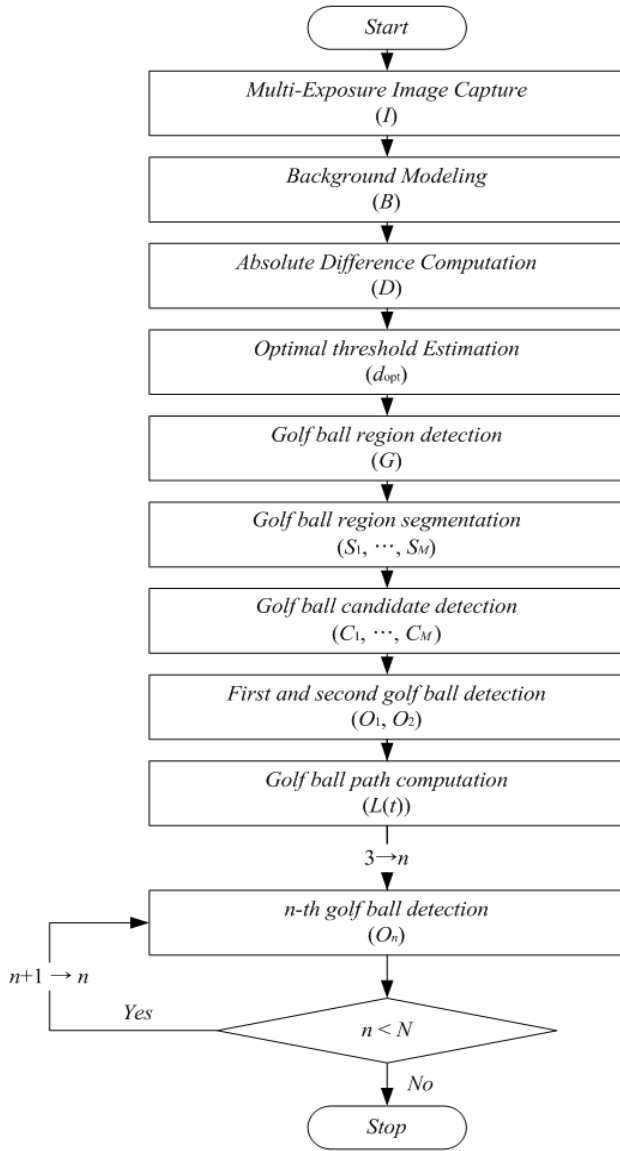


Figure 4. Flowchart of the proposed technique

where

$$I_n(u, v) = I(u + u_n, v + v_n), \quad (9)$$

$$E_n = \frac{1}{(2.5r + 1)^2} \sum_{u=-1.25r}^{u=+1.25r} \sum_{v=-1.25r}^{v=+1.25r} I_n(u, v), \quad (10)$$

$$V_n = \frac{1}{(2.5r + 1)^2} \sum_{u=-1.25r}^{u=+1.25r} \sum_{v=-1.25r}^{v=+1.25r} (I_n(u, v) - E_n)^2. \quad (11)$$

Figure 3 demonstrates the above adaptive ball detection and selection process. The flowchart of the proposed technique is shown in Fig. 4.

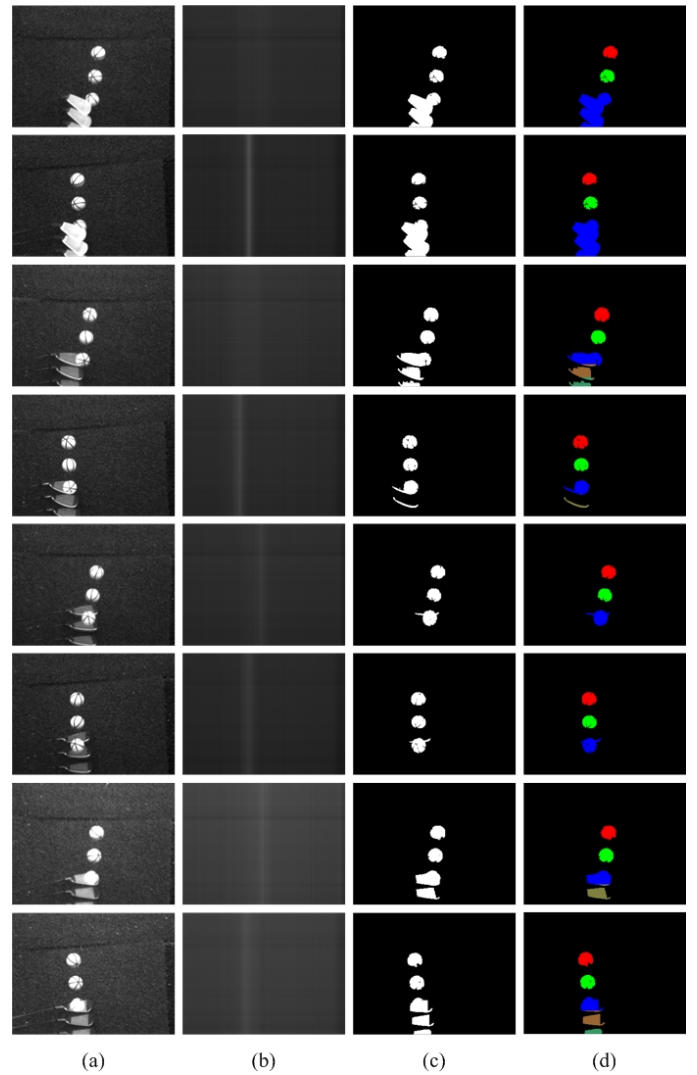


Figure 5. Results of the automatic region-of-interest detection process in the proposed technique. (a) Input image. (b) Background model. (c) Regions of interest of golf ball. (d) Segmented regions of interest of golf ball

