EFFICIENT BARBELL TRAJECTORY EXTRACTION ALGORITHM FOR KINEMATIC ANALYSIS USING VIDEO SPATIAL AND TEMPORAL INFORMATION

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ABSTRACT
In this paper, we proposed a novel efficient barbell trajectory extraction algorithm and further implemented a computer aided weightlifting training system with our proposed algorithm. The proposed method extracts the barbell trajectory from the video sequence both considering spatial and temporal information which are the barbell color and motion information between each frame. The experimental results show that the proposed algorithm can gather the barbell trajectory in high accuracy and efficiency. The implemented computer aided weightlifting training system saves about 95% operation time comparing to traditional kinematic analysis software. It makes athletes, coaches and researchers evaluate the sport performance more easily.

KEY WORDS
Sport Biomechanics, Weightlifting, Kinematics, Object Tracking

1. Introduction

As one of the research topic of sport biomechanics, kinematic analysis has been widely researched and acceptable applied for sport performance evaluation. Kinematic analysis software provides professional kinematic parameters such as trajectory or moving speed which help researchers to understand the condition of the athletes. However, difficultly and manually usage of the kinematic analysis software consumes huge operation time. On the other hand, difficultly usage also dedicates the usage intention of the coaches or athletes.

Sport video contains a lot of useful information. This information not only satisfies entrainment, but also kinematics analysis. Researchers or athletes observe the sport video to obtain the sport performance. Not only evaluating self sport performance, the sport video can also used to gather rivals' intelligence. This intelligence helps athletes to understand rivals' strategy and further develop new tactic to win the competition.

Video analysis is a popular research topic in computer vision area. Since sport video has much useful information such as human motion, video analysis technique can analyze these videos for sport training or kinematic analysis. Traditional kinematic analysis software adopts the advent of 3D opto-reflective which both considering passive and active tends to be laboratory based require expertise for body marker placement. These markers help motion analysis software to create human body model and track the limb moving in high accuracy. However, these markers restrict the body motion and decrease the sport performance. On the other hand, most of the kinematic analysis softwares are not suit for outdoor using. User spends expensive time to setup the experimental environment, but may not gather high accuracy experimental results. These limitations restrict the growth of the computer aided sport training. The usage willing of the coaches or athletes might be decreased.

Weightlifting is a popular athletic sport and one topic of the Olympic Game. Athletes enhance their skill to win the competition. Not only for the athletic weightlifting, powerlifting and dumbbell fitness are also used by people to enhance their bodies. Kinematic parameters are the key way to evaluate the sport performance. This evaluation can diagnostic the problem of the gesture, not only enhance the sport performance, but also further prevent sport injuries. Since the trajectory is the most popular way to observe the gesture, in past year, many researchers are interesting in the barbell route. Sato *et al*., Lenjannejadian *et al*. and Rahmati *et al*. utilize sensor such as triaxial accelerometer to gather the trajectories of the barbell [1]-[3]. Sensor is one of the efficiency ways to gather the barbell path. However, when lifters drop the barbell after finishing the action, the total mass is almost 170.1G [1]. The accuracy may be lost even if the sensor may be damaged. On the other hand, although the sensors can provide accuracy kinematic parameters, however, they cannot be suitable in the competition. The real sport performance cannot be obtained. Thus, video analysis technique might be the accuracy and efficiency way to gather the trajectory of the barbell to aid the kinematic analysis for computer aided weightlifting training. Hence, we aim on video analysis technique to propose an efficiency barbell tracking algorithm to extract the trajectory from the video sequence.

In this paper, we proposed a high efficiency barbell recognition and tracking algorithm. The proposed algorithm recognizes the barbell in each frame and then

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tracks the recognized barbell in the video sequence. Spatial and temporal information are both considered in the proposed method. The high motion area in a frame is found in advance, the color information is then be used to find the barbell. After the coordinate of the barbell in current frame has been determined, the coordinate of the barbell will be added into the trajectory.

The rest of this paper is organized as follows. In Section 2, the relevant works are reviewed. We introduce the detail of the proposed barbell trajectory extraction scheme in Section 3. The experimental results are shown and discussed in Section 4. Finally, in Section 5, the proposed algorithm is concluded.

