Nonparametric data association for particle filter based multi-object tracking: application to multi-pedestrian tracking

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Abstract—This article deals with the following issue: how to track a varying number of pedestrians through observations by means of a 4-plane laser sensor. In order to answer to the multiple target tracking problem and more specifically pedestrian tracking, we propose in this paper a statistical approach using a particle filter based on nonparametric data association methods. This approach allows to go beyond the conventional Gaussian assumption and to use as well as possible each particle during track/observation association by means of either a "Parzen Window" kernel method or a K-nearest neighbor algorithm. Simulated and experimental results show the relevance of this method compared to the usual Gaussian window methods.

I. INTRODUCTION

Much research is carried out in robotics concerning the detection of moving targets and then the estimate of the characteristics of moving objects. Multi-target tracking consists in estimating the trajectory and speed of an unknown number of moving objects. To solve this problem, observations coming from an object detection algorithm with its false or false positive alarms are available. All the difficulty of multi-target tracking lies in the association of the new observations which are continuously taken into account with the assumptions generated by a model of evolution.

Thus, two distinct problems have to be jointly solved: data association and estimates.

The conventional approaches are based on the linear Kalman filter [1], or its linearized extension (EKF) [2], and lead to data association algorithms such as the JPDAF [3], the MHT [4] or the PMHT [5] which differ in their association techniques but which all share the same Gaussian assumption. Such algorithms were used to solve many problems resulting from signal or image processing but they regularly failed to work out in case of a non-linear evolution model or in case of non-Gaussian noise models, which often occurs. Over the last years, the Monte Carlo methods aroused an increased interest in the scientific community particularly with the particle filters [6] which establish their superiority over others for non-linear filtering. The idea consists in representing the posterior density function by a set of random samples with associated weights and to compute estimates based on these samples and weights.

This article is organized as follows. In Section 2 our approach is explained. In Section 3, the principles of particle filters are briefly reminded. Section 4 describes the nonparametric data association method which is proposed in this article and its implementation into two algorithms. Finally, results are presented and analyzed in the last section in sequences of moving pedestrians.

II. OUR APPROACH

The purpose of our work is to track pedestrians from a moving vehicle. To develop our own approach, our research interest is focused on particle filters [7] because we don’t have any a priori knowledge or assumption about the movement of a pedestrian.

Multiple objects tracking with a particle filter generally uses a data association step, in which each target is mapped to an object hypothesis. Conventional approaches propose a Gaussian framework where a covariance matrix [3] is computed from the set. Since the particle set is generally not Gaussian, we propose in this paper a method based on a nonparametric approach [13] [14] using the particle set to compute probabilities for each data association. The basic idea is to keep in a state vector the a priori distribution without approximation in order to respect the particle filter stochastic character.

III. SEQUENTIAL MONTE CARLO METHODS

In the following section the theory of the sequential Monte Carlo methods in the framework of multiple object tracking is briefly reminded. For more details, the reader can refer to Doucet’s work [7].

A. General

Let us consider a discrete dynamic system:

\[ x_k = f(x_{k-1}) + w_k \]  \hspace{1cm} (1)

\[ z_k = h(x_k) + v_k \]  \hspace{1cm} (2)

where \( x_k \) represents the state vector at instant \( k \). No assumption is made on the two functions \( f \) and \( h \), whereas \( v_k \) and \( w_k \) are supposed to be two independent white noises.
B. Particle Filters

Particle filters provide an approximate Bayesian solution to discrete time recursive problems by updating an approximate description of the posterior filtering density \( p(x_k | z_{1:k}) \). This posterior density function represents some degree of belief in the state \( x_k \) at time \( k \), given the data \( z_{1:k} \) up to time \( k \).

