A modular system for tracking players in sports games

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***Abstract*—** Detection, recognition and tracking of the players in sports games which is based on image processing and computer vision is the topic of interest of various research groups. Different approaches regarding choice and placement of the acquisition hardware exist. Regardless of whether a custom set of static cameras is used or the images are acquired from directed TV coverage, player detection and tracking is a complex process. Robustness of such a system is the main goal of its designers. In this paper, a modular system for tracking indoor and outdoor team games using computer vision is proposed and described. Proposed approach is flexible and expandable so it can be said that overall system framework provides robustness of detection, recognition and tracking.

***Keywords*—** modular system, tracking players, computer vision

I. Introduction

FOR many years people are trying to find the best way for tracking players. Different approaches and various methods were applied in order to accomplish this task. Some approaches are using microphones placed on the edge of the field, some are using GPS transmitters and some are based on the image processing and computer vision. Regardless of the type of sport, camera and computer appliance provides a wide range of possibilities. Generally, systems based on computer vision can be divided into three parts. The first part relates to camera system, second is dedicated to the detection and identification of players, and third is oriented towards methods and algorithms used for players tracking.

A specialized camera system as well as directed TV images can be used for detection and monitoring. Sulivan [1] uses a system with four wide screen Wide angle camera with high resolution. Iwase [2] used eight cameras, set of four cameras placed on each side of the playground. Xu [4] also uses eight cameras, but they are positioned differently. Four cameras are placed on one side of the field, and two behind every goal. Gedikli [3] uses video clips and calculate players orbit.

A captured image is needed to be processed in order to get information, in this case, information about the location of a particular player. The easiest way to find players is subtraction picture and known background [1] and [2]. Figueroa [9] uses a player separation algorithm without background subtraction. Gedikli [3] segment players with known models of color and then with templates and known color distribution calculate the most similar model. After that he uses prediction while separation and labeling of players is done using the previously calculated data.

For tracking players, authors [1], [2], [4] and [9] calculates orbit of earlier detected and marked objects. Each one of them has its own algorithm for tracking which is linked with player detection algorithm. Neither of these systems is fully automated. In any case human is supervisor which takes initiative when determines that system is wrong. Introduction of neural networks for target position identification and tracking [21] and fuzzy logic [22] for sports oriented applications is also the possibility that should be investigated. In this work methods provided by different authors and based will be described. Based on the possibilities provided by various methods and approaches, a modular system that can independently track players during the match will be proposed.

II. Methods overview

As it has already been stated in the introduction, a computer vision system for tracking players generally consists of three main steps: camera system, players detection and players tracking (Figure 1).

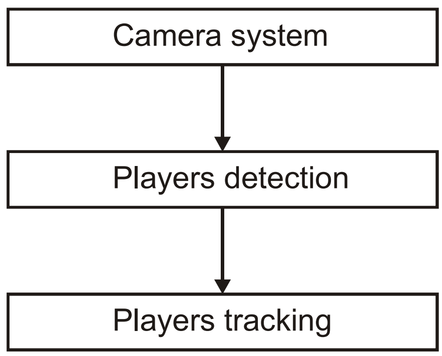

Fig. 1 Main steps of computer vision system for tracking players

More details on each of these steps will be explained in the following subsections.

A. Cameras positioning

Camera positioning depends on needs of particular system.

With custom placement of the cameras, it is easier to track players as reference points are known. For this case, the camera position is well known, there is no zoom and camera movements, so calculations are much easier to make. On the other hand, mounting and calibration of the cameras before the game is necessary. Because the system is not standardized, it is necessary to have special equipment.

Using pre-existing system simplifies use for user (sport clubs, TV networks), but requires different ways of player detection which complicates calculations.

Directed match images can be used for a particular type of analysis, but cannot be used to track all players during the entire game.

Sulivan's [1] system with four wide angle wide screen high resolution camera can locate players when they are isolated and easily monitor their movement. Problems occur when player occlusions appear. Then path length measure stops. Iwase [2] solve occlusion problem with more cameras around the field. This author placed eight cameras, four on each side of the playground. According to him, the first step is to track every player with each camera. When occlusion occurs other camera is used to determine identity of the player. As camera position is known it is easy to get position of each player.

