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Minimizing of Target Localization Error using Multi-robot System and Particle Filters

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Abstract—In recent years a number of applications with multi-robot systems (MRS) is growing in various areas. But their design is in practice often difficult and algorithms are proposed for the theoretical background and do not consider errors and noise in real conditions, so they are not usable in real environment. These errors are visible also in task of target localization enough, when robots try to find and estimate the position of the target by the sensors. Localization of target is possible also with one robot but as it was examined target finding and localization with group of mobile robots can estimate the target position more accurately and faster. The accuracy of target position estimation is made by cooperation of MRS and particle filtering. Advantage of usage the MRS with particle filtering was tested on task of fixed target localization by group of mobile robots.

Keywords—Multi-robot system, particle filter, position estimation, target localization.

I. Introduction

TARGET searching and localization task is used in daily life, day by day. However, when there is a task to find a dangerous object as a mine or source of radiation is, searching is dangerous for people because of their threat to health or life. It is similarly also in the tasks where the searched target is in dangerous terrain, for example when it is necessary to find victims in the ruins of buildings after the devastating disaster. In such cases for finding and localizing the target, robots are used. Nowadays, the trend shifts from one robot searching to a multi-robot searching that can time of localization, which is often crucial in many cases, significantly reduced. With MRS it is also possible to ensure continued searching and localization in case of damage some of the robots. Another big advantage of using a group of robots in such tasks is the fact that the cooperation with the target localiziton is not only faster but also more accurate. This is not only because of a common position calculation from partial results, but also because of the fact that sensor noise is filtered with particle filters.

The aim of this article is to highlight the advantages of using a group of robots for target localization and examined the localization accuracy for different number of robots in the multi-robot system. Results of cooperation in MRS are in section IV compared with results from the localization by MRS using particle filters, and the results attained by one robot. There can be found also a comparison of the cooperation in MRSs of different size with different number of particles in the particle filter, and then the conclusions are drawn.

The theoretical findings were verified on algorithm of static target localization by mobile robots with considering real errors arising from the measurement properties of the environment. Therefore, for more accurate estimation of target position, particle filters were used. A noise occurs on sensors that localize target and it has normalized normal probability distribution. In this case, the robots know exactly their position and they move toward the jointly estimated position of target.

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II. Particle filtering in robotics

Particle filters are the type of probabilistic suboptimal non-parametric filters. The main idea is the implementation of sequential Monte Carlo estimation, that is built on the particle representation of the probability density. Particle filters were introduced in 1969 [1]. At this time, however, the idea of particle filters has been overlooked and ignored. The main contribution to the development of particle filter was the creation on resampling step [2] because particles before after a certain number of iterations starts to degenerate. The general principle of particle filters can be found in [3], [4].

One of the great advantages of their widespread use is the ability to filter any error probability distribution and they are not limit only to normal Gaussian probability distribution errors, as is the case for example Kalman filter. Their other advantage is their flexibility to almost any characteristics of sensors or distribution of noise, power calculation is mainly concentrated in the neighbourhood of high probability, computational complexity can be easily changed with the number of particles and the implementation of the algorithm is quite simple [5]. Despite of all the benefits, it is important to note that the computational complexity of particle filter is often higher that in other conventional types of filters. However, currently particle filters can be used in robots, they can be implemented on microcontrollers, or for acceleration of the calculation can be used FPGA circuit [6]. The field of application in robotics is called probabilistic robotics.

In respect of that the area of the multi-robot systems is in the field of observation, and most of the tests carried out at the level of simulations and experiments in testbed, the use of particle filters is more particularly in the field of a one robot usage, the use of group of robots is still used rarely [7], [8]. In the field of robotics, particle filters are used in research tasks, terrain mapping, localization [9], [10], simultaneous localization and mapping [11], tracking static or moving targets [12] etc.

The task, which is mentioned in this article, may be the part of more complex tasks such as target finding in the exploration of terrain, or in the terrain mapping problem.

III. Theoretical principles of proposed algorithm for target localization

The proposed algorithm of target localization can be divided into two main parts: localization by MRS and filtering the noise of measurement with particle filter.

A. MRS algorithm for target localization task

Before the algorithm is written, the principles of task will be explained. Consider that the MRS searches and localizes target in open terrain. The robots are mobile and the target is static. The aim of robots is to estimate the position of target jointly and move toward the estimated position of target.