2. Review of Relevant Works

Many researches utilize sensors to gather the trajectory of the barbell. However, the contactable sensors may restrict the sport performance and may not be suitable in a real competition. In this paper, we consider the video object recognition and tracking scheme to extract the trajectory.

Ren *et al*. observe sport videos and obtain that the characteristics of the weightlifting barbell and dumbbell motion in the video sequence is periodical activities. Hence, they utilize the periodical motion pattern to detect and count the barbell activity [4]. Jocic *et al*. consider the color information to track the object in the video sequence. They utilize the scene illumination change as the training set and use OpenGL library to enhance the recognition performance [5]. Zikovic *et al*. utilize mean-shift method combined with color histogram as the kernel function. They proposed 5-degree of freedom color histogram based non-rigid object tracking algorithm [6]. Joic *et al*. and Zivkovic *et al*. both consider color information. Although the color information is easily gathered, however, the color information might be influenced by light changing which decreases the recognition and tracking accuracy. Therefore, some researchers further consider other information to enhance the recognition performance.

Zhang *et al*. proposed multi object tracking algorithm for soccer game to track the players moving in the court. They both consider color and shape of the target object [7]. Wang *et al*. proposed object tracking for video surveillance by integrating color and shape-texture. They use mean-shift method and select reliable feature from color and shape-texture as the kernel function, and update target model by similarity [8]. Yilmaz *et al*. proposed a complete object region tracking algorithm which adapts changing visual features. Also, color and texture are both modeled by semiparametric model. The shape is used to recover the missing object region during occlusion by handling [9].

Above object tracking methods which consider shape, texture and color are in high recognition accuracy, however, huge computational complexity makes realization difficultly. Hence, in our proposed barbell trajectory extraction method, we consider color information with motion information to achieve the efficiency and accuracy with low computational complexity.

3. Proposed Efficient Barbell Trajectory Extraction Algorithm by Considering Spatial and Temporal Information

In this section, the proposed efficient barbell trajectory extraction algorithm is introduced. We both consider color characteristics of the barbell and temporal information. Temporal information is applied in advanced to determine the high motion area in a frame. The color information of the barbell is then be utilized to find out the position in the high motion area in each frame. The detail of the proposed method is shown as follows.

3.1 Flowchart of the Proposed Barbell Trajectory Extraction Algorithm

Figure 1 shows the flowchart of the proposed algorithm. Since we need reference frame to determine the high motion area in current frame, the proposed method begins the procedure from the second frame. Image preprocessing is utilized in advanced to eliminate the noise. For enhancing the recognition performance, the smooth filter such as mean filter is used in preprocessing to smooth the image.

