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A Bayesian Solution to Track Multiple and Dynamic Objects Robustly from Visual Data

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Abstract—**Different solutions have been proposed for multiple objects tracking based on probabilistic algorithms. In this paper, the authors propose the use of an only particle filter to track a variable number of objects. The estimator robustness and adaptability are increased by the use of a clustering algorithm. Measurements used in the tracking process are extracted from a stereovision system, and thus, the 3D position of the tracked objects is obtained at each time step. Tracking results are presented at the end of the paper.**

Index Terms—**Clustering, Multi-tracking, Particle Filters, Probabilistic, Robustness**

I. Introduction

Probabilistic algorithms in their different implementations (Multi-Hypothesis Techniques -MHT- [1], Particle Filters -PF- [2], [3] and their diversifications [4], [5]) have fully shown their reliability in estimation tasks. Nowadays these methods are widely applied to solve positioning problems in robot autonomous navigation [6], [7].

The idea of tracking multiple objects appeared with the first autonomous navigation robot, to overcome the obstacle avoidance problem and soon probabilistic algorithms, such as PF [8], [9] and KF [10], [11], were applied to achieve this aim. The objective is, in any case, to calculate the posteriori probability ($p(\vec{x}_t \mid \vec{y}_{1:t})$) of the state vector in the recursive two steps standard estimation process (see (1)), in which, at least, some of the involved variables are stochastic, and by means of the Bayes rule:

$$p(\vec{x}_t \mid \vec{y}_{1:t}) = \eta \cdot p(\vec{y}_t \mid \vec{x}_t) \cdot \int p(\vec{x}_t \mid \vec{x}_{t-1}) \cdot p(\vec{x}_{t-1} \mid \vec{y}_{1:t-1}) \cdot \partial \vec{x} \quad (1)$$

To solve the multiplicity problem, an expansion of the state vector to include that of all the elements to track (see (2)) was the first solution proposed in [12].

$$\vec{\chi}_t = \{\vec{x}_t^1, \vec{x}_t^2, \ldots, \vec{x}_t^k\} = \bigcup_{i=1}^{k} \vec{x}_t^i \quad (2)$$

The computational load of the resultant estimator does not allow achieving a real time execution of the algorithm for more that 4 or 5 objects [13].

Another solution for the multiple objects tracker is to use a standard estimator to track each object but, apart of the inefficiency of the final algorithm [14], it cannot deal easily with a dynamic number of objects [15].

On the other hand, in order to work with independent estimators, it is necessary to include an association algorithm to assign each measurement to one of the trackers. Most of the association solutions are based on the Probabilistic Data Association (PDA) theory [16], such as the Joint Probabilistic Particle Filter (JPDAF) like in [17] or in [18]. Again, the problem related to these techniques is the execution time.

In this context the authors propose in [19] another solution to the multi-tracking problem based on a single PF whose multimodality is exploited to perform the multi-tracking task. The algorithm is called Extended Particle Filter (XPF). This solution has been tested in complex indoor environments with sonar [19] and stereo-vision data [20] with good results. A clustering algorithm is used in this point to organize the measurements and the information involved in the estimation process, and to increase the robustness and reliability of the final estimator.

In this paper, a general revision of the tracking system developed, based on stereovision measurements, is presented, a slight description of the XPF developed in [19] is then included; the functionality of the two proposed clustering methods is deeply described; and finally some results and conclusions obtained from the segmentation processes applied to the probabilistic estimator are exposed.

II. General description

Most of the tracking systems developed in the last years for autonomous navigation and surveillance applications are based on visual information.

Measurements obtained from a vision system are generated both by the environment and the objects to track. To use this information in the tracking task a process to distinguish the data set that comes from the objects to track is needed. This pre-processing algorithm is especially important to achieve a real time execution, due to the big amount on measurements included in the vision image.

Fig. 1 shows the functional block diagram of the global tracking system in which a classification pre-process has been included to organize the measurements that come

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from the vision system in two groups:

- Those that inform about the position of the objects.
- Those that are generated by the elements in the environmental structure (such as floor and walls).

With the mentioned functionality, the classification pre-process behaves as an obstacle detection module.

As it is showed in Fig. 1, measurements classified as environmental structure ones can be used to implement a partial reconstruction of the environment in which the tracked objects and the robot itself are moving. This process, that is independent of the taking application, is still under development by the authors.