Suppose that robots in target localization task know exactly their position. Then the target position has to be determined by measuring of sensor technology. Define the vector of robots positions $\mathbf{R} = \{\mathbf{R}_j, j = 1, ..., n\}$ where n is the number of robots. Each robot estimates the position of target:

$$\mathbf{x}_k^{(R_j)} = (r_k^{(R_j)} \quad \alpha_k^{(R_j)}), \tag{1}$$

which is determined by the distance between target and $j - th$ robot $r_k^{(R_j)}$ and the angle between target and robot $\alpha_k^{(R_j)}$ (Fig. 1). k is corresponding to the continuous time t_k and sampling interval $T_{k-1} \triangleq t_k - t_{k-1}$. This estimated position is dependent on the accuracy of measurement, here the measurement error is entering.

The jointly estimated position of target

$$\mathbf{T}_k^{est} = (x_k^{(T^{est})} \quad y_k^{(T^{est})}), \tag{2}$$

and then the position of $j - th$ robot

$$(R_j)_k = (x_k^{(R_j)} \quad y_k^{(R_j)}) \tag{3}$$

are expressed by two coordinates in Cartesian coordinate system. Robots are mobile, so their position is changed after each time step:

$$(\mathbf{R_j})_k = \begin{cases} x_{k-1}^{(R_j)} + \cos(\alpha_{k-1}^{(R_j)}). \\ \cdot\sqrt{\left(x_{k-1}^{(T^{est})} - x_{k-1}^{(R_j)}\right)^2 + \left(y_{k-1}^{(T^{est})} - y_{k-1}^{(R_j)}\right)^2}; \\ \\ y_{k-1}^{(R_j)} + \sin(\alpha_{k-1}^{(R_j)}). \\ \cdot\sqrt{\left(x_{k-1}^{(T^{est})} - x_{k-1}^{(R_j)}\right)^2 + \left(y_{k-1}^{(T^{est})} - y_{k-1}^{(R_j)}\right)^2}, \end{cases} \tag{4}$$

and new position of robot depends on the previous position and on the jointly estimated position.

Algorithm 1 Target localization - part for each $j - th$ robot of MRS

1: $k \leftarrow 1$;
2: set your new position according to (4);
3: make new measurement of target position (7);
4: (use SIR particle filtering;)
5: send $\mathbf{x}_k^{(R_j)}$ to central point;
6: $k \leftarrow k + 1$;
7: go to step 2;

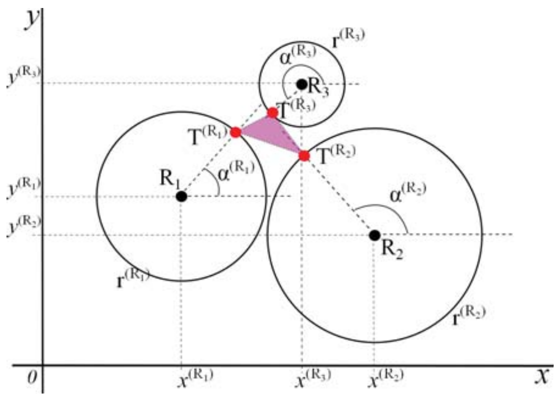

Fig. 1. Target localization by Multi-robot system - principles

Robots independently localize position of the target using its sensors (algorithm 1). Their estimations are evaluated centrally in that way that the estimation of each robot has the same weight as the total weight of the robot.

$$\mathbf{T}_k^{est} = f(\mathbf{x}_k^{(R_j)}, \mathbf{p}_k^{\mathbf{R}}), \tag{5}$$

where $\mathbf{p}_k^{\mathbf{R}}$ is the weights of all robots in system.

$$\mathbf{p}_k^{(R_j)} = f(|\mathbf{x}_{k-1}^{(R_j)} - \mathbf{T}_{k-1}^{est}|, r_k^{(R_j)}), \tag{6}$$

This means that the weight, which robot contributes into the common estimation of target position $\mathbf{T}^{est}$ depends inversely on its estimated distance to the target $r_k^{(R_j)}$ in the current step and the distance between its own estimation and joint estimation $|\mathbf{T}_{k-1}^{(R_j)} - \mathbf{T}_{k-1}^{est}|$.