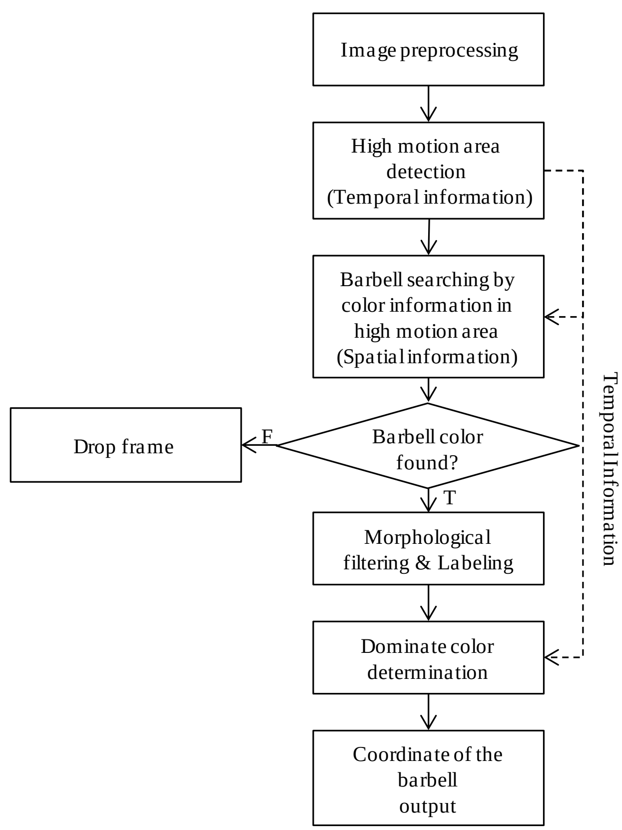


Figure 1. Flowchart of the proposed weightlifting barbell tracking algorithm

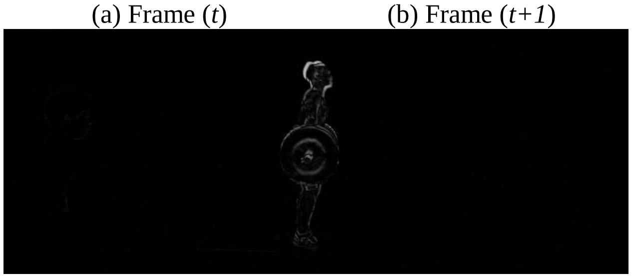
After image preprocessing, temporal information is utilized to determine the high motion area which described in Section 3.2. High motion area can reduce the computational complexity and enhance the recognition performance since the barbell must exist in this area. In barbell searching scenario (see Section 3.3), the proposed algorithm finds the barbell which refers to the lower and upper bound of the barbell's color distribution. Since there might be holes on the candidate barbell areas and noise in the background, the morphological filter and labelling scheme is used to fill of the holes, eliminate the background noise and label all candidate color in each frame. Finally, the candidate object with maximum area will be chosen and the coordinate of the chosen barbell will be added into the trajectory.

3.2 High Motion Area Detection

The temporal information is utilized in advanced to determine the high motion area. Figure 2 shows an example of continue frames of the weightlifting video sequence captured from a general training course.

Figure 2 (a) shows Frame *t*, (b) shows Frame (*t+1*) and (c) is the difference frame. In these figures, we can observe that most of the white points distribute around the athlete and barbell. It can be seen as the high motion area. The other area has less or no white points. It is the low motion area which is the background. From this observation, we can obtain that our target object, barbell, must be in the high motion area. Since the limited computation power, frame difference is utilized to gather the high motion area in each frame.

(a) Frame (*t*) (b) Frame (*t+1*)



(c) Difference Frame

Figure 2. Continue frames of weightlifting video sequence

Equations (1) and (2) calculate the frame difference and gather the high motion area, respectively. In Eq. (1), $F_{current}$ and $F_{previous}$ denote current and previous frame, respectively, where *i* and *j* are pixel index.

After calculating all pixels in the current frame by Eq. (1), Eq. (2) is applied to decide the high motion area. In this equation, d_{diff} denotes the frame difference calculating from Eq. (1), and *i* and *j* are the pixel index. If d_{diff} is greater or equal to the threshold *th*, this point lays on the high motion area, and is set to 1. Otherwise, the d_{diff} is smaller than *th*, this point is set to 0 which means the low motion area.

$$d_{diff}(i,j) = \left| F_{current}(i,j) - F_{previous}(i,j) \right| \tag{1}$$

$$\begin{cases} HighMotion\,Area(i,j) = 1 & d_{diff}(i,j) \geq th \\ HighMotion\,Area(i,j) = 0 & d_{diff}(i,j) < th \end{cases} \tag{2}$$

$$th = \left(\sum_{i=0}^{i} \sum_{j=0}^{j} d(i,j) \right) \times k \tag{3}$$

We can further observe Figure 2 (c). It can be found that there are some residual in the frame far from the athlete and barbell. This residual may be the shadow, light changing or background objects. This residual might influence the spatial procedure further decreasing the recognition performance. Hence, Eq. (3) is utilized to determine the threshold, *th*, for Eq. (2) to eliminate the residual in the low motion area and makes our temporal information in high accuracy.

After observing more than 500 weightlifting videos, the *k* value in Eq. (3) is set as 0.85. It means that if the frame difference of the point is greater or equal to 85% of the average frame difference, it is the high motion area in this frame.

3.3 Barbell Searching by Considering Color Information

Figure 3 shows the high motion area determined by previous stage. The green box in the frame is the high motion area. The temporal information reserves the athlete and barbell, and further eliminates the background noise such as audience. This procedure not only enhances the recognition accuracy since the background noise has been removed, but also reduces the computational complexity.

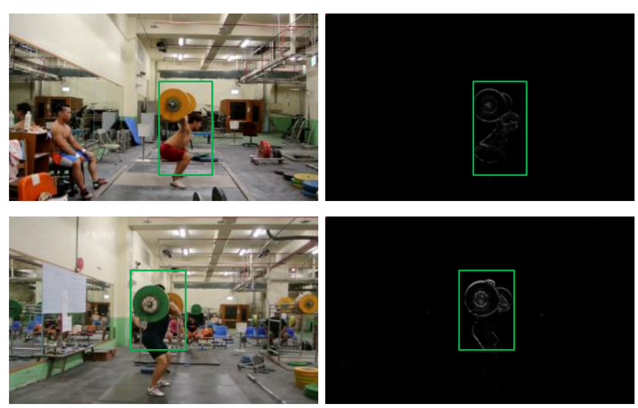


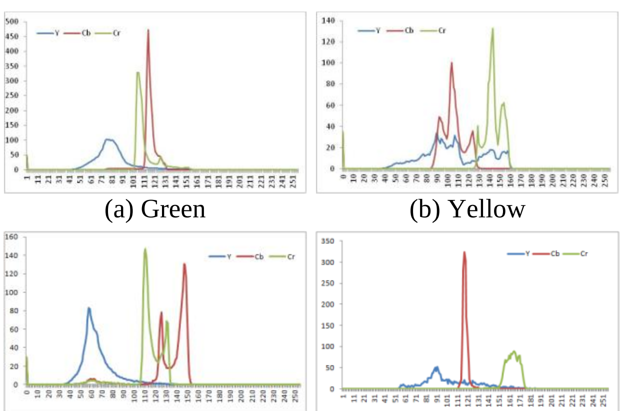
Figure 3. High motion area from temporal information

Since International Weightlifting Federation (IWF) stipulates the color of the barbell, the proposed algorithm utilizes the specific color of the barbell to recognize the barbell in high motion area. Table 1 shows weight and color which stipulated by IWF. From this table, we can obtain that the color of the barbell is unique, thus, the color distribution of the barbell can be used to recognize the barbell. YCbCr color space is concerned in our proposed method since it can be easily gathered from most of the compressed video bitstream or image. On the other hand, YCbCr color space can withstand the light influencing which may change the color of the target object.

Table 1
Barbell specification stipulated by IWF

Weight (kg)	10	15	20	25
Color	Green	Yellow	Blue	Red

Figure 4. Examples of barbell training set



(a) Green (b) Yellow

(c) Blue (d) Red

Figure 5. Color distribution obtained by barbell training set

Table 2
Upper and lower bound for the Cb and Cr value of barbells

Color		Green	Yellow	Blue	Red
Cb	Upper	129	148	152	131
	Lower	113	132	137	111
Cr	Upper	129	116	121	176
	Lower	113	100	102	153

Figure 4 shows examples of the barbell training set. We carefully captured the barbell from the weightlifting video sequences and gathered the color distribution from the captured barbell images. The color distributions of each barbell are obtained in Figure 5. Figure 5 shows the distribution of YCbCr color space for green, yellow, blue and red barbell, respectively. From this figure, it is obvious that the color distribution of each barbell is unique to identify. Thus, we decide the upper bound and lower bound of the barbell's color distribution as the threshold.

To avoid light influencing, Cb and Cr components are considered in the proposed algorithm. Table 2 shows the upper and lower bound for Cb and Cr value of the barbell which obtained from 500 weightlifting videos. If the pixel value lay on the high motion area, the current pixel will be set as the candidate barbell. All candidate pixels will be connected with morphological filter and the color with maximum area must be the barbell. Then, the center of the maximum color area is the coordinate of the barbell and that will be added into the barbell trajectory.

3.3 Flowchart of the Implemented Computer Aided Weightlifting Training System with the Proposed Barbell Trajectory Extraction Algorithm

For widely application and verification the performance of the proposed algorithm, we implement a computer aided weightlifting training system with proposed barbell trajectory extraction algorithm.

