Proceedings of 2009 APSIPA Annual Summit and Conference, Sapporo, Japan, October 4-7, 2009

An Improved Mean Shift Algorithm Based Tracking System for Soccer Game Analysis

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***Abstract*— In this study, an improved mean shift algorithm based tracking system with motion prediction and object window enlarging for soccer game analysis is proposed. The objective of the proposed system is to track soccer players (moving objects) efficiently and accurately. Discriminative color selection for modeling soccer players is employed, occlusions are well handled, and incoming and outgoing players are detected and handled in the proposed system. Based on the experimental results obtained in this study, the tracking results as well as the recall and precision rates of the proposed system are better than those of the three comparison systems.**

I. INTRODUCTION

Object tracking is an important and essential topic in computer vision. Recently, many object tracking techniques have been proposed to deal with some challenging issues, such as moving background with noises or shadows [1], non-rigid or articulated targets [2]-[3], occlusion handling [4]-[5]. A tracking system usually uses some additional information specified to a particular scenario where the object tracking system is applied. For example, within the baseball trajectory extracting system in [6], the characteristics of general baseball videos are used to detect baseball candidates.

Most object detection methods use only information of a single image. A typical technique is supervised learning [7], in which a detecting function is generated by learning from a large number of training samples. Wu and Nevatia [8] detected humans in a single image by combining some part detectors. The part detectors are based on the edgelet feature, which is a new type of silhouette features, and are learned by an enhanced boosting algorithm. To reduce computations and false alarms, some object detection methods exploit temporal information in image sequences. Background subtraction is an object detection technique using temporal information, in which a background model is built and then updated frame-by-frame. Object detection results are generated by the deviations from the background for each input frame. The background can be modeled as a Gaussian distribution [9], which can adapt gradual changes in the background, but may fail when some clutters (e.g., shadows or tree shakings) appear in the scene. Zhou and Hoang [1] used adaptive learning and enhancing foreground determination to cope with these problems, where a mixture of Gaussians is used to model an image pixel. Lee [10] used a Gaussian mixture learning algorithm to update Gaussian parameters, which is incorporated into the background subtraction framework. Additionally, state space approaches [11], eigenspace decomposition [12], and nonparametric kernel [13] can also be used for background modeling.

Most tracking methods can be roughly divided into three categories, namely, point tracking, silhouette tracking, and kernel tracking [14]. For point tracking, an external detection mechanism (e.g., Harris, KLT, and SIFT detectors) is used to extract interest points in videos. Gabriel, et al. [15] used a color version of the Harris detector to obtain interest points on objects, which are tracked by interest point matching using the Mahalanobis distance. Veenman, Reinders, and Backer [16] used several motion constraints to track interest points on moving objects. For silhouette tracking, silhouette trackers can be classified into two subcategories: shape matching and contour tracking. Hutternlocher, Noh, and Rucklidge [17] carried out shape matching with an edge-based representation, in which the Hausdorff distance is used as the similarity measure between edge sets. Kang, Cohen, and Medioni [18] matched the shapes using weighted histograms of color and edges as object models. On the other hand, contour tracking evolves an initial contour to its new position in the current frame. To evolve a contour, state space models are used and the states of contour points are modeled. In terms of shape and motion parameters, states are predicted and corrected, and then the most possible state with the highest posterior is obtained. Contour tracking may be transformed into a problem minimizing an energy function in terms of optical flow or appearance statistics from moving objects and the background. Gradient descent or some greedy algorithms are then used to minimize the energy function defining the fitness of a contour to an object. For silhouette tracking, some methods use only silhouette boundary information, whereas others may use the complete region inside the silhouette. To reduce computational complexity, instead of using the complete object region, only rude object positions are used in kernel tracking. Objects are represented by primitive geometric shapes, such as rectangles or ellipses, which are

+ This work was supported in part by National Science Council, Taiwan, Republic of China under Grants NSC 95-2221-E-194-020-MY3 and NSC 96-2221-E-194-033-MY3.

tracked frame by frame. This type of methods is divided into tracking using template and density-based appearance models and tracking using multiview appearance models. Schweitzer, Bell, and Wu [19] proposed an efficient template matching algorithm for object tracking. Another type of object representation methods is density-based models, e.g., histograms and probability distributions. Adam, Rivlin, and Shimshoni [20] presented a fragment-based tracking algorithm. Each patch for tracking is represented by an integral histogram data structure [21]. In Fieguth and Terzopoulos [22], an object is represented by the mean value of the pixels inside the rectangular object region. Then, the current object position is generated by evaluating the similarity between the object model and the value at the hypothesized position. Additionally, object tracking using multiview appearance models generates the appearance models offline by training with object appearances from different views, in which principal component analysis (PCA) is usually used to acquire a subspace model of the appearances of an object.