III. EXPERIMENTAL RESULTS

The effectiveness and efficiency of the proposed technique was tested with real multi-exposure images of golf shot for our virtual golf system in Fig. 7. All test images were captured with the multi-exposure camera module that was set to be exposed three times per capture, i.e., $N=3$. For experiment, the delay time between camera exposures was set to 1.53ms and the camera resolution was set to be 640×480 pixels.

Figure 5 shows some results of the automatic region-of-interest detection process in the proposed technique. As shown in that figure, segmented regions of interest of golf ball were well obtained from each test image by using the automatic process. Figure 6 shows the results of the adaptive ball detection and selection process for the test images used in Fig. 5. As shown in that figure, the classic circular Hough transform shows poor performance under heavy occlusion but the proposed technique addresses the occlusion problem.

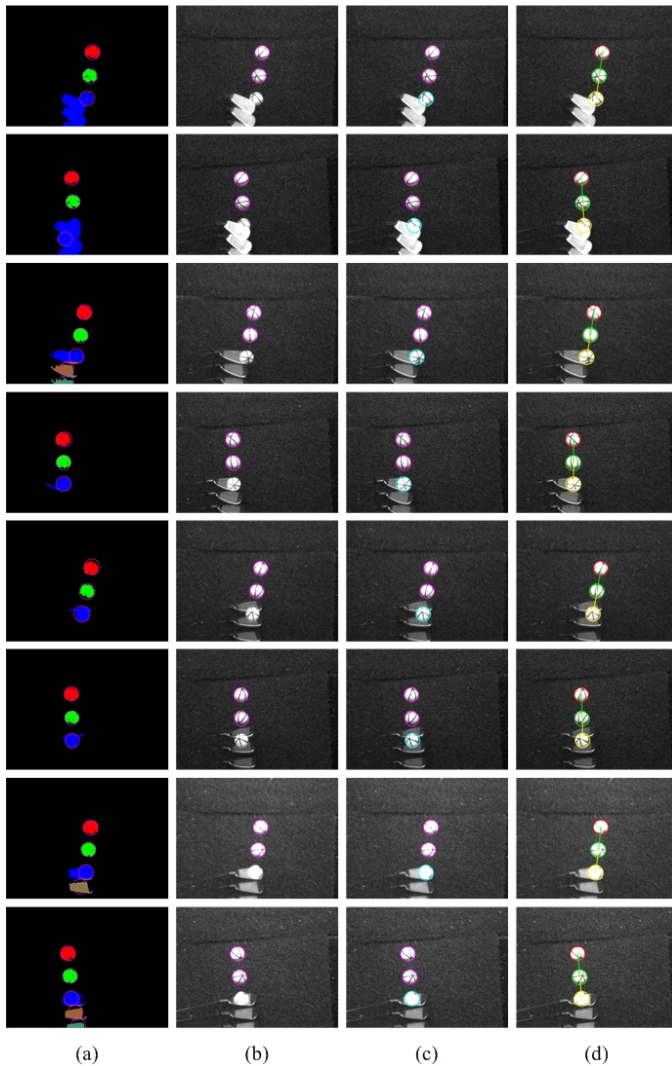


Figure 6. Results of the adaptive ball detection and selection process in the proposed technique. (a) Golf ball candidates. (b) First and second locations of golf ball. (c) Third location of golf ball. (d) Final locations of golf ball

IV. CONCLUSIONS

We proposed an automatic technique for detecting golf balls from multi-exposure images of golf shots for virtual golf. The proposed technique consisted of two processes. First, an automatic region-of-interest detection process based on image thresholding and labelling techniques was employed to separate regions of interest of golf ball from each multi-exposure image. Then, a novel adaptive ball detection and selection process that combined the circular Hough transform and circular shape correlation was applied to each region of interest of golf ball for determining the location and radius of golf balls with high accuracy irrespectively of the existence of heavy occlusion. The effectiveness of the proposed technique was verified with real multi-exposure images of golf shots. Experimental results showed that the proposed technique was capable of automatic golf ball detection under heavy occlusion.



Figure 7. Our virtual golf system with a multi-exposure camera module

ACKNOWLEDGMENT

This research was supported by the Ministry of Culture, Sports and Tourism (MCST) and the Korea Creative Content Agency (KOCCA) in the Culture Technology (CT) Research & Development Program 2010 [2-10-7602-003-10741-00-003].

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