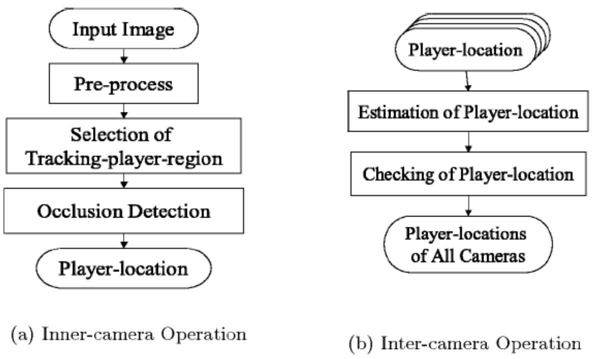

Fig. 2 Iwase method

Iwase mentioned two terms, “Inner-camera Operation” and “Inter-camera Operation”. “Inner-camera Operation” is done separately for each camera for tracking players. When occlusion occurs “Inter-camera Operation” is processed. Figure 2 represent flow chart of these two methods.

Due to large number of cameras, tracking player can be done from all angles what makes tracked player analysis easier. The problem of this system is heavy equipment which is necessary for monitoring the large number of input parameters (pictures from eight cameras) that need to be processed.

Xu [4] also uses eight cameras: four cameras are placed on one side of the field, and two behind each goal. Each camera observes a certain part of field. Described system [4] is not used to track and analyze individual player, but to recognize teams to help future tracking. The same author in his other work [5] uses described system for tracking.

Tracking players also can be done using directed TV broadcast. Some authors use TV images or direct TV broadcast from a playing field to track player(s). Gedikli [3] presents ASPOGAMO system which count players path based on video recordings. This system can give information about a particular player based on recorded TV broadcast. Although the system finds player on the field, problem is that TV transmission cover only part of the field. Also, with this system it is possible to provide information based on individual sequences, but it is not possible to constantly monitor all players. The advantage of this system is that captured image can be used for recognition methods which could not be applied when the camera is far away. Example is face recognition or player number recognition. In addition, it should be mentioned that broadcast cameras are requiring calibration [8], [13].

To decide what kind of camera system should be used, it is necessary to know what will be monitored. System with multiple cameras is suitable for monitoring whole game in order to obtain characteristics of all players.

Systems with existing cameras on the ground have some limitations. They cannot monitor all players throughout the game. Such cameras are mainly focused in the area where is a ball. This cameras as well as directed recordings are used when it is needed to get certain data from sequences, like players when performing free strokes or corner.

Qu [7] and Iwase [2] use camera collaboration. Such way of cooperation between cameras provides the ability to more accurately monitor individual player when occlusion occur.

B. Obtaining 3D/2D position

For the 3D position determination of the particular object, the DLT (direct linear transformation) method can be used [19].

The basic DLT reconstruction method equation is given:

$$\begin{aligned} x'(t) &= \frac{L_1 x_a(t) + L_2 y_a(t) + L_3 z_a(t) + L_4}{L_9 x_a(t) + L_{10} y_a(t) + L_{11} z_a(t) + 1} \\ y'(t) &= \frac{L_5 x_a(t) + L_6 y_a(t) + L_7 z_a(t) + L_8}{L_9 x_a(t) + L_{10} y_a(t) + L_{11} z_a(t) + 1} \end{aligned} \qquad (1)$$

where (x' , y') are the digitised coordinates and (x_a, y_a, z_a) are the 3D locations of digitised points. L_1 , ... L_{11} are the DLT parameters. Defining of the DLT parameters L_1, L_{11} is usually done using static calibration frame but for outdoor sport events other objects with known dimensions can be used. For the soccer, goal dimensions, as well as pitch height and width (or other known line-determined areas) may be used. In that case, for the determination of the parameter values, measured coordinates are not time dependent, taking into account that the cameras are also non-movable. As it can be noticed, the equation (1) is more general because planar and spatial coordinates of the observed points can be time dependent. Indeed, they are if the observed object is moving.