III. The Classification Algorithm

Developing obstacle avoidance tasks requires 3D information about the objects position in the environment. To obtain these data, a stereo-vision system has been used as shown in Fig. 1.

Fig. 2 shows the process used to detect and extract the array of measurements from the stereo-vision system, which is explained in the following paragraphs.

The stereo-vision system proposed is formed by two black and white digital cameras whose acquisition is synchronized. The 3D points are obtained from each pair of frames, by means of an epipolar technique.

As the amount of information in each image is too big to be computed in real time, matching pixels for the epipolar equation are taken among the edge image obtained applying a canny filter to the input frame.

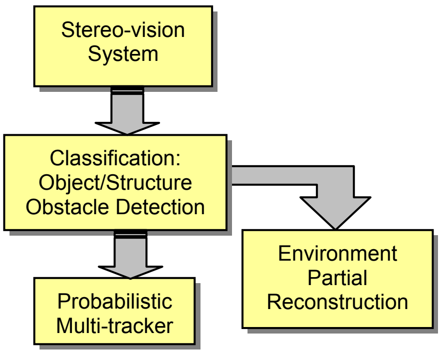

Fig. 1. Block diagram of the global tracking system.

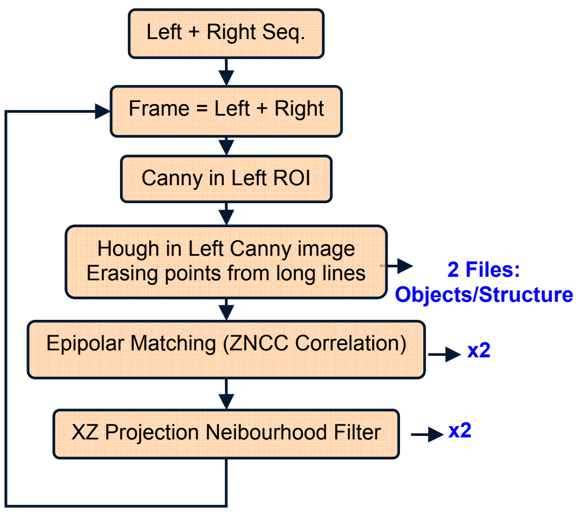

Fig. 2. Block diagram of the stereo-vision classifier and object detector.

With the pixels in the edge image, the classification process is performed. Different strategies have been tested to achieve the best results classifying the measurement set, both in execution time and in reliability.

Edges corresponding with environmental structures have the common characteristics of forming long lines.

Due to this fact, the Hough transform has been selected as the best procedure to erase the pixels from the edge image that should not be part of the object measurement array.

The execution time of the developed classifier is around 60ms, which is an acceptable solution to implement a real time acquisition image process of 15fps to 33fps.

Different solutions are still under development to achieve a more robust classification process.

IV. The Multi-tracking Algorithm

As mentioned in the introduction, a PF is used as a multimodal tracker to estimate the position and speed of the objects in the environment, from the measurement array obtained in the classification process.

PF is a particularization of the Bayesian estimator in which the densities related to the posteriori estimation (also called belief) is discretized. A detailed description of the PF mathematical base can be found in [2] and in [5].

As the state vector is not discretized, like it is in most of the rest Bayes filter implementations, the PF is more exact in its estimation than the KF or estimators based on a grid (MonteCarlo estimators). Moreover, due to the same reason, the computational load of this Bayes filter form is smaller in this than in other implementations, and thus, more adequate to implement real time estimation.

Finally, PFs include an interesting characteristic for multi-tracking applications: the ability of representing multiple estimation hypotheses with an only algorithm, through the multimodality of the belief. This facility is not available in the optimal implementation of the Bayes estimator, the KF. For all these reasons, the PF has been thought as the most appropriated algorithm to develop a multi-tracking system.

A. The XPF

Most of the solutions based on a PF presented in the related scientific literature do not use the multimodal character of PF to implement the multi-tracker. These alternative solutions, mentioned in the introduction of this paper, are however less efficient in execution time.

In order to adapt the standard PF for its use tracking a variable number of elements, some modifications must be included in the basic algorithm. In [19] and [20], the authors propose what is called the extended particle filter (XPF), an adaptation of the standard PF for tracking a variable number of elements.

The XPF first approach appears in [21]. The algorithm proposed there was nevertheless not used in real tracking tasks because it is not robust enough. The XPF proposed by the authors in [20] includes a clustering algorithm to improve the behaviour of the first extended PF, giving as a result the XPF-CP process, shown in Fig. 3.