Algorithm 2 Target localization by Multi-robot system with use of particle filtering- central point

1: $k \leftarrow 1$;
2: compute the weights $\mathbf{p}_k^{\mathbf{R}}$;
3: make n-angle with the estimated position as vertices;
4: compute the centre $\mathbf{T}_k^{est}$ of this n-angle according to weights;
5: $k = k + 1$;
6: go to step 2;

Note that measurements from sensors are driven into measurement vector:

$$\mathbf{z}^{(R_j)} = (z(r^{(R_j)})_k \quad z(\alpha^{(R_j)})_k), \tag{7}$$

It is obvious that if the particle filtering is not used:

$$\mathbf{x}_k^{(R_j)} = \mathbf{z}_k^{(R_j)} \tag{8}$$

B. Particle filtering in target localization task

Sensors that scan for target have the sensor noise with a normalized normal probability distribution N(0,1) and for its filtration the particle filtering algorithm Filter Sampling / Importance Resampling (SIR) is used [13], for the resampling is used Systematic Resampling Algorithm [14]. Note that in this work is not so essential type of used particle filter, more

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important is to point out of its features when working with MRS. Therefore it was selected one of the basic algorithms for particle filters, which was used in all measurements described in the section IV.

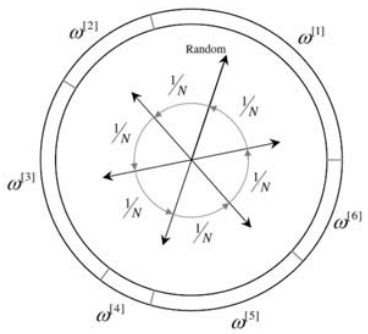

Fig. 2. Systematic Resampling Algorithm; from [14]

Target state $\mathbf{x}_k$ in time index k is set according to the following discrete-time stochastic model:

$$\mathbf{x}_k = f_k(\mathbf{x}_{k-1}, \mathbf{v}_k), \tag{9}$$

where f_k is known function of the state $\mathbf{x}_{k-1}$ and $\mathbf{v}_k$ is process noise sequence. The measurements have relationship with the state of the target through measure equation:

$$\mathbf{z}_k = h_k(\mathbf{x}_k, \mathbf{w}_k), \tag{10}$$

where h_k is known function and $\mathbf{w}_k$ is the process noise sequence. Noise sequence $\mathbf{v}_k$ and $\mathbf{w}_k$ are considered as white noise with known probability density function (pdf) and they are independent.

The filtrated estimation $\mathbf{x}_k$ based on the sequence of all the available measurements $\mathbf{Z}_k = \{\mathbf{z}_i, i = 1, ..., k\}$ up to time k is searched. From the Bayesian perspective, problem is to quantify recursively some degree of belief in state $\mathbf{x}_k$ in time k, with using different values, taking data $\mathbf{Z}_k$ up to the time k. So it is necessary to construct the posterior pdf $p(\mathbf{x}_k|\mathbf{Z}_k)$. Then in principle, pdf $p(\mathbf{x}_k|\mathbf{Z}_k)$ can be reached recursively in two steps: prediction and update [15].

That involves update of pdf prediction through the Bayesian rule:

$$\begin{aligned} p(\mathbf{x}_k|\mathbf{Z}_k) &= p(\mathbf{x}_k|\mathbf{z}_k, \mathbf{Z}_{k-1}) \\ &= \frac{p(\mathbf{z}_k|\mathbf{x}_k, \mathbf{Z}_{k-1})p(\mathbf{x}_k|\mathbf{Z}_{k-1})}{p(\mathbf{z}_k|\mathbf{Z}_{k-1})} \\ &= \frac{p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{Z}_{k-1})}{p(\mathbf{z}_k|\mathbf{Z}_{k-1})} \end{aligned} \tag{11}$$

SIR algorithm is derived from the basic SIS algorithm in that way that the density function $p(\mathbf{x}_k|\mathbf{x}^i_{k-1}, \mathbf{z}_{1:k})$ is independent of the measurement vector $\mathbf{z}_k$. Advantage of this filter is that the significant weights are easily assessed and therefore essential density can be easