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TRACKING MULTIPLE AND DYNAMIC OBJECTS WITH AN EXTENDED PARTICLE FILTER AND AN ADAPTED K-MEANS CLUSTERING ALGORITHM

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Abstract: The work presented is related to the research area of autonomous navigation for mobile robots in unstructured, heavy crowded and highly dynamic environments. One of the main involved tasks in this researching area is the obstacle tracking module that has been successfully developed with different kind of probabilistic algorithms. The reliability that these techniques have shown estimating position with noisy measurements make them the most adequate to the mentioned problem, but their high computational cost has made them only useful with few and structured objects. In this paper a computational simple solution based on a multimodal (or extended) particle filter is proposed to track multiple and dynamic obstacles in an unstructured environment and based on the noisy position measurements taken from sonar sensors.

Keywords: Extended particle filters, multiple objects tracking, multimodal probability distributions, dynamic unstructured and crowded environments.

1. INTRODUCTION

The origin of the probabilistic estimators arrives quite early on the fifties, with the idea of representing the state vector to predict with its probability distribution and applying this idea not only to the area of tracking in robot navigation. There were many advantages in the also called Bayesian method (also known as Sequential MonteCarlo) from the stochastic ones: the system model should not necessary be linear, and the noise coupled to measurements should not necessary be Gaussian.

The standard particle filter (PF) is a sampling weighed representation of the Bayesian filter, where each one of the samples taken from the continuous probabilistic distribution is called particle. The set of particles must be independent and identically distributed to achieve a correct approximation to the continuous distribution, but this can be easily solved with a big enough number of particles randomly acquired. These techniques are not extensively used until the end of the 90s in the area of interest (Isard and Blake, 1998) with the introduction of a selection step in the PF loop to avoid the degeneration of the algorithm with time (Gordon *et al.,* 1993). The idea consists on selecting (or resample) and multiplying the particles with high importance weights and rejecting the rest. Different alternatives for this part were also designed (Van der Merwe *et al.,* 2001).

To achieve a multiple objects tracker different options have also been designed during the last years (Orton and Fitzgerald, 2000). An initial solution is to use a standard PF to track each object but this is not efficient as it does not work with a dynamic number of objects. Some other solutions include an association among the detected objects and the particles of the filter over the time (JPDAF) (Schulz *et al.* 2001), although these techniques have shown very good results, this work's aim is to find an alternative to JPDAFs, with the same reliability, higher robustness and faster results. The standard PF, which is proved to be un-efficient

tracking multiple objects that appear and disappear dynamically, is modified in this work to achieve the these specifications.

2. DESCRIPTION OF THE DESIGNED ALGORITHM

The dynamic and multi-object tracker designed for the application mentioned is based on a PF, thus in the following paragraphs both the standard algorithm and the improvements made will be described.

2.1 The standard PF

The main loop of a standard PF at time t starts with a set $S = \{s_i / i = 1..N\}$ of random particles representing the posterior distribution of the state vector to be estimated $p(\vec{x}_{t-1}|\vec{y}_{1..t-1})$ at the previous time step (t-1). These particles are propagated by the system dynamics to obtain a new set S' that represents the prior distribution of the state vector at time t, $p(\vec{x}_t|\vec{y}_{t-1})$. The weight of each particle $W = \{w_i / i = 1..N\}$ is then obtained based on the comparison of the measured output vector $\vec{y}_t$ and the estimated one based on the prior estimations. Applying the selected resample scheme, a new set S'' is obtained with the most probable particles that will be the new $p(\vec{x}_t|\vec{y}_{1..t})$.

The functionality of the algorithm is described in Fig. 1. See (Doucet *et al.,* 2000) for a more detailed explanation.

2.2 The multimodal PF

The standard PF estimates quite well the evolution of any kind of a single object defined by its model, but as it was already mentioned at the introduction of this paper, it has not been designed to track a multiple and variable number of them.