The clustering algorithm whose functionality is presented next in this document, organize the data in

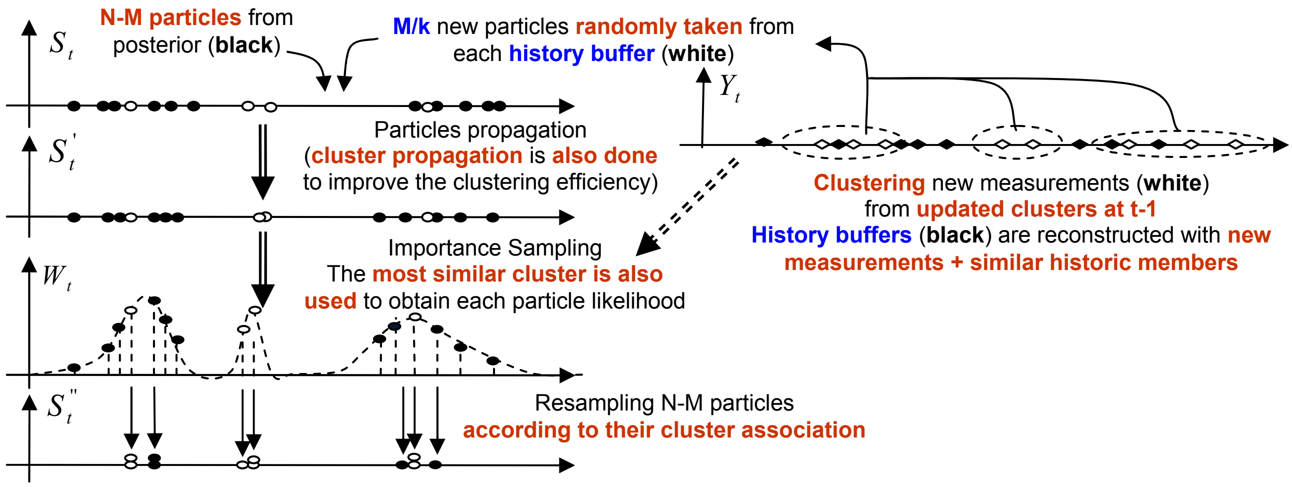

Fig. 3. Description of the XPFCP functionality.

clusters that represent all objects in the scene.

These clusters are then used in the tracking algorithm. With the clustered data two important innovations are included in the standard PF in order to facilitate the multi-tracking process:

a) Re-initialization step: M from the N total number of particles that conform the belief distribution in the PF are directly included in this step previous to the prediction step. With this step, measurements related to newly appearing objects in the scene have a representation in the estimator belief.

To improve the robustness of the estimator, the inserted data are not selected randomly from the array but from its segmentation. Choosing measurements from every cluster ensures a probable representation of all objects in the scene, and therefore, an increased robustness of the multi-tracker.

Thanks to this re-initialization step the posteriori distribution dynamically adapts itself to the different objects present in the scene.

b) Resampling step: This step is also modified from the standard PF. On one hand, only (N-M) samples of the belief have to be extracted in this step, as the M resting particles would be inserted in the re-initialization.

On the other hand, the clustering process is also used in this step, because the importance sampling function used to weight the particles is obtained from the similarity between each one of them and the centroid of the clustered input data set.

Using the cluster centroids to weight the particles related to the newly appeared objects, the probability of these last ones is increased, improving the robustness of the final estimator.

Without the clustering process, the solution proposed in [21] rejects the hypothesis related to new objects, and thus, the multimodality of the PF cannot be exploited.

The robustness problem has been the main reason in the researching community for not using the PF multimodal capability. With the algorithm proposed in this paper, a new solution for multiple tracking using an only estimator is designed.

B. Clustering

Two different algorithms have been developed for clustering the set of measurements. Its reliability is similar, though the proposal is to select which to use depending on the environmental situation. Fig. 4 and 5 show their functional description. A more detailed analysis of these algorithms can be found in [22].

The clustering process presented in Fig. 4 is based on the deterministic "k-means" algorithm, which has been modified to handle a variable and initially unknown number of clusters. A clustering updating pre-process is included in the algorithm in order to minimize its execution time.

