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Proposal of a Player Multi-Target Tracking Algorithm applied in Teams Sport

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Abstract

Nowaday, Database in economic and industrial area are increasing at a very high speed and are regularly growing and creating a strong interest in automated summarization and semantic indexing of video content in diverse areas notably in teams sport. The aim of this paper is to proposed the Player Multi-Target Tracking Algorithm (PMTTA) that forms a recursive estimator of the complete formations including all player positions and this estimation is advanced to the time of the current measurement scan by predicting the locations according to a particular motion model.

Keywords: Multi-target tracking, Real-time Tracking Solution; Position-based Identification.

1. Introduction

Database are continually increasing and creating a strong interest in automated summarization and semantic indexing of video content in different areas notably in teams sport (Gordon & al., 2002). In fact, we require computer systems to capture, recognize and interpret all data and activity included in the video which opens the way for applications of new sports technologies (Welch & Bishop, 2001) (Maalej & al, 2016).

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This problem is so complex and complicated due to many reasons such as: 1) Multiple targets interact and need to be monitored at the same time, 2) while simple occlusions of common players occur frequently, the movement of human players is complex, 3) the position of invisible athletes can be predicted for a limited period of time, hiding the process of cutting out the scattered material, 4) players of the same team are hardly distinguishable and similar in appearance, which complicates their re-identification after an interruption of the video stream, and 5) lighting conditions or the number of teams traveled or characteristics of players are not known in advance and can be added or changed during the game which increases the complexity of computing to be done in real time (Mlouhi & al., 2018) (Wang & Ma, 2007).

The objective of this paper is to present the Player Multi-Target Tracking Algorithm (PMTTA). Then, we present implementational remarks, the simulation and the evaluation. This algorithm allows us to track multiple targets of similar appearance and the performance of Player Multi-Target Tracking Algorithm was evaluated on several demanding applications, proving its effectiveness and real-time capability.

2. Player multi-target tracking algorithm

The Player Multi-Target Tracking Algorithm (PMTTA) forms a recursive estimator of the full formations including all player positions and this estimation is advanced to the time of the current measurement scan by predicting the locations according to a certain motion model (Weedham & Boyle, 2001).

The PMTTA is depicted in figure 1. Particles for the current estimate are gathered from the preceding ones by sampling associations between the current measurements at a rate proportional to the former weights and the predicted formations and fusing the corresponding positions in an optimal way: max-likelihood So, the probability densities are determined by the frequencies of the samples that resulted in the same association, as well as the likelihood of this association (Maalej & al., 2016) (Lakhoua & al., 2015).

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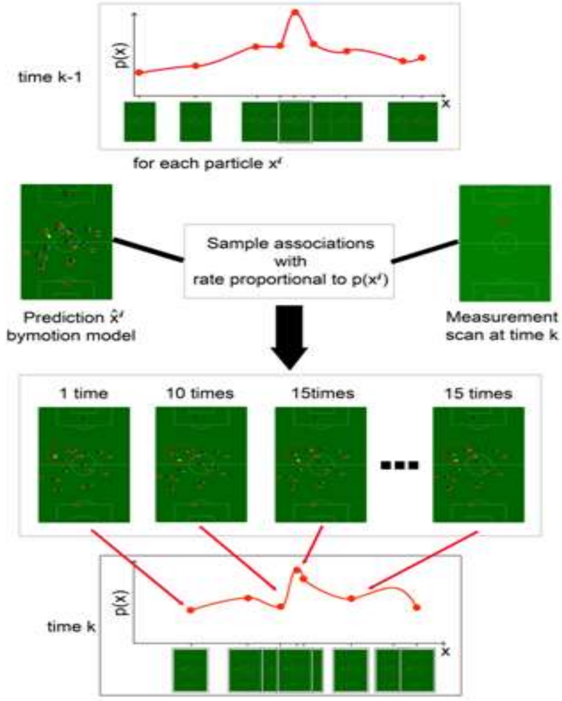
Figure 1: Player Multi-Target Tracking Algorithm (PMTTA) applied to the African club



The Player Multi-Target Tracking Algorithm (PMTTA) constitutes a Sequential Importance Resembling (SIR) particle filter as joint tracker in the product multi-object state space (Messaoudi & al., 2007) (Doucet & &l., 2001) (Bardet & al., 2009).