To do so, different solutions depending on the final application have been proposed as it has already been explained in the introduction. The most interesting of them for the work proposed in this paper is the one presented in (Koller-Meier and Ade 2001), because with a single probability distribution a variable number of objects can be tracked with high reliability and with no need of doing a previous association between the different measurements and the particles of the distribution.

The most important innovations that were implemented at (Koller-Meier and Ade 2001) to adapt a standard PF to a multimodal estimator are the following:

1. *Initialize (only at t=0):* Obtain the sample set S with N particles from the posterior distribution $p(\vec{x}_{t-1}|\vec{y}_{1..t-1})$ (this will be done with the prior distribution $p(\vec{x}_0)$)
2. *Propagate:* Obtain the new prior set S' with the model of the state vector to estimate:
   $\vec{x}_t = f(\vec{x}_{t-1}, \vec{v}_{t-1}) \quad \Rightarrow \quad S' = f(S, V)$,
   where $\vec{v}_{t-1}$ is the noise signal associated to the dynamics of the state vector model, and from which V is obtained as a vector of standard random variables with statistics defined by $\vec{v}_{t-1}$.
3. *Importance Sample:* Calculate the importance weights of S' from the likelihood $p(\vec{y}_t|\vec{x}_t)$:
   $$W_t = W_{t-1} \cdot \frac{p(\vec{y}_t|\vec{x}_t) \cdot p(\vec{x}_t|\vec{x}_{t-1})}{q(\vec{x}_t|\vec{x}_{0..t}, \vec{y}_{0..t})}$$
   $$W_t = W_{t-1} \cdot p(\vec{y}_t|\vec{x}_t)$$
   where $q(\vec{x}_t|\vec{x}_{0..t}, \vec{y}_{0..t})$ is the best proposal approximation of the posterior distribution. In most works this best approximation is substituted by the prior one, so the equation is simplified.
4. *Resample*: Multiply/reject samples of S' with high/low importance weights respectively to obtain a posterior distribution $p(\vec{x}_t|\vec{y}_{1..t})$ represented by a new set S'' with N particles.
5. *Output:* The final estimated vector state is usually obtained calculating the mean of the posterior.
6. *Go to step 2…:* The sample set S'' from the posterior distribution $p(\vec{x}_t|\vec{y}_{1..t})$ at time t is then used as the new set S for the algorithm implementation in the next step, at time t+1.

Fig. 1. Description of the standard PF functionality.

Re-initialization: In the standard PF a new appearing object is not going to be considered unless its state vector is close enough to an already existing one, as the output vector does not modify directly the sample set of the estimated state vector itself but only their importance weights.

To solve this problem a re-initialization of the sample set S at each time step has to be done, inserting on it M samples directly from the output vector. With this modification, information from the new environmental configuration $p_m(\vec{x}_{t-1}|\vec{y}_{1..t-1})$ is combined with the posterior

distribution $p_p(\vec{x}_{t-1}|\vec{y}_{1..t-1})$ to obtain a new expression for it:

$$p(\vec{x}_{t-1}|\vec{y}_{1..t-1})=\gamma\cdot p_m(\vec{x}_{t-1}|\vec{y}_{1..t-1})+(1-\gamma)\cdot p_p(\vec{x}_{t-1}|\vec{y}_{1..t-1})$$

where γ is the factor that weights the distribution association up, and that is fixed by the relation between the M samples inserted directly from the output vector measured at t-1 and the total number of samples (N) in the particle set S ($\gamma = {}^{M}\!/_{N}$).

With this new initialization the single probability distribution will adapt itself over time to finally represent simultaneously the state vector of all the different objects that exist in the environment at each time. On the other hand, as new particles are directly taken from the output vector, they will be very near from the correct value of each new object state vector, so they will be assigned with a high weight as the algorithm evolutions. This fact allows choosing a small value for γ (thus the evolution of $p_p(\vec{x}_{t-1}|\vec{y}_{1..t-1})$ distribution is not affected) without the risk that the particles related to new objects in S disappear with the resample.

Resample: To insert the new M particles as mentioned, the resample phase is also modified. In this case, only N-M samples have to be selected from the N existing at the S' sample set. The resampling process, as well as the rest of the PF algorithm is for the rest equal to the standard PF.