The main purpose of particle filters is to approximate the a priori distribution of the recursive Bayesian filter \( p(x_k | z_{1:k-1}) \) as a set of samples, using the following equation:

\[
p(x_k | z_{1:k-1}) = \frac{1}{N} \sum_{i=1}^{N} \delta(x_k - x_k^i)
\]

where \( \delta \) is the discrete Dirac function. Then the a posteriori distribution \( p(x_k | z_{1:k}) \) can be estimated by:

\[
p(x_k | z_{1:k}) = p(z_k | x_k) \sum p(x_k | z_{1:k-1})
\]

This approach can be implemented by a bootstrap filter or a Sampling Importance Resampling (SIR) filter reminded in Table I.

<table>
<thead>
<tr>
<th>TABLE I</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAYESIAN BOOTSTRAP (SIR) ALGORITHM</td>
</tr>
<tr>
<td>1) ( k = 0 ), generate ( N ) samples ( {x_0^i}_{i=1}^{N} ) from the initial distribution ( p(x_0) ).</td>
</tr>
<tr>
<td>2) Compute the weights ( w_k^i = p(z_k</td>
</tr>
<tr>
<td>3) Generate a new set ( {x_k^i}<em>{i=1}^{N} ) by resampling with replacement ( N ) times from ( {x_0^i}</em>{i=1}^{N} ), according the probability ( p(x_1</td>
</tr>
<tr>
<td>4) Predict (simulate) new particles, i.e., ( x_k^i+1 = f(x_k^i, v_k) ), ( i = 1, \ldots, N ) using different noise realizations for the particles.</td>
</tr>
<tr>
<td>5) Increase ( t ) and iterate to item 2.</td>
</tr>
</tbody>
</table>

IV. DATA ASSOCIATION

Data association is a crucial problem for multiple target tracking applications. Several methods have been proposed in the literature and different methods are often discussed in estimation and tracking literature [3][8].

Conventional methods such as the Nearest Neighbor Standard Filter (NNSF), the Joint Probabilistic Data Association Filter (JPDAF), and also the method called Multi Hypothesis Tracking (MHT) calculate the update of each assumption from a Gaussian approximation of the probability distribution \( p(x_k | z_{1:k}) \) which is given by \( p(x_k | z_{1:k}) = \mathcal{N}(\hat{x}_k, P_k) \) with:

\[
\hat{x}_k = \frac{1}{N} \sum_{i=1}^{N} w_k^i x_k^i
\]

\[
P_k = \frac{1}{N} \sum_{i=1}^{N} w_k^i ((\hat{x}_k - x_k^i)(\hat{x}_k - x_k^i)^T)
\]

where \( \hat{x}_k \) and \( P_k \) are the first two moments of the predicted Gaussian density. In this case, the validation window is the ellipsoid of size \( N_c \) (dimension of measurement vector) defined such as:

\[
\text{val}_k = \{ z_k : (z_k - \hat{z}_k)P_k^{-1}(z_k - \hat{z}_k)^T \leq \gamma \}
\]

The threshold \( \gamma \) is obtained from the chi-square tables for \( N_c \) degrees of freedom and represents the probability that the (true) measurement will fall in the gate.

When using a Kalman filter or its extensions like Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) [9] or Ensemble Kalman Filter (EnKF) [10], these association methods are correct because they are based on the same Gaussian assumptions as these filters.

Nevertheless, in the case of particle filters it can be dangerous to estimate the set of particles thanks to a Gaussian density centered on the center of gravity of the set of particles (for example multi-modal distribution).

Starting from these observations, we focus our research interest on the development of a windowing method followed by a data association allowing to take into account more efficiently and globally the spatial dispersion of the particles without approximating it to a deterministic distribution. In this article, we present two algorithms of nonparametric data association which have been developed in the framework of our work concerning the pedestrian tracking on board vehicles.