Recently, demands for analyzing sport videos are increasing. For example, for soccer games, tracking trajectories of soccer players is very helpful. Kristan, et al. [23] presented a multiple player tracker based on the particle filter. To extract trajectories of soccer players, the mean shift algorithm is an efficient method. However, in the mean shift algorithm, it is assumed that some object portion in the current frame is inside the object window determined in the previous frame. This assumption might be violated when players moves rapidly. Hence, in this study, an improved mean shift algorithm based tracking system for soccer game analysis is proposed. The proposed system will handle the occlusion problem, newly-incoming players, and outgoing players.

The paper is organized as follows. The proposed tracking system is addressed in Section II. Simulation results are addressed in Section III, followed by concluding remarks.

II. Proposed Tracking System

As shown in Fig. 1, the proposed system contains two stages, namely, the initial stage and the running stage. In the initial stage, each object window will be defined, the color channel for each team will be selected, and models of soccer players will be built in the first video frame. When color channels are selected, the appearance of each object window can be modeled by a one-dimensional histogram and an object list constituted by player models is built. In the running stage, subsequent input frames will be processed. For each soccer player (a moving object) in the object list, an improved mean shift tracking algorithm is used to find its position via the appearance model. Then, occlusion detection is applied on each moving object. If a moving object is occluded, occlusion handling is employed. When an occlusion is caused by some teammates, the color information might be not useful and the object motion information is employed to tackle the occlusion problem. Additionally, the system will examine if a soccer player leaves from the field of view or a new soccer player enters into the field of view so that the object list will be updated accordingly. The implementation details are described as follows.

A. Initialization

Color is a useful feature to track soccer players (moving objects). Many color coordinate systems, such as RGB, HSI, and YUV, have been used in object tracking. In the proposed system, only one characteristic color channel is chosen for each team.

In the proposed system, testing color channels include red, green, blue, hue, saturation, value, and intensity. The most discriminative color of one team is obtained by comparing the dissimilarities between the histograms of a team and other terms in all testing color channels. In this study, instead of using the composite color, only the most discriminative color channel is selected for each team. The similarity measure, namely, the Bhattacharyya coefficient, used in the proposed system is the similarity measure between two discrete probability distributions. The Bhattacharyya coefficient $BC(p, q)$ is defined as:

$$BC(p,q) = \sum_{x \in X} \sqrt{p(x)q(x)}\ , \tag{1}$$

where p and q are two probability distributions. If the Bhattacharyya coefficient is a small value, two distributions are different and the testing color channel is more discriminative, and vice versa.

In the initial stage, the model of each soccer player will be built. In most tracking systems, the information of the object window is recorded to track the moving object. The related information includes the center position, width, and height of the object window. To track soccer players, which team each soccer player belonging to is important. In the proposed system, some other information is employed. First, to model the appearance of the object window, a 1-D histogram is computed based on the selected color channel, which can be quantized into bins. Because the mean shift algorithm is employed, a converting map associating a pixel value with a probability that the given pixel belonging to the object region is needed. Second, the information of both the current and previous windows is recorded for occlusion handling. To check if a soccer player leaves from the field of view, a variable $v_{i,j}$ is employed. As a summary, the object model $O_{i,j}$ of the jth player in the ith frame can be defined as:

$$O_{i,j} = \left(w_{i,j}, pw_{i,j}, cm_j, t_j, v_{i,j}\right), \tag{2}$$

where $w_{i,j}$ and $pw_{i,j}$ denote the information of current and previous object windows, including the center position, width, and height, cm_j is the converting map of the jth moving object, t_j is the team number of the jth moving object, and $v_{i,j}$ is a variable used to check if the jth moving object leaves from the field of view in the ith frame.

B. Tracking

In the running stage, to find soccer players' positions in each frame, an improved mean shift algorithm is employed in the proposed system, as shown in Fig. 2. To convert each frame into the corresponding probability distribution image, histogram back-projection [24] is employed in the proposed system. Here, it is assumed that the histogram of a moving object is narrowly distributed, whereas the histogram of a frame is widely distributed. Histogram back-projection can be formulated as:

$$r(c) = \frac{M(c)}{I(c)}, \qquad c = 1,2,\ldots, N_b, \\ BPI(c) = 255 \times r(c), \quad c = 1,2,\ldots, N_b, \tag{3}$$

where $M(c)$ and $I(c)$ represent the color histogram value in bin c of the selected color channel of the object and the whole frame, respectively. $BPI(c)$ is the discrete value of bin c, and N_b is total number of bins.