DLT parameter calculation is based on calibration using at least six known spatial positions of the markers on the calibration frame. Equation (1) is implemented for each camera. After determination of parameters, they are used for position calculation of any other object that has obtained 2D coordinates by at least two cameras.

More simple approach can be used for the particular area of implementation. As the elevation coordinate can be ignored comparing to the size of the pitch, 2D position of a player may be obtained even by using only one camera and implementation of projective transformations. This is also matrix-oriented geometric transformation of the 2D coordinates of the known points in the image acquired by static camera. Input points (x, y) are transformed into output points (u, v) using the following equations and solving the nine coefficients of the matrix T_{inv}:

$$\begin{bmatrix} u_p & v_p & w_p \end{bmatrix} = \begin{bmatrix} x & y & w \end{bmatrix} \cdot T_{inv} \quad (2)$$

$$u = \frac{u_p}{w_p}; v = \frac{v_p}{w_p}; T_{inv} = \begin{bmatrix} A & D & G \\ B & E & H \\ C & F & I \end{bmatrix} \quad (3)$$

$$\begin{aligned} u &= \frac{Ax + By + C}{Gx + Hy + I}; \\ v &= \frac{Dx + Ey + F}{Gx + Hy + I} \end{aligned} \quad (4)$$

Matrix T_{inv} coefficients are calculated solving the Eq. 2 with the known image point coordinates and corresponding world coordinates for the objects with the known position on the pitch (corners, sixteen meter lines, centre, posts, etc.).
Additionally, it should be noted that camera coefficients corrections may due to the lenses distortion may be required.

C. *Player detection*

Most authors are looking for the simplest way to find object in an image. Knowledge about playfield background is one of the methods. Sullivan [1] uses algorithm that includes known background and player jersey. After applying Gaussian distribution, algorithm finds objects (players) on image. Such player labelling as objects provides the possibility of tracking them, but does not define a specific player. Iwase [2] uses background subtraction. Then he converts an image into a binary image, filters out noise and detects certain regions. Problem occurs with player shadow and overlaps so it is necessary to have an additional algorithm that divides overlapped players. Same authors like Iwase, Figueroa [9] separate players and track them. These separated segments Figureoa label as “blob”. In his algorithm he uses intensity vertical distribution of “blob” to determine to which team recognized player belongs.

Gedikli [3] uses player segmentation with known colour types, then with known template and colour distribution calculates model. After that, using the predicted positions and previously calculated data separates players and labels them.
Xu [4] and [5] use Gaussian distribution for background separation.

Authors which use their own camera systems usually use background separation methods which cannot be used on images accrued from TV broadcast. Beetz [10] presents ASPOGAMO system that use special colour model and separate green soccer field. He also uses Gedikli method [3] for labelling players.

D. *Tracking players*

Our aim is to create system that independently and precisely can track players.

Some authors [1], [2], [4] and [9] calculate path of detected and labelled objects. All algorithms include tracking and labelling of particular player. Path is calculated between two frames and depends on player location on each.

Comaniciu [6] uses Mean Shift tracking method for tracking American football players. Beetz [10] uses MHT (Multiple Hypothesis Tracker) for tracking in ASPOGAMO system. This method is based on theory and prediction. Some authors use particle filters. This combination of Bayes theorem and Monte Carlo method has very good results for the real time tracking. Nummiaro [11] uses particle filter algorithm based on colour and compares it with Mean shift. Needham [14] combine condensation algorithm and Kalman filter. Kalman filter is also used in Xu [5] and Liu [15] paper for tracking ball. Smith [12] presents particle filter algorithm for tracking people and solve occlusion problems.

Lefevre [16] presents “Fast Snake – based” algorithm for tracking using the non-stationary camera. This is contour based algorithm that does not use any prediction. Similar algorithm is explained in Hsiao’s [17] work.

Okuma [18] presents Boosted particle filter for detecting and tracking hockey players. This method has very good results and it can be used as a base for tracking in any sport.

Additionally, as it will be explained in the following section, close-up shots from the TV broadcast camera can be used for recognition of particular player. For this kind of images, player identification can be based on face recognition techniques [23-25] or it can be based on some other available feature such as jersey number [20].