This version of the also called extended PF works quite well if all objects are sensed with more or less the same accuracy, but the authors of (Koller-Meier and Ade 2001) explain that if it does not occurs (as it can happen easily working with ultrasound sensors, as it is the case in the application presented in the paper) the sample set may degenerate as the related weights can be much larger for some objects than for some others. To solve this problem different improvements have been made to this extended PF in the algorithm proposed in this paper, as it will be explained next.

2.3. The clustering algorithm

A clustering algorithm has been designed to organize the measurements that come directly from the sonar in k detected objects. The parameter k is dynamically obtained from the measurements obtained at each moment, thanks to a prediction process implemented in the PF loop.

The clustering process is based on a standard kmeans algorithm (Kanungo *et al*., 2002), but some improvements have been included to adapt it to its specific use at the probabilistic estimator:

Standard kmeans: The functionality of the standard algorithm is the following:

a. Select randomly k centroids for the clusters.
b. While the distance from each measurement is not minimum to its assigned cluster centroid.
c. For 1 to all measurements: assign it to the cluster whose centroid is the nearest.
d. If the distance from the measurement to any centroid is bigger than a limit, create a new cluster, whose centroid is the measurement itself (k=k+1).
e. Recalculate all cluster centroids using the mean.
f. If a cluster is empty or has very few members it is erased (k=k-1).

Cluster movement estimation: Instead of assigning randomly the initial centroids they are obtained from the previous clustering process, thus the algorithm is shorter as the clusters to find are slightly predefined. The cluster movement can be estimated calculating its dynamics centroid.

Cluster candidate: When a new cluster is created (does not come from an initial centroid) it is converted into a candidate that is not validated to be useful in the probabilistic algorithm until it is possible to follow its evolution with its related dynamics for a variable number of times. The same process is used to erase a cluster. This method ensures the robustness of the probabilistic estimator to spurious measurements and so increments its reliability.

The information obtained from the clustering algorithm is used in different parts of the PF loop incrementing the possibilities and reliability of the probabilistic estimator, as follows:

At the re-initialization step: With a cluster organization it is possible to select the measurements to be inserted in the prior distribution $p_p(\vec{x}_{t-1}|\vec{y}_{1..t-1})$ at the re-initialization step, according to their preliminary object assignation (in general M/k measurements from each cluster). As newly inserted particles are chosen randomly from groups with high level concentration of measurements their likelihood is very high from the beginning. This fact prevents from situations in which particles related to objects poorly sensed are erased from the multimodal distribution at the resampling step, as occurred in (Koller-Meier and Ade 2001). The M/k particles to be inserted from each cluster are completed with some others randomly selected from its accumulation buffer, which contains measurements assigned to each cluster in previous time steps and that are not very distant from its actual centroid. New particles taken from the accumulation buffer make the estimation more stable.