For the improved mean shift algorithm, after the image frame is converted into the corresponding probability distribution image, object tracking can be performed by iteratively searching for the peaks of the probability distribution. At the peak, the hypothesized region and the object model are similar. However, for the situation that soccer players are relatively small in far-view frames and soccer players may move rapidly, a soccer player (a moving object) in the current frame may totally be outside from its object window in the previous frame. For this situation, the distribution within the object window is low and flat, i.e., there is not enough information about which direction to seek. Thus, a high-velocity moving object might be lost in object tracking. To cope with this problem, an improved mean shift tracking algorithm is proposed. First, motion prediction is employed. The motion vector of an object window in the current frame t is obtained by subtracting the centroid of the object window in the current frame t from that in the previous frame t-1. Then, the centorid of the object window in the next frame t+1 will be predicted as:

$$c_{i+1,j} = c_{i,j} + (c_{i,j} - c_{i-1,j}), \tag{4}$$

where $c_{i,j}$ is the centroid of the jth object window in the ith frame.

Second, each object window can be enlarged if necessary. The distribution area, i.e., the total probability within the object window, is used to check if a moving object is inside this object window. If the distribution area of an object window is less than a threshold, no moving object is inside the object window, i.e., the moving object is "lost." In this situation, the object window will be enlarged. If a portion of the moving object is inside the enlarged window, the moving object will be tracked accordingly. Once the moving object has been tracked by the improved mean shift algorithm, the object window should be shrunk to a new object window having the standard size. Because the motion displacement of a soccer player (a moving object) between two consecutive frames is bounded, an upper bound for the object window size is set in this study. This enlarging procedure for object window is formulated as:

$$s = s \times m, \text{if } M_{00} < TH \text{ and } s < TH_w, \tag{5}$$

where s is the window size, including the width or the height, m is a scaling rate, M_{00} is the distribution area, TH is the threshold for M_{00}, and TH_w is the upper bound of the object window size.

C. Occlusion Handling

Occlusions may be caused by teammates, competitors, or referees. Because competitors have distinct appearances, occlusion handling between competitors is usually simpler than occlusion handling between teammates. When an occlusion is caused by two teammates having similar appearances, a partial occlusion might severely disturb the tracking system, especially small appearances in far-view frames. To cope with appearance insufficiency, object motion is another clue for occlusion handling in the proposed system.

To detect occlusions, a simple scheme is employed in the proposed system with rectangular object windows. If the overlapping ratio is defined as the overlapping area divided by the whole area of the standard object window, an occlusion might happen when the overlapping ratio between two object windows exceeds a threshold. The threshold of the overlapping ratio for object occlusions caused by competitors is reasonably set to a larger value, as compared with that for object occlusions caused by teammates. Because for partial occlusion, an occluded soccer player is visible and distinct if the partial occlusion is caused by competitors. On the other hand, if a partial occlusion is caused by teammates, a small overlapping ratio may make a mistake if occlusion handling by motion is not performed.

1) Handling occlusions between competitors: For partial occlusions, or even temporally total occlusions between competitors, the proposed system works well. However, some hazards happen when this type of occlusions continues for a span and the occluding and occluded moving objects move only a small distance.

To cope with this problem, a solution is proposed as follows. Because the mean shift algorithm always seeks for the local peak of the probability distribution. Only the occluding object resides in the occluded object's window when the occluded object is totally occluded. Hence, the occluding object's position is the peak of the probability distribution of the occluded object's window. Although the occluding object's position gives high probability in the neighbourhood of the occluded object's window, the probability is still much less than that of the real position of the occluded object. Therefore, the distribution area of the occluded object's window is used to check if the moving object inside the occluded object's window is the occluded object. If the distribution area is smaller than a threshold, the occluded object is not tracked successfully, and the occluded object's window is enlarged to find the occluded object. An upper bound of the object window size is also set in this occlusion handling process. If the distribution area of the occluded object's window is not large enough and the enlarging window size exceeds the upper bound, it means the occluded object is still occluded by the occluding object. Then, the occluded object's window will track the occluding and occluded objects until the occluded object reappears.

2) Handling occlusions between teammates: If the occlusion is caused by the teammates, the handling will be more difficult. Because the appearances of the teammates are almost the same in far-view frames of the soccer videos, motion is more credible to search for the moving objects' positions and is used for handling occlusions between teammates in this study.