Fig. 5 describes the second proposed clustering algorithm, which is a fuzzy/probabilistic classifier based on the standard "subtractive" one. This second option has a longer execution time, though it has the advantage of giving secondary information about the clusters found in the input data, such as their likelihood. This extra information is very useful in the PF based estimation process.

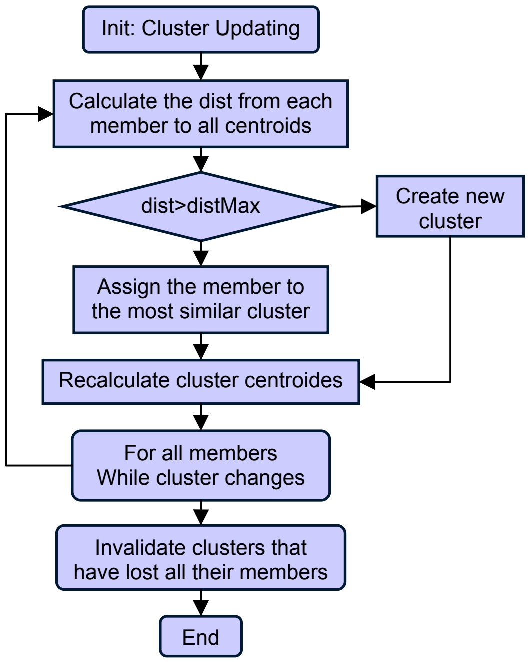

Fig. 4. Description of the 'k-means' clustering algorithm.

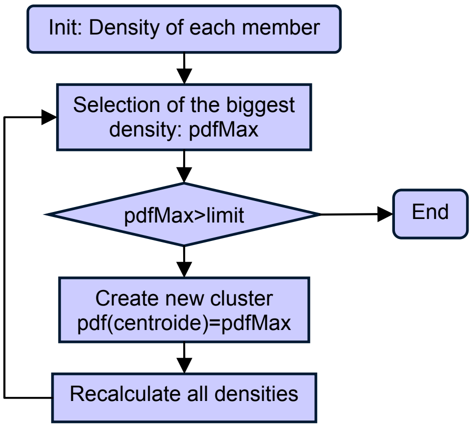

Fig. 5. Description of the subtractive clustering algorithm.

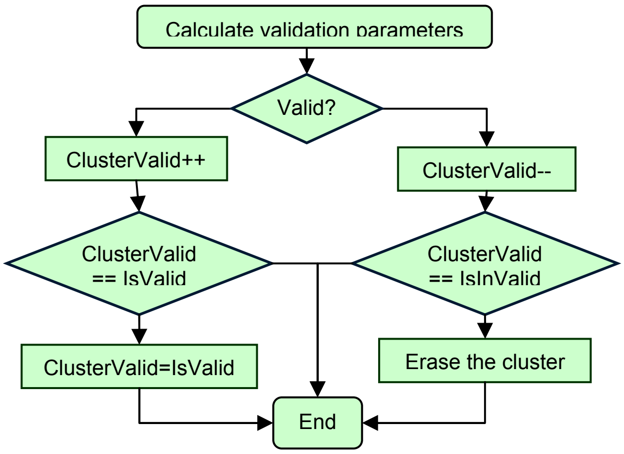

Fig. 6. Description of the validation process for the clustering algorithm.

A validation process is added to the clustering algorithm in order to increase the robustness of the global algorithm to spurious measurements. The validation process functionality (shown in Fig. 6) is the following:

- When a new cluster is created, it is converted into a candidate that will not be used in the probabilistic algorithm until it is possible to follow its dynamic evolution.
- The same procedure is used to erase a cluster when it is not confirmed with new measurements for a specific number of times.

V. RESULTS

The global tracking algorithm based on a stereo-vision system shown in Fig. 1 has been implemented in a mobile 4-wheeled platform. Different tests have been done in unstructured indoor environments, whose results are shown in this section.

The stereo-vision system is formed by two black and white digital cameras synchronized with a Firewire connection and located in a static mounting arrangement, with a gap of 30cm between them, and at a height of around 1.5m.

The classification and tracking algorithms run in a PIV with 512Mbyes of RAM, with a global execution time around 80ms. With these data, a real time multi-tracking system is developed at a speed of more than 10fps.

Fig. 7 shows the output of the classifier in one of the experiments, with 5 frames of a global sequence.