A. Nonparametric methods

The nonparametric methods allow to take into account the samples and their space distributions in the space parameters. Let \( N_t \) be number of objects to track which is unknown at instant \( k \). Multi-target tracking consists in estimating the state vector made by concatenating the \( N_t \) vector of all targets. The vector \( X_k^i = \{x_k^i, \ldots, x_k^{N_t}\} \) is given by the state equation (1) decomposed in \( N_t \) equations:

\[
X_k^i = F_k^i(X_{k-1}^i, W_k^i) \quad \forall i = 1, \ldots, N_t
\]

with \( N \) the number of particles, and \( W_k^i \) that are independent white noises. The observation vector collected at time \( k \) is denoted by \( Z_k = (z_k^1, \ldots, z_k^{N_t}) \), with \( N_c \) the number of observations deduced from the process:

\[
Z_k^j = H_k^j(X_k^i, V_k^j) \quad \forall j = 1, \ldots, N_c
\]

Once again, the noises \( V_k^j \) are supposed to be independent white noises.

We propose to introduce the association vector \( A_k^{i,j} \) to describe the association between the measurements \( z_k^j \) and the target \( i \). In fact \( A_k^{i,j} \) is a discrete random variable associated to the probability \( p_j^i \) so that \( P(A_k^{i,j}) = p_j^i \) is the probability that the object \( i \) is associated with the observation \( j \). We propose to estimate \( p_j^i \) with a nonparametric method using the object "marginalized" set of \( p(x_k^i) \).

In fact, the probability \( P \) that a vector \( x \) will fall into a region \( R \) is given by:

\[
P = \int_R p(x)dx; \quad \text{if } R \text{ is small and } P(x)
\]

continuous then \( \int_R p(x)dx = \text{area of } R \) (finally). An estimate of \( P(x) \) is given by \( P(x) = \frac{k}{n} \) where \( k \) is the number of samples which fall into \( R \), \( V \) is the volume enclosed by \( R \) and \( n \) is the total number of samples.
There are two techniques which make it possible to generate a succession of areas which satisfy good conditions of estimate:

1) by fixing the volume of the area like a function of \( n \), for example \( V_n = \frac{1}{n^2} \).

It is the "Parzen Window" method.

2) by adapting the size of the areas with sample numbers \( k_n \) fixed according to \( n \), for example \( k_n = \sqrt{n} \).

It is the K nearest neighbors method.

We are going to use the "Parzen Window" method.

### B. Parzen association for particle filter

The Parzen window algorithm calculates the distance between an observation \( z^l_k \) located in the image and all its neighbors \( x_i^l \) as follows:

\[
p^*_j = \frac{1}{N} \sum_{i=1}^{N} \varphi(z^l_k, z^l_i)
\]

where \( \varphi(z^l_k, z^l_i) \) is the kernel function which allows to modify the influence zone of observation with its neighbors.

\[
\varphi(z^l_k, z^l_i) = \frac{1}{2\pi \cdot |\Sigma|^{\frac{1}{2}}} \exp \left[ -\frac{1}{2} (z^l_k - z^l_i)^T \Sigma^{-1} (z^l_k - z^l_i) \right]
\]

This method allows to compute the matrix \( A^l_k \) which represents the probability map enables to select the track/observation association from \( N \) particles at each time.

From this matrix, a validation window \( \text{val}_k \) of size \( N_z \) (dimension of the measurement vector) defined by (12) allows to accept or reject an association track/observation.

\[
\text{val}_k = \{ z^l_k : p^*_j \geq \alpha \}
\]

The threshold is determined by taking into account the influence of a maximum of particles close to an observation. This algorithm is summarized in Table II.

### C. K-NN association for particle filter

The "Parzen Window" kernel method requires to choose a suitable window size. The K-NN method avoids this problem. In fact, the principle consists in including a fixed number \( N_T \) of samples \( n \) among samples defining the class in order to have sufficient samples to contribute to the definition of \( p(x) \).

Let \( V[D(x, \delta)] \) be the homothetic field of the unit volume centered on \( x \) and of homothety ratio \( \delta \). The method of the nearest neighbors consists in increasing the \( \delta \) value until \( D(x, \delta) \) includes \( N_T \) samples. The estimator of the probability density is then given by:

\[
p^*_j = \frac{n_T}{V[D(x, \delta)]}
\]

This density estimator to compute the matrix \( A^l_k \) which allows take a decision of track/observation association.

In this case, the validation window is directly given by the size of volume allowing to include \( n_T \) particles of dimension \( n_z \) (dimension of the measurement vector) defined by:

\[
\text{val}_k = \{ z^l_k : p^*_j \geq \alpha \}
\]

The threshold \( \alpha \) is determined so that the diameter of volume is not higher than the maximum speed of a moving pedestrian (2m/s). This algorithm is summarized in Table III.

### V. SIMULATION / EXPERIMENTS

This section presents simulations and experiments which have allowed to validate our algorithms of data association and of pedestrian tracking. To evaluate the relevance of our two algorithms (SIR/Parzen and SIR/K-NN), we propose to compare them with the conventional algorithm of data association with Gaussian assumptions (Table IV). First, we
and correct association is given by the Parzen algorithm i.e. O1 is associated to object 2 and O2 to object 1, whereas the correct association is given by the Parzen algorithm i.e. O1 with object 1 and O2 with object 2.

proposing to study the behavior of the tracking algorithm on simulated cross-trajectories. In Fig 4, we test data association on rectilinear trajectories which cross each other in various points. Secondly, we confront these three algorithms with an experimental study performed on board our AIPV.

VI. SYSTEM OVERVIEW

Firstly, this section presents the IBEO laser sensor used in our experiments. For more details concerning the sensor, see Fuerstenberg et al [11]. Secondly, the equipped vehicle is described.

A. The IBEO Laserscanner

The IBEO lasercanner (see Fig. 2) has a variable scan area up to 270° but limited here to 150° for our experiments.

B. The equipped vehicle

In this study, the sensor is mounted so that the second layer of the sensor will be parallel to the ground. If the position of the sensor was such that the first layer was parallel to the ground, the fourth layer could detect only "tall" pedestrians beyond a 20 m range and nothing beyond a 30 m range. Moreover, the first layer can be used to monitor the pitching of the vehicle [11].

C. Simulations

With regard to the dynamics of the pedestrian’s movements, we suppose we do not have any a priori information on its trajectory (change in pace, direction, sudden stop, etc.). In order to predict all these trajectory modifications as well as possible, we use an evolution model with a circular motion [12] where the heading angle is used as a disturbance of the predicted trajectory. The model with circular motion applied to each particle is defined below.
and \( \theta_{k+1} = \theta_k + b_k \) with \( b_k \sim \mathcal{N}(0, \sigma_k) \). \( \sigma_k \) is the standard deviation of the heading angle concerning the pedestrian’s trajectory.

The state vector used summarizes all the information observed in the scene, i.e. the number of observed pedestrians and their characteristics:

\[
X_k = (O_k, x_1^k, \ldots, x_i^k, \ldots, x_N^k)
\]

with \( O_k \) a discrete random variable representing the number of pedestrians present in the scene and \( x_i^k = \{p^i_k, I^i_k\} \) the state vector associated to the object \( i \). The position and speed characteristics are given by \( p^i_k \) and the identifier and the age of the object by \( I^i_k \).

\[
Z_k = [I_{2+2}][X_{k+1} + v_k]
\]

where \( X_{k+1} \) represents the object position. Noises \( w_k \) and \( v_k \) are assumed to be a Gaussian function, of zero-mean and of respective covariances:

\[
Q_k = \begin{bmatrix}
\sigma_w^2 & 0 \\
0 & \sigma_y^2
\end{bmatrix}, \quad R_k = \begin{bmatrix}
\sigma_{x1}^2 & 0 \\
0 & \sigma_{y1}^2
\end{bmatrix}
\]

The variances of the added noises depend on the maximum movement amplitude possible for a pedestrian i.e. \( \sigma_{x1}^2 = \sigma_{y1}^2 = 2m \) and maximum errors of sensor measurements are \( \sigma_{x2}^2 = 0.2m \) and \( \sigma_{y2}^2 = 0.2m \).