E. *Particle filter*

The main idea of particle filtering is to track interested particles as they evolve over time [26]. They were developed to track object which the posterior density p(Xt|Zt) and the observation density p(Zt|Xt) are often non-Gaussian. Base of this method is to construct a sample based representation of all *pdf*. It is used multiple particles and each one is associated with a weight that signifies the quality of that specific particle. An estimate of the variable of interest is obtained by the weighted sum of all particles.

Algorithm for particle filtering is recursive and works in two phases:

- Prediction
- Update

In prediction stage each particle after each action is modified according to the existing model. Also it is included random noise to simulate the effect of noise on the variable of interest.

In update stage each particle's weight is re-evaluated based on the latest available information.

Particles with small weights are eliminated and process is called resampling.

Formally, the variable of interest at time t=k is represented as a set of M particles where the index j denotes the particle, Each particle consisting of a copy of the variable of interest and a weight (w_j^k) that defines the contribution of this particle to the overall estimate of the variable.

If pdf of previous instant (t=k-1) is known at time t=k it is possible to model the effect of the action to obtain a prior of the pdf at time t=k. That means that prediction stage uses a model to simulate the effect that action has on the set of particles when noise is added.

Update phase uses the information obtained from sensing to update the particle weights in order to describe object movement.

Particle filter Algorithm:
Require: A set of Particles fo object i at time 0: $S_i^0 = \left[x_j, w_j : j = 1...M\right]$

$W = w_j : j = 1...M$

while (exploring) **do**
k=k+1;
if (ESS(W)<β*M) **then**
index=resample(W);

$S_i^k = S_i^k(Index);$

end if
for (j=1 to M) **do /* prediction after action α */**

$x_j^{k+1} = \hat{f}(x_j^k, \alpha)$

end for
s=Sense()
for (j= 1 to M) **do /* update the weights */**

$w_j^{k+1} = w_j^k * W(s, x_j^{k+1})$

end for
for (j=1 to M) **do /* normalize the weights */**

$$w_j^{k+1} = \frac{w_j^{k+1}}{\sum_{j=1}^{M} w_j^{k+1}}$$

end for
end while

ESS is the effective sample size:

$$ESS_t = \frac{M}{1 + cv_t^2} \qquad (5)$$

where

$$cv_t^2 = \frac{\mathrm{var}(w_t(i))}{E^2(w_t(i))} = \frac{1}{M}\sum_{i=1}^{M}(Mw(i) - 1)^2 \qquad (6)$$

Liu [27] refer to two different measures that estimate the number of near-zero-weight particles: one is the coefficient of variation cv_t^2 (equation 6) and the other is the effective sample size (Equation 5)

When the effective sample size drops below a certain threshold, then the particle population is re-sampled eliminating particles with small weights and duplicating ones with higher weights.

III. Modular tracking system

Basic idea of our modular system is to provide a system with independent and also mutually compatible modules. Every module provides result which is part of the global system solution.

The system is divided into separable modules which independently perform a specific operation and produces result. Functionality of the system is possible without individual modules, but it is also possible to add new.

In this work we combine methods explained in earlier papers. Modular approach allow user to simply decide what part of system will be used without losing system functionality.

Added modules improve system functionality and each part of the system can work without a specific module.

The system is divided into three levels: camera system level, player detection and labelling level and player tracking level.

Common part is auto-correction module which represents feedback and correct wrongly marked or tracked players.

Central database contains all necessary data for system functionality. Time-space calibration module joins and calibrates connected modules and mark player label and position on the field based on reference points.

Figure 3 shows preliminary solution with two separate systems for monitoring (system A and system B).

System A includes fixed cameras located along the ground. Idea is to get image of entire field and players. As a reference points are known we can determine objects and their positions on the field. The system and connected modules are connected with the central database which contains all the necessary information that individual module uses.

- Module to determine location of players on the field provides information about player position based on knowledge about the team, tactics and player location likelihood.

- Occlusion detection module is activated when player overlap with another player. According to previous knowledge about position, speed and player movement direction, system split and label overlapped players.