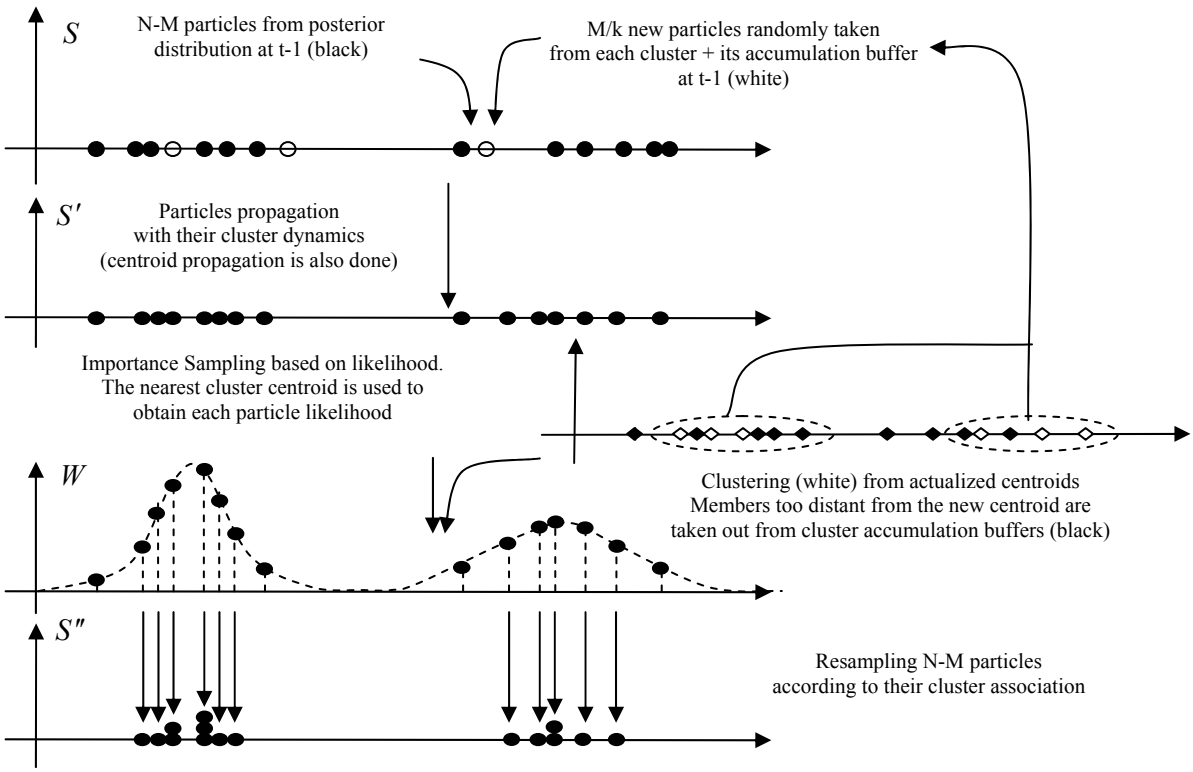

Fig. 2. Description of the functionality of the extended PF designed.

At the propagation and importance sampling step: The cluster structure is used to make particles evolution and their likelihood according to their one most similar cluster model and output vector respectively. With this method the predicted sample set S' is going to be very close to the real state vector, obtaining high values for the likelihood function at the importance sampling step, and thus improving the robustness and reliability of the global estimator.

At the resampling step: The cluster information can be used to do a dynamic assignation of the N-M particles to resample among the k different clusters detected, and according to their likelihood too. Particles are effectively resample, so the cluster structure is only used to select the most adequate likelihood measurement. This fact also prevents from the situations of objects poorly measured whose related particles are erased from the posterior, as mentioned before.

It is important to remark that the clustering process is only a help to insert with likelihood enough, the newly detected objects into the obstacle position density function. A PF is needed to obtain the stochastic model of the position measurements, which will be useful to implement a position estimator.

This clustering process is, probably, the most interesting contribution of the presented work.

Fig. 2 shows the functionality of the extended PF designed, including the clustering algorithm.

3. RESULTS

Different tests have been developed with a robotic platform (from ActivMedia Robotics), in a dynamic environment. The robot has 16 sonar all around its body with a 3m range. In one of the tests the robot has been wandering around by an unstructured environment with diverse obstacles appearing in the scene, in a manual driving mode.

Fig. 3 show different moments of an experiment, each one with four graphics with the following meaning:

- *Left upper corner:* actual 3D density function of the occupied space represented by the particle set in the x-y space.
- *Right upper corner:* representation of the robot actual situation in the environment. The circles show validated obstacles generated by the PF output step.
- *Left lower corner:* accumulated representation of the PF output, all along the covered path. Different identified clusters are represented with different shapes for their centroid point. The darker line shows the robot position all along the path.
- *Right lower corner:* actual histogram of the particle set state vector components. The obstacle positioning model is based on the state

vector: $\vec{x}_t = [x_t \quad y_t \quad vx_t \quad vy_t]$, and only its two first components are shown here (these are directly obtained from the sensor model, the other two are estimated). The different groups that can be distinguished at the histograms would result in different clusters (different distinguished obstacles).

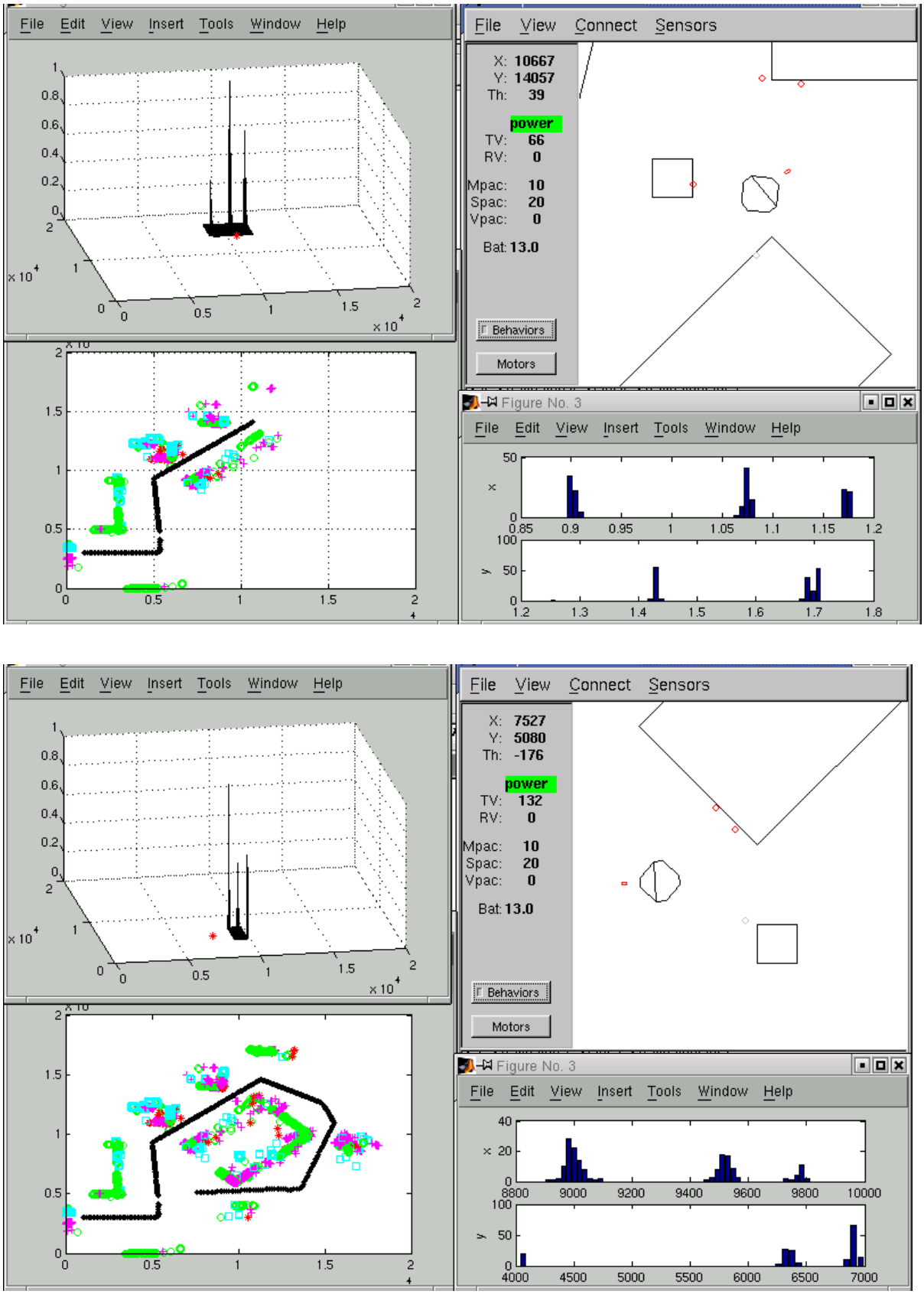

Fig. 3. Results from the probabilistic tracker developed.

4. ACKNOWLEDGEMENTS

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