When an occlusion between teammates is detected after the tracking procedure, the result derived from appearance-based tracking should be replaced by that derived from motion prediction (Eq. 4). Once the occluded and occluding objects separate from each other, the improved mean shift algorithm (based on moving objects' appearances) will continue to track the moving objects precisely.

D. Handling for Incoming and Outgoing Players

1) Handling for incoming players: For tracking a new player entering into the field of view in some subsequent frames, a detection scheme for incoming soccer players is proposed in this study. In particular, the moving background in soccer games will disturb the detection scheme, resulting in a high computational load. In this study, a background subtraction based detection scheme is employed. To reduce computational complexity, only one color channel is used to model the background. Selection of the color channel is similar to that for soccer players (moving objects). The difference is that selection of color channel here is determined by the dissimilarities between the playground region and each player region. Then, the discriminative color channel is used to model the background. Note that the detection scheme is applied only on the image boundary region. In the proposed system, the running average operation is used to model each background pixel. The two parameters, μ_t and σ_t^2, for each background pixel in the image boundary region at time *t*, p_t, is updated as:

$$\begin{cases} \mu_t = p_t \times \frac{1}{t} + \mu_{t-1} \times \frac{t-1}{t}, \\ \sigma_t^2 = (p_t - \mu_t)^2 \times \frac{1}{t} + \sigma_{t-1}^2 \times \frac{t-1}{t}, \end{cases} \tag{6}$$

where μ and σ^2 are the mean and the variance of the background pixel model. Besides, the discriminant is described as:

$$\begin{cases} p_t \text{ belongs to the background, if } \frac{(p_t - \mu_t)^2}{\sigma_t^2} \le B_{th}, \\ p_t \text{ belongs to the foreground, otherwise,} \end{cases} \tag{7}$$

where B_{th} is a threshold for discrimination and p_t means the pixel $p(x,y)$ at time t. If $p(x,y)$ is determined as the background, the background model at (x,y) should be updated.

2) Handling for outgoing players: Here, each outgoing player can be detected via the distribution area and the parameter $v_{i,j}$. If a soccer player (a moving object) locates around the image boundary region and the distribution area of its object window is very low in some consecutive frames, it is claimed that he might leave from the field of view. That is,

$$v_{i,j} = \begin{cases} v_{i,j} - 1, \text{if } M_{00} < E_{th}, \\ \lambda, \text{otherwise,} \end{cases} \tag{8}$$

where E_{th} is a threshold for the distribution area, and λ is the time threshold of the soccer player staying around the image boundary region in some consecutive frames. If $v_{i,j}$ is equal to zero, it is claimed the soccer player leaves from the field of view, who should be removed from the object list.

III. Simulation Results

In this study, the proposed system is evaluated and compared with three comparison systems using five soccer game videos, including World Cup, Premier League, and Primera división de Liga games. In the five video sequences, there are various challenging problems for object tracking, such as quick motion, occlusion, soccer players' (moving objects') entering or exiting, and illumination change.

Here the image size of these videos is 720×480 and the standard object window for soccer players (moving objects) are defined manually. To evaluate the performance of the proposed tracking system, three comparison methods, namely mean shift [25], CamShift [26], and particle filter [27], are implemented in this study. The proposed detection scheme for outgoing players is also included within the three comparison systems.

The "Australia versus Italy" game sequence contains 190 frames. There are four Italian players and seven Australian players in the playground in the first frame. Italian players wearing blue clothes are circled by black object windows. For the occlusions caused by teammates, Australian players wearing yellow clothes are circled by various color object windows to obtain transparent tracking results. In addition to the occlusion between teammates during frames 151 to 159, another occlusion between competitors happens during frames 160 to 162. Within frames 180 and 187, an Australian and an Italian player enter into the field of view, respectively. Some soccer players leave from the field of view on frames 2, 6, 15, and 47. A new challenging problem is that the soccer players (moving objects) move in the light playground for one-third of the period and compete in the shady playground for the residual time. If the sudden light change after frame 59 damages the tracking performance is examined.

Fig. 3 shows the tracking results of the "Australia versus Italy" game sequence processed by the proposed system. The occlusions, especially caused by teammates, heavily damage the performances of the three comparison systems. For the proposed system, the soccer players (moving objects) are tracked well after the occlusions caused by teammates and competitors. Moreover, the successful tracking results after undergoing light change confirms the robustness of color channel selection in the proposed system. Fig. 4 shows the tracking results of the "Australia versus Italy" game sequence by the four tracking systems, which demonstrates the benefits of occlusion handling and incoming player detection within the proposed system. The recall and precision rates of the four tracking systems are shown in Tables I.