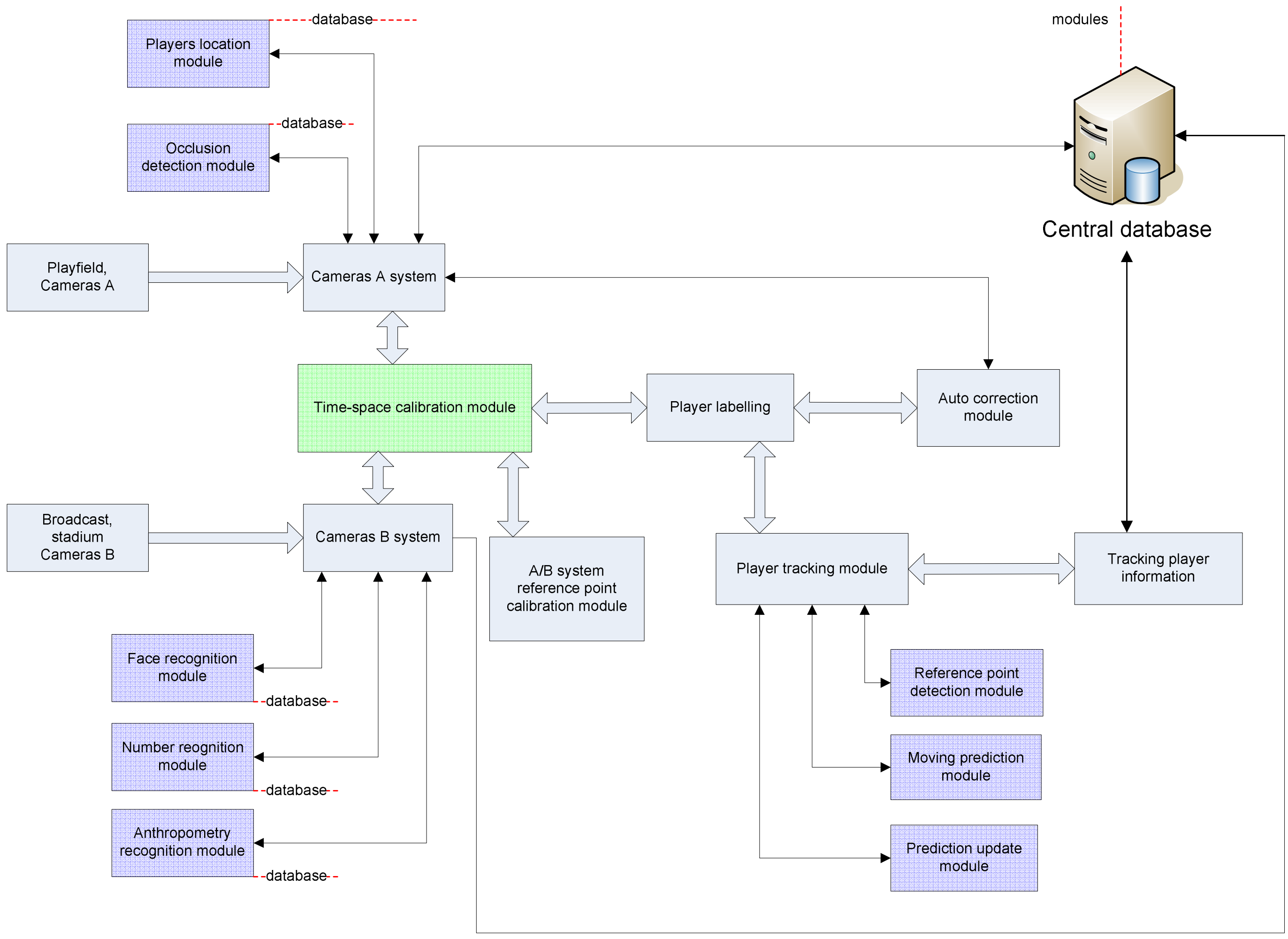

Fig. 3 Modular tracking system

Figure 4 shows the application of boosted particle filter to the soccer game between professors on Faculty of Electrical Engineering Mechanical Engineering and Naval Architecture. Okuma [18] presented this method to track hockey players. This game is filmed with static camera (system A). In Figure 4, trajectory for one player with 100 particles during 20 seconds is outlined. Player tracking analysis has been processed through 550 frames. To obtain world coordinates of the tracked player(s), two main approaches can be used. First one is calculation of coordinates based on the image coordinates of the tracked object from only one camera. Image object coordinates are transformed using the projective transformations knowing world coordinates of some characteristic objects in the image (field dimensions, goal position, etc…). Another approach is, as it has already been explained, based on the tracked coordinates in images obtained by two or more static cameras and implementation of 3D algorithms for determining spatial position of object such as DLT method [19].