The iteration of the SIR particle filter are:

Draw $\{x_k^i\}_{i=1}^{N_p}$ from importance density (1)

Calculate importance weights $w_k^i = w_{k-1}^i \dfrac{p(z_k / x_k^i)p}{q(x_k^i / x_{k-1}^i, z_k)}$ (2)

Normalize weights $\overline{w}_k^i = w_{k-1}^i \dfrac{w_k^i}{\sum_{i=1}^{N_p} w_k^i}$ (3)

Resample with replacement $\{x_k^i\}_{j=1}^{N_p}$ from $\{x_k^i\}_{i=1}^{N_p}$ where $P_r(x^i = x^i) = \overline{w_k^i}$ (4)

Return $\{x_k^j, N_p\}_{j=1}^{N_p}$

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Figure 1 allows describing the PMTTA algorithm and shows that its complexity is linear in the number of targets, particles and measurements. Significance sampling is split into prediction solved analytically, fusion of predicted targets and sampling of associations and measurements according to the sampled association (Oh & al., 2008) (Mlouhi & al., 2017) (Lakhoua & al., 2016) (Chen & al., 2007). The maximal number of measurements assigned to the same target can be constrained, while a measurement is assigned to a single target at max. The association likelihood can realize the fusion of identity evidence. Smart deterministic resampling and memorization improve the efficiency of PMTTA, while the use of negative information gains performance.

An iteration of the Player Multi-Target Tracking Algorithm (PMTTA).

PMTTA:
$i = 0$
for $m = 1 : N_p$
Draw prediction $\hat{x}_k$
$\tau \longleftarrow \phi$
for $j = 1 : \lfloor N_p w_{k-1}^{m} \rfloor$
Draw association j_k
If $j_k \notin \tau$
$\tau \leftarrow \tau \cup \{j_k\}; i \leftarrow i+1; N_i \leftarrow 1$
Draw x_k^i by fusing $\hat{x}_k$ and z_k given j_k Calculate unnormaliza importance weight w_k^i
else
Calculate unnormaliza importance weight w_k^i
$N_i \leftarrow N_i + 1$
$N_p \leftarrow i$
Normalize weights $w_k^i \leftarrow \dfrac{N_i w_k^i}{\sum_{i=1}^{N_p} w_k^i}$
return $\{x_k^i, w_k^i\}_{i=1}^{N_p}$

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3. Implementation al remarks

A number of improvements were used to advance the performance of the method PMTTA during his implementation and test such as (Haque & al., 2008) (Zhang & al., 2007) ((Briers & al., 2004) (Wright, 1990) :

Parallelization: Because all particles can be independently sampled and filtered. The individual associations can be drawn in parallel if the multiplicity of associations for a single target is unconstrained without forgetting that an appropriate partition of the measurements is presupposed.

Log-space and restricted co-domain: All the probabilities are calculated in the log -space to avoid digital problems seen that these probabilities can be very small and must be added frequently for normalization. Therefore, we propose a fast version for summing two numbers that are given in log-space. This saves the computation of one power operation by an extra of one comparison, two additions and a subtraction and reveals an average saving of 20% time for this operation.

$$LOG\left(e^{a}+e^{b}\right)=\begin{cases} a+\log\left(1+e^{b-a}\right) & a>b \\ b+LOG\left(1+e^{a-b}\right) & if\ a\leq b \end{cases} \tag{5}$$

Negative information has been used for tracking, for example, in tracking based on GPS it was used (Bouielle & Wright, 1990) ((Oh & al., 2004). In our approach we tried to use some advantages of negative information for tracking in broadcasted videos. So, we assume that players are occluded only for a short time due to interactions. Then if the player is not assigned to measurements obtained by a certain device over a fairly long period of time, the probability that this player is outside the visible area of this camera increase.

If the probability becomes greater and exceeds the predefined threshold, the player will be pushed to the nearest point outside the polygon describing the visible area and his speed will be set to zero.

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Then if the player is not assigned to measurements obtained by a certain device over a fairly long period of time, the probability that this player is outside the visible area of this camera increase. In the case of broadcast football games, negative information is useful for panoramic cameras that do not capture the total playing field. For this, if a player leaves the visible area of a camera for a certain time, it will be assumed to remain outside the visible area if no measure suggests otherwise.

Thus, these players are repeatedly pushed to the nearest point outside the observed area until they can be reassigned to new measurements (Pu & al., 2004).

4. Simulation and evaluation

The simulation for the proposed Player Multi-Target Tracking Algorithm was based on an important concept which is the ability to handle a very large number of targets and measurements.

We adopted a simulation similar to the one described in ((Bwielle & Wright, 1990) (Ashbrook & Staner, 2002) to investigate the ability of the proposed method of tracking a high number of targets with multiple measurements through clutter.

Hundred targets are initialized to positions, which are uniformly distributed in $[-2000;2000]^2$, and velocities drawn from the distribution $N(0;20^2)$.

The time between the measurement sweeps is set to 1, the targets being monitored for 100 measurement sweeps.

These measurements are taken separately on the basis of the true target positions, whereas each position measurement has an independent error which is distributed according to $N(0;20^2)$. The number of measurements generated by a single target is Poisson distributed with $\lambda = 3$. The Clutter is therefore drawn according to a Poisson distribution with $\lambda_c = 100$, which is uniformly distributed over all tracking area $M = [-4000;4000]^2$.

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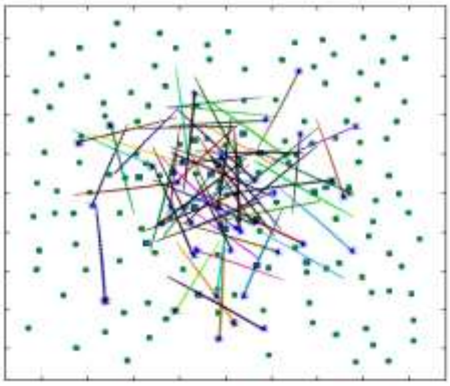
Fig.2 shows the last point in time of an exemplary simulation for tracking of hundred simulated targets which generate multiple measurements in clutter.

Figure 2: Tracking of hundred simulated targets



To do simulation we fixed the power spectral density of the process noise at $\bar{q} = 1.0$ and we used at most 50 particles to track 100 targets. We have initialized our tracker with actual target positions and a zero velocity with an uncertainty in the target state set at $100.00\mathrm{I}_4$; and we assumed that tracking would be considered a failure if the target position followed differed from more than one hundred of the real target position to the last point in time. For this, we followed the targets in a first run assuming that the individual assignments only and the second run assumed the correct Poisson distribution. The result is summarized in Table 1 which shows the mean number of failures during 100 simulation runs.

TABLE 1. Results for the simulation experiment

Assignment	Single only	Multiple
Failures	37.01	8.21
Time (ms)	473.5	561.1

Fig.3 shows the median distance of the tracked targets to their true position with 0.25 mid 0.75 quantiles for a single simulation run tracking with multiple measurements. Without doubt, we wished that this error remained within the measurement generation distribution $N(0;20^2)$. Tracking seemed futile since the measurement density was very high and accompanied by a high uncertainty of each measurement.

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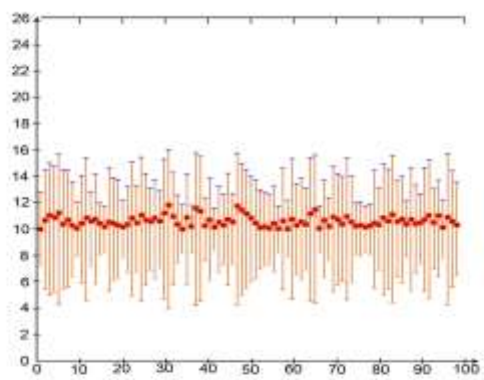
For this, arbitrary traces could be supported by observations resulting in low tracking performance. The novel simulation generated 400 tracks without clutter but did not offer tracking errors except computation time only. So, we have made the same simulation, but tracking seemed futile since the measurement density was very elevated and accompanied by a high uncertainty of each measurement. For this, arbitrary traces could be supported by observations resulting in low tracking performance (Cheikhrouhou & al, 2015).

Figure 3: Median distance of the tracked targets to their true position



5. Conclusion

In this paper we have proposed the Player Multi-Target Tracking Algorithm (PMTTA) as an approach for probabilistic real-time multi-target tracking which is a challenge for every multi-target method, solving the problem of building consistent estimates of trajectories from noisy, cluttered measurements. This approach is designed to track multiple targets of similar appearance and the performance of PMTTA was evaluated on several demanding applications, proving its effectiveness and real-time capability.

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