이미지 블롭 할당을 이용한 축구 선수 추적

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Soccer Player Tracking Using Blob Assignation

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Abstract

In this paper particle filter is used as an underlying algorithm to track multiple objects, which are soccer players. Multi-object tracking becomes difficult when two or more players get close to and overlap each other because particles of the filters tend to move to a region of higher posterior probability. To resolve this problem, a blob assignation algorithm which identifies the separated image blobs after occlusion, based on the predicted states according to the dynamic model is suggested. This method performed well on the sequences under general camera work.

1 INTRODUCTION

This paper confines the domain of tracking problem to the video of soccer game, and our main goal is to keep traces of players through the sequence. In this environment, the most challenging problem is when there is a occlusion between players of the same team, some particles of players may migrate to other players who are more attractive in a image processing sense. This will result that particles of a tracker are separated and populate on two or more players and it appears that the tracker is losing its trace.

Object tracking algorithm has been developed thanks to sequential Monte-Carlo(SMC) method, since it provides a robust non-parametric estimation of posterior probability through sequential iteration of random sampling and likelihood evaluation. The CONDENSATION(CONditional DENSity propagATION) algorithm showed its powerful performance in tracking a contour shape [1][2]. For multiple object tracking with problems of management for occlusion reasoning, insertion and deletion, the exclusion principle is proposed to solve the coalescence problem between trackers of identical shapes [3]; OAP(occlusion alarm probability) successfully managed to control the particle population by probabilistic weighting of the likelihood of a particle according to the distance to its neighbors [4]. The suggested tracker does not make measurement during occlusion and assign image blobs after occlusion to trackers followed by reinitialization of the particle filters.

Section 2 briefly introduces the general sequential Monte-Carlo algorithm and the particle filter. Section 3 provides our image processing algorithm. Measurements of the tracking algorithm are taken on the pre-processed image at every time. Dynamic model of the particle filter and likelihood model are given in Section 4. Blob assignation algorithm is detailed in Section 5, and real experimental results are showed in Section 6. Finally, Section 7 concludes this paper.

2 PARTICLE FILTER

In brief, a particle filter, one of the sequential Monte-Carlo(SMC) methods estimates a non-parametric representation of posterior distribution $p(x_t|z_t)$ sequentially, where x_t is the state and z_t is the measurement at time t, given a sequential dynamic system with Gauss-Markov process. A proposal distribution, q of known random sampler can be adopted to compute the posterior represented by the pairs of particle s and its weight w.

$$w_t = w_{t-1}\frac{p(x_t|z_t)p(x_t|x_{t-1})}{q(x_t|x_{0:t-1}, z_{1:t})}$$

After computation of w_t's for N particles generated from q and normalization $\sum_1^N w_t^i = 1$, the set of particles comes to represent the posterior distribution. The particle filter takes the proposal distribution as $q = p(x_t|z_{t-1})$ resulting in $w_t = w_{t-1}p(z_t|x_t)$, that is, the posterior can be estimated by evaluating the likelihoods of particles generated from the prediction process of system dynamics. Incorporated with resampling, the weight update equation can be further reduced to

$$w_t = p(x_t|z_t),$$

3 IMAGE PROCESSING

Before applying particle filtering, an input image frame at each time step is pre-processed to remove background area

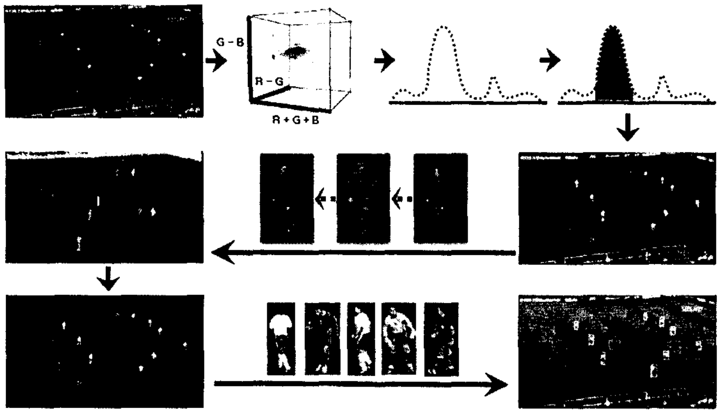

Fig 1: image processing

and extract meaningful regions. We use an image processing algorithm similar to [4]. The play ground area is marked black according to the 3D-histogram of the image, as shown in Fig 1. Then applying morphological filtering, connected component labelling and size filtering, we extract blobs of candidate player regions. When the first frame is given, the blob of each player is extracted and its model histogram is derived to evaluate the likelihood of particles in following frame.