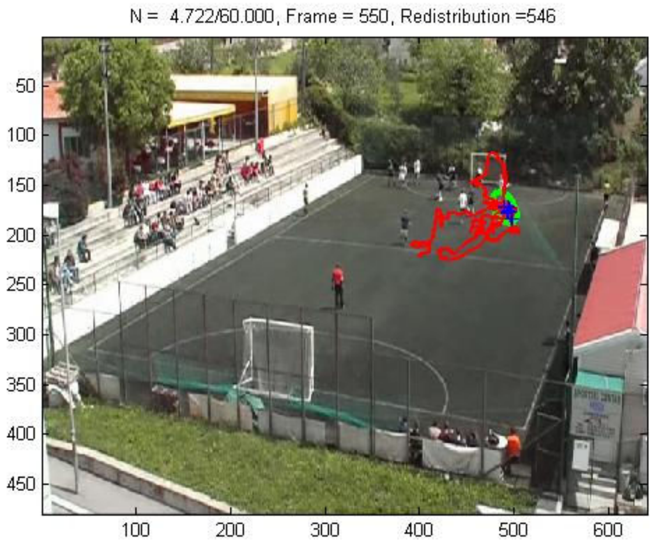

Fig. 4 Boosted particle filter tracking

System B receives TV broadcast camera or already existing cameras on playfield information. Unlike system A which uses calibrated and fixed cameras, images from system B cameras are varying. They display only one part of the field and image can be zoom-in or zoom-out.

As there are more of such cameras and TV broadcast is directed, image can be shown from different angles. Such system can not be used to track all players on the field, but as part of complete system proposed in this paper. It can be used to improve player labelling in cases which are unclear when system A is applied.

System B is also compatible with different modules.

- Face recognition module provides information about the player by recognizing players face and comparing it with the face of players in the database.
- Number recognition module recognizes number on a jersey and compares it with information in database (Figure 5).
- Anthropometry recognition module recognizes player characteristics based on several features. The set of features is expandable and it may include body height/width ratio, shape compactness, run/gait characteristics as well as some other features that can be used for description and recognition of particular player.

Figure 5 shows jersey number detection as a result of number recognition module. Recognition algorithm uses HSV colour model [20] and module gets directed image from TV broadcast camera (system B).

Figure 6 shows result of face recognition [28] that can be used in face recognition module. Recognition use SIFT detector for tracking face characteristics in different frames.

The information acquired with system B could be obtained with system A if high-resolution cameras are used. However, processing time would be slower and it would be impossible to track players in real time.

Fig. 5 Number recognition from close-up shots

System A and system B information are connected and calibrated through time and space calibration module. It compares system reference points and provides information about the player with certain probability. This is very important module for the overall reliability and accuracy of the system.

Fig. 6 Face recognition from close-up shots

Player is labelled in labelling module which creates a basic prerequisite for tracking players. Auto-correction module checks the selected player according to data of system A. If a certain player has low probability, correction module corrects player label.

After player is marked, tracking module tracks player and writes data records in the database.

IV. Conclusion

This article is the result of studying a large number of articles related to detection, separation and monitoring of people and sports activities. Shown methods provide overview and base to create modular system for tracking players. Proposed and explained modular system is result of weak-points analysis of present systems. The main idea is to create a system with independent modules that can be connected together to provide better and more robust results. Presented approach provides flexibility and openness for further expansions, inclusion of different algorithms and their activation/deactivation as well as possibility of different system configurations without losing main functionality. Further development of the system will be focused on improving player detection and tracking module and adding new, game-strategy type knowledge to the system's database.

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