Classification results for each one are displayed in 3 images organized vertically:

- The one on the top shows the edge image obtained directly from the left frame. Both obstacles and environmental structure borders are mixed in the image.
- The picture in the middle shows the result of the classification process in the XY projection (x range is from -5m to 5m, and y range is from 0.2m to 20m). White dots represent the measurements that, according to the classifier results, belong to obstacles.
- The bottom one shows the final left image in which points classified in the obstacle measurement are highlighted with a colour according to the height where they are measured.

From this figure, it can be concluded that the classification objective has been achieved. The resulting obstacle data set can now be inserted in the estimator.

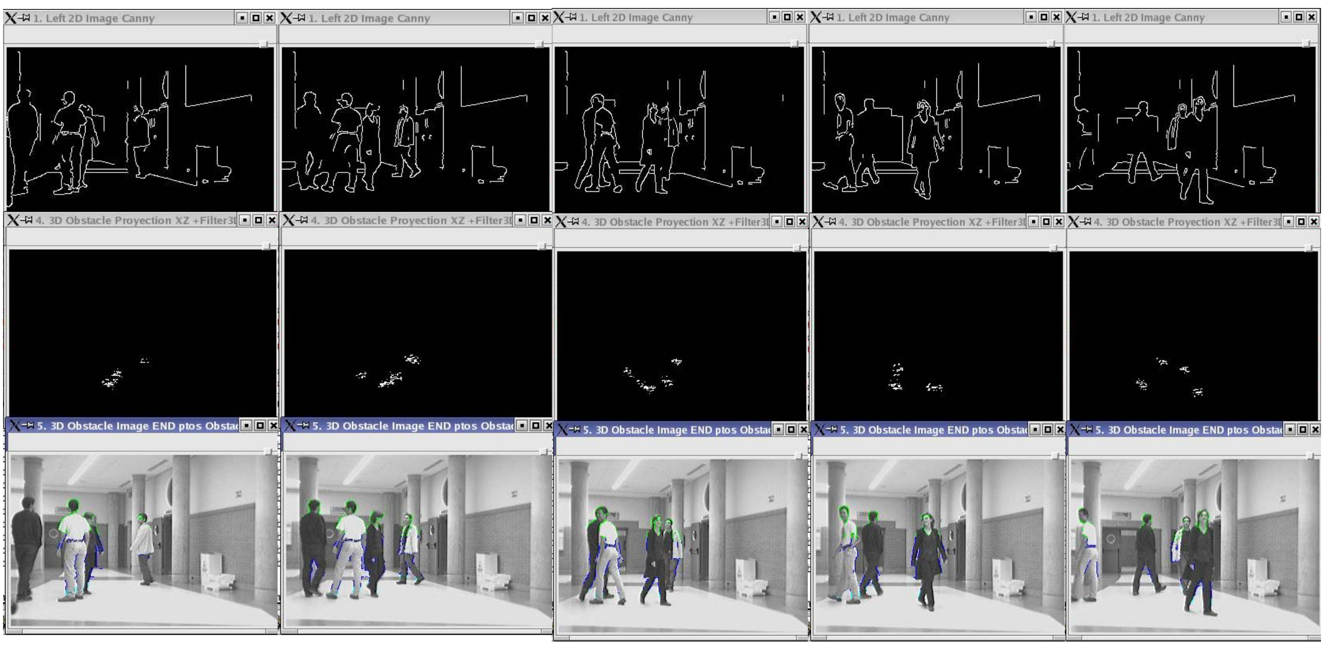

Fig. 7. Results of the classification algorithm in a real situation

Fig. 8. Results of the multi-tracking algorithm XPF in a real situation

It is interesting to point out that the number of objects present in each frame cannot be easily extracted directly from the measurement data set. Therefore, the probabilistic tracker will be necessary to determine it.

Fig. 8 displays the results obtained in one of the tested situations. Thanks to the classification algorithm, only measurements related to obstacles in the environment are taken into account by the probabilistic estimator.

The figure shows the XPF output in 5 frames in a global sequence. As it can be noticed, the experiment has been developed in a complex and unstructured indoor environment.

Two images organized vertically are shown for each:

- The upper one displays the left frame with green dots showing the measurements' position from the previous classification process, and rectangles representing the clustering algorithm output. Clusters are modelled as cylinders in the 3D world, thus their image projection are rectangles.
- The lower image shows the same frame where red dots have been plotted to represent the PF particles position in that moment. The clustering process has also been used as a final step of the PF to obtain a deterministic output.