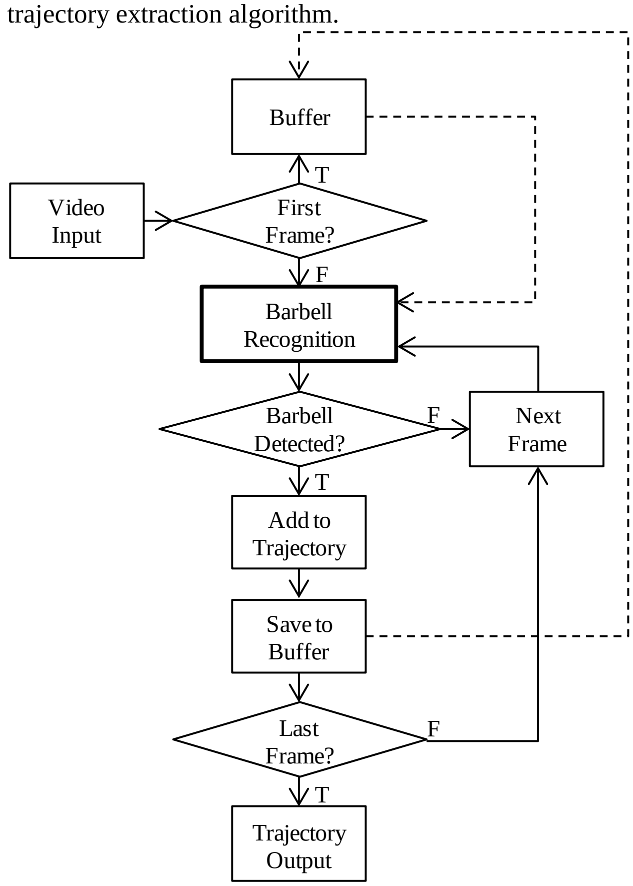


Figure 6. Flowchart of the computer aided weightlifting training system with proposed barbell trajectory extraction algorithm

Figure 6 depicts the flowchart of our implemented computer aided weightlifting training system. As mentioned, first frame is directly moved to the buffer as the reference frame.

From the second frame, the proposed method utilizes the temporal and spatial information to recognize and track the barbell in each frame. Motion information and color information are both considered in this scenario. If the barbell is found, the coordinate of the recognized barbell will be added into the barbell trajectory. Otherwise, if the barbell is not found, the current frame will be dropped.

After all frames are input into the implemented computer aided weightlifting training system, the complete barbell trajectory will be extracted the output to user to evaluate the sport performance.

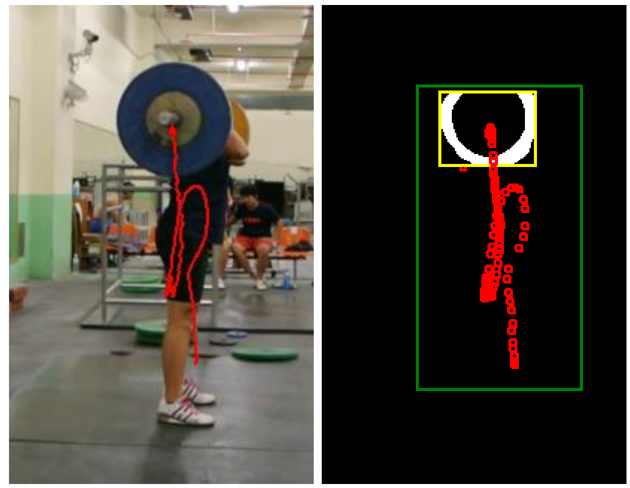
4. Experimental Results

The experimental results are shown and discussed in this section. The weightlifting videos are gathered from public competitions and normal training courses. Public competitions are 2003 Taiwan High School Game and 2002 Taiwan University Weightlifting Competition. The videos of the normal training course are captured from University of Taipei weightlifting team. All the videos are captured by consumer video camcorders with a tripod. The position and focal length of the camcorder are fixed in one shot. More than 500 weightlifting videos are gathered. In these videos, 250 video sequences are randomly chosen for training set. The training videos are used to determine the upper and lower bound of the color distribution and threshold of the temporal information. The rest of 250 videos are used to evaluate the recognition performance.