4 SINGLE PLAYER TRACKING

4.1 State model

The shape of player is modelled by a rectangle of the position $\mathbf{p}_t = [x_t, y_t]$ and the half width and height $h_t, v_t$of the rectangle to describe the state $\mathbf{X}_t = [x_t, y_t, h_t, v_t]$ of a player at time t. We use first order auto-regressive(constant velocity)model for the dynamics of the shape position:

$$\mathbf{p}_t = 2\mathbf{p}_{t-1} - \mathbf{p}_{t-2} + B_p \mathbf{v}_t$$

where $\mathbf{v}_t \sim N(0,1)$ and $B_p B_p^T$ is the covariance matrix of system dynamics. The width and height change is modelled by

$$h_t = h_{t-1} + B_h u_t$$

$$v_t = v_{t-1} + B_v u_t$$

where $u_t \sim N(0,1)$ and B_h^2, B_v^2 is the variances respectively.

4.2 Observation model

The likelihood of a particle is evaluated by histogram matching with the model histogram obtained at the first frame. Here the histogram is 3 dimensional with axes of R-G, G-B and R+G+B respectively where R,G,B are the red, green and blue values of a pixel [5]. On the pre-processed image, the non-black pixels in rectangle region of each particle are binned and normalized by dividing each bin with the rectangle size. In this paper total divergence is used to measure the difference between two histograms [6]. Given two histograms h_i, h_j, the total divergence D is

$$D(h_i, h_j) = 2\log 2 + \sum_{y \in Both} \left\{ h_i(y) \log \frac{h_i(y)}{h_i(y)+h_j(y)} + h_j(y) \log \frac{h_j(y)}{h_i(y)+h_j(y)} \right\}$$

where y is the index of bins and the set of y $Both$, is as following.

$$Both = \{y : h_i(y) > 0, h_j(y) > 0\}$$

4.3 Single player tracking

In the case of non-overlapping situation, a single player is easily tracked using the dynamic and observation models by particle filtering. At the initial image processed frame, the extracted player blobs are bounding-boxed and the initial width, height and model histogram the rectangle region are determined. When the player came close to a player of the same team, the particles started to wander between the two players, showing multi-modal posterior. Sooner or later multiple independent trackers would happen to track the same player.

5 BLOB ASSIGNATION

To resolve the problem mentioned at the top of Section 1, we suggest a simple algorithm that takes prediction by system dynamics as estimate during occlusion period and assigns splited blobs to corresponding trackers.

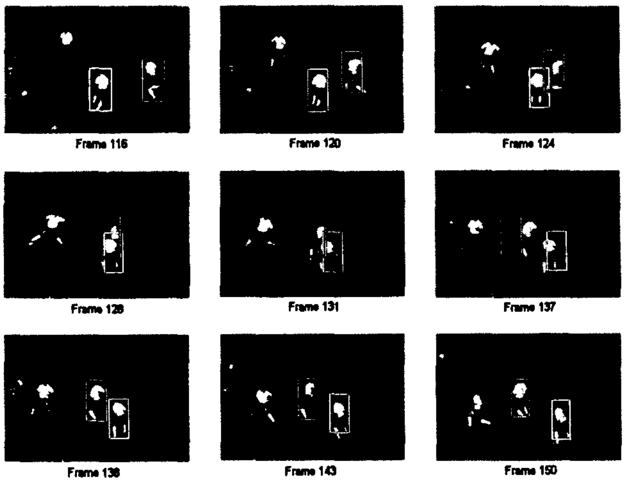

Fig 2: result images

5.1 Prediction as estimation

Without any systematic control, migration of particles is irresistible during occlusion. particle migration is due to high likelihood region of adjacent players and the likelihood is the result of measurement. The suggested method takes a sort of deterministic way which does not take particles nor measurement. It just makes prediction by dynamic model. At least there is no particle migration by this way in some sense. Prediction is taken as estimation until the blobs of players are separated from each other.

5.2 Blob assignation

After separation of image blobs as the signal of the end of occlusion is detected, the system has to figure out which blob belongs to which tracker. It is done according to the distance between the predicted state of tracker and that of the blob, that is, a blob goes to a player whose predicted position is closer to it than the others of interest. The best image blob which shows the least deviation from prediction is processed first and the worst last. After assignation the tracker reinitializes the particle filter.

6 RESULTS

In Fig 2 some subimages of the sequence shows the result of tracking. The players A, B are under consideration and tracked using regular particle filters until frame 124 where their image blobs are merged into one. From frame 124 to frame 137 there are two players with one blob and their positions are estimated by prediction from the state of frame 123 and dynamics. In frame 138, the image blob is separated into two and they are assigned to each player according to the predicted states. Player B gets its blob first because its prediction and the corresponding blob shows better agreement.

7 CONCLUSION

In this paper particle filter is used for soccer player tracking and blob assignation method is used to identify the blobs after occlusion. There is no particle migration since blob assignation algorithm does not deal with particles during occlusion. Too long period of occlusion and too large deviation from dynamic model may cause low performance.

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