IV. Conclusion Remarks

In this study, an improved mean shift based tracking system for soccer game analysis is proposed. In the proposed system, a discriminative color channel is selected automatically to model each moving object. Then, the improved mean shift tracking algorithm with motion prediction and object window enlarging is proposed. Occlusions between teammates and competitors can be handled very well. To handle the cases that incoming soccer players (moving objects) enter into the field of view and some tracked soccer players leave from the field of view, an incoming player detection scheme and an outgoing player detection scheme are developed in the proposed system. Based on the experimental results obtained in this study, the tracking results as well as the recall and precision rates of the proposed system are better than those of the three comparison systems.

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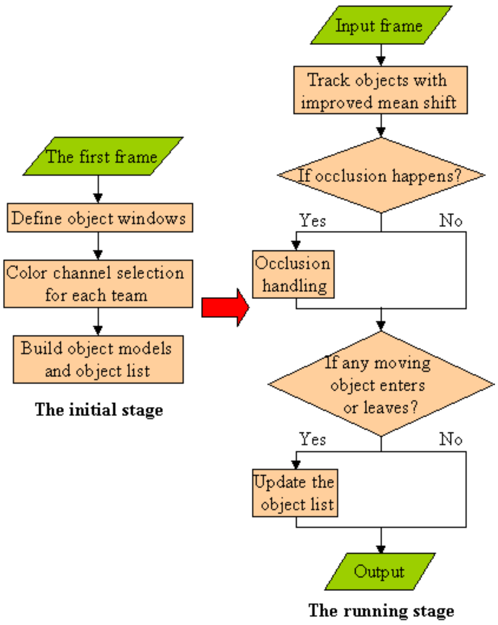

Fig. 1. The proposed tracking system.

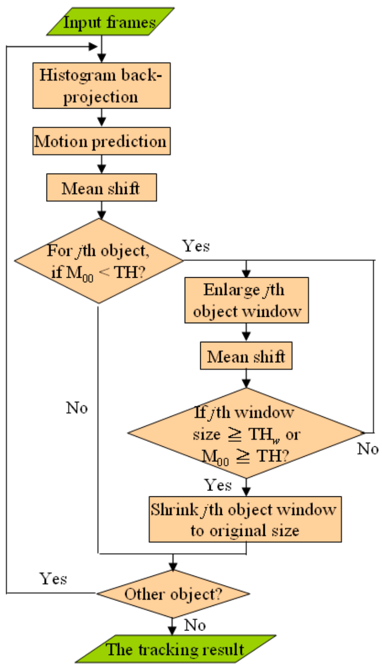

Fig. 2. The improved mean shift tracking algorithm.

Fig. 3. The tracking results of the "Australia versus Italy" game sequence by the proposed system: (a) frame 0; (b) frame 60; (c) frame 66; (d) frame 150; (e) frame 158; (f) frame 189.

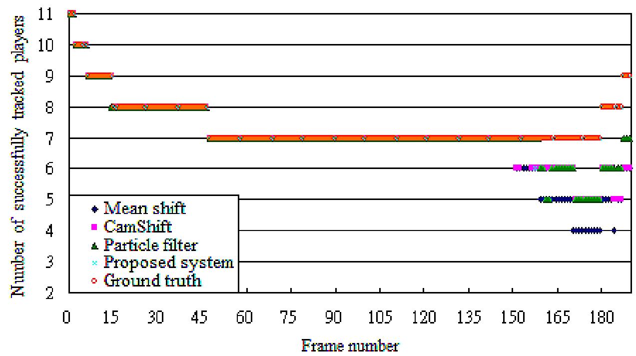

Fig. 4. The numbers of successfully tracked players of the four tracking systems for the "Australia versus Italy" game sequence (incoming player detection is included within the four comparison systems).

TABLE I
RECALL AND PRECISION RATES OF THE FOUR TRACKING SYSTEMS FOR THE "AUSTRALIA VERSUS ITALY" GAME SEQUENCE (INCOMING PLAYER DETECTION IS INCLUDED WITHIN THE FOUR COMPARISON SYSTEMS).

	Recall	Precision
Mean shift	0.9356	0.9356
CamShift	0.9568	0.9562
Particle filter	0.9625	0.9618
Proposed	0.9993	0.9993