The proposed algorithm is implemented in Microsoft Windows 7 platform with Visual Studio 2010. Since we consider computational complexity and easily using in the weightlifting court, the proposed algorithm is simulated in a laptop with ATOM CPU and 2G RAM. The average computation time, correct recognition rate and subjective quality are provided and discussed.

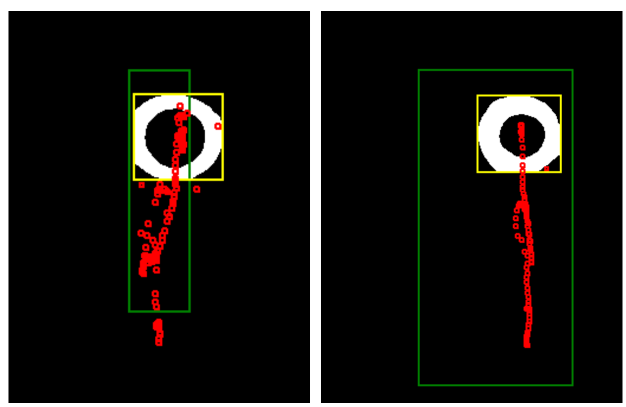
The average computation time of the proposed algorithm is 66 msec for each frame. 93% of the correction recognition rate is obtained. It means that one round, from ready phase to finish (lifter drops the barbell, about 600 frames), just takes 30 seconds to show the complete trajectory and history map. Comparing to the kinematic software manually gathering the trajectory may take 10 minutes, the proposed barbell trajectory extraction saves more than 95% operation time.

The objective quality is then discussed. Figure 7 shows an objective quality for blue barbell. Figure 7 (a) is the original video sequence with extracted barbell trajectory drawn in real-time and frame by frame. The extracted trajectory follows the barbell moving in each frame in high accuracy. This trajectory can be used to evaluate the athlete's skill. For example, we can observe the highest point and the dropping depth of the force phase from the trajectory. The sport performance can be obtained easily. Figure 7 (b) is the history map provided in our computer aided weightlifting training system. The green box and yellow box are the high motion area and barbell position in current frame, respectively. The red circles in the history map are the positions in each frame which projected into the current frame. The distance between neighbouring two red cycles shows the moving speed of the barbell. Coaches and athletes can utilize the moving speed to observe the force in each phase.



(a) Extracted trajectory of blue barbell (b) History map

Figure 7. Objective quality of the proposed algorithm (blue barbell), (a) Complete extracted trajectory; (b) History map including position(small red circle), barbell(yellow square) and high motion area(green square)



(a) Normal athlete (b) Professional athlete

Figure 8. Comparison of the sport performance between normal athlete and professional athlete

Figure 8 is also the objective quality of the implemented computer aided weightlifting training system with the proposed barbell trajectory extraction algorithm. In this figure, we compare two different level athletes. Figure 8 (a) and (b) are normal lifter and professional one. We can observe that there are many disorder red cycles in the history map from Figure 8 (a).

This means the lifter wastes much strength to lift the barbell. Comparing to Figure 8 (b), the red cycles in the history map of the professional athlete are almost lay on the vertical path. Furthermore, in Figure 8 (a), we can further observe the distance between neighbouring two points is not the same. It means that the moving speed of the barbell is not stable. The moving speed in Figure 8 (b) is more stable than Figure 8 (a). We can utilize this observation to suggest the coaches or athletes change the training course. Thus, we can obtain that the computer aided weightlifting training system with barbell trajectory extraction algorithm can help athletes to evaluate and enhance the sport performance.

5. Conclusion

An efficient barbell trajectory extraction algorithm is proposed in this paper. Spatial and temporal information are both considered to enhance the recognition performance with limited computation power. Furthermore, we implement a computer aided weightlifting training system with our proposed barbell trajectory extraction algorithm to evaluate the athletes sport performance.

In the experimental results, we can observe that the proposed barbell extraction algorithm achieve high efficiency with limited computation power. The trajectory follows the barbell in high accuracy. Furthermore, the implemented computer aided weightlifting training system with proposed barbell trajectory extraction algorithm helps users to obtain the sport performance efficiently and easily. This training aided system saves more than 95% operation time comparing to the manually kinematic software. It improves the efficiency of kinematics analysis software and helps athlete enhance the skill more efficiently.

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