The intensity of the corresponding colour at each image shows the probability of each clustered hypothesis, i.e. the greenest the input cluster, the more measurements there are at each cluster, and the reddish the output cluster, the more probable the tracked path is.

Comparing the upper and lower image in Fig. 8, it can be noticed that the XPF filters can manage temporal occlusions and dual hypotheses generated in the input clustering process.

Fig. 9 displays the results extracted from another real time experiment. In this case, the lower image presents the tracking results XZ projection, in the same way that was shown in Fig. 7.

In this new figure, it is also shown a circle representing the XZ projection of each output cluster cylindrical model.

This figure shows the complementary effect to the one extracted from Fig. 8. The clustering algorithm and the validation method included in it, improve the filtering process developed by the XPF, and thus, increase the robustness of the global tracker.

The results displayed in Fig. 8 and Fig. 9 show that the tracker follows correctly each obstacle position in the dynamic and unstructured indoor environment.

VI. CONCLUSIONS

The main conclusions of the developed work described in this paper are the following:

- A robust estimator of the movement of the obstacles in unstructured and indoor environments has been designed and tested. The proposed XPFCP is based on a probabilistic multimodal filter, and is completed with a clustering process, obtaining high accuracy and robustness in the tracking task in complex environments.

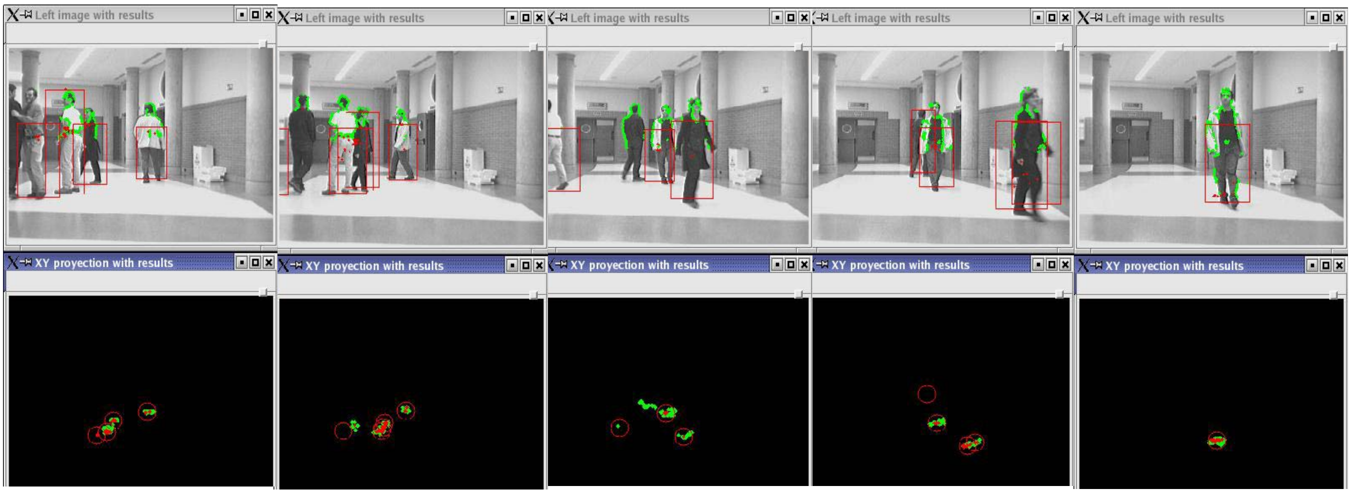

Fig. 9. Sequential images of a real time experiment with stereovision data.

- A specific classification algorithm for stereovision data has been developed. This process is able to separate vision measurements acquired from obstacles from those acquired from elements that are part of the environment, simplifying the XPF dynamic estimation task.
- The test has been run with a total number of 600 particles. As this amount is kept constant, the XPF execution time is also constant, which is a very important fact to achieve a real time development.
- The clustering process increases the likelihood of the new appearing obstacles, improving the robustness that other multimodal estimators show.
- The XPF designed can easily handle data coming up from different kinds of sensors. This fact makes the final application more flexible than the solutions proposed in the related literature, based on rigid models for the input data set.

Some improvements to the global multi-tracking system, which have been mentioned within the document, are still under development. In any case, an estimator to track a variable and multiple numbers of objects has been successfully developed.

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