Table V shows the result of a Monte Carlo simulation of the scenarios illustrated in Fig. 4. All these scenarios were repeated 1000 times with the same initial conditions for the three algorithms tested (same noises, same thresholds). Table ?? It is the kernel function used for the Parzen methods which explains these results because this kernel function allows a better selection of the particles around a given observation.

This section presents the experiments conducted with our AIPV vehicle to validate the methods suggested to track pedestrians. Fig. 5 presents the scenarios which were processed with our algorithms during our experiments. So, the results located in Table V are interesting concerning the performances. The various algorithms were tested in many different situations such as an urban scene, a semi-urban scene, or a car park with of course, many pedestrians going in all directions. These examples were obtained with our AIPV moving at about 10 km/h. For security reasons, we have not addressed yet the real situations at higher speeds.

Figures 6 and 7 are given as examples of one scenario recorded on board our vehicle to compare the results of tracking methods (SIR/Chi-square vs SIR/Parzen). As it was explained previously, the association algorithm is based on the distribution of the particles which results directly from the stochastic Monte Carlo algorithm. Of course, statistically (see Table V) the various filters can give similar results on the same scenario.

Table VI presents comparative performances of the three algorithms. This table shows the advantage of SIR/Parzen over the other two algorithms. It should be noticed that the situations met during the experiments on board the vehicle are less intricate (in terms of pedestrian cross-trajectories) than those studied during simulation, which explains why the correct rate of track/observation association is much better on real data than on simulated data.

As shown by the various examples to illustrate our different algorithms, in certain cases the SIR/Parzen filter may be more robust (Fig. 6 and Fig. 7: inside the black ellipses). The SIR/Parzen filter allows not to be mistaken in the choice of observations and to ensure the tracking of the pedestrian.
involved. However, as shown in Table V and VI, these three filters have close error rates of association. Indeed, according to the situation present in the observed scene, statistically none of these filters is bound to make a better decision than the others.

### Table VI

**Comparative Table of Data Association Performances of the Three Algorithms Representing More Than Ten Minutes of Experiments in Various Situations.**

<table>
<thead>
<tr>
<th>Association correct object/observation</th>
<th>SIR/Chi-square</th>
<th>SIR/Parzen</th>
<th>SIR/K-NN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>94%</td>
<td>98%</td>
<td>94%</td>
</tr>
</tbody>
</table>

Fig. 6. Result of multi pedestrians AIPV tracking with SIR/Chi-square. Measurements are represented in grey circles.

Fig. 7. Result of multi pedestrians AIPV tracking with SIR/Parzen. Measurements are represented in grey circles.

### VII. Conclusions and Future Work

#### A. Conclusions

This study proposes an alternative to the Gaussian approximation density of the SIR filter predicted particles at the stage of data association. First, we studied pedestrian movement dynamics, which led us to choose a circular motion evolution model in order to follow more easily the pedestrian random movement which can include abrupt trajectory changes. Second, we examined the relevance of the parametric data association methods for particle filters. Thus we chose to replace conventional Gaussian assumptions with nonparametric statistical methods in order to take into account more efficiently the unspecified character of the distribution of particles predicted by the SIR filter. Accordingly, we developed two sequential algorithms for multi target tracking (SIR/Parzen and SIR/K-NN) which were compared with the conventional algorithm SIR/chi-square in order to evaluate the relevance of these methods. This work made it possible to emphasize that the SIR/Parzen algorithm is more robust than the other three with a better rate of association both on simulated and real data.

In conclusion, this work permits to propose an interesting alternative at the stage of data association when using a particle filter for tracking purposes. The SIR/Parzen algorithm seems definitely more effective for pedestrian tracking thanks to the use of a kernel function.

#### B. Future Work

Future work will focus on the robustness of tracking methods by studying the difficult issue of object occultations when pedestrians walk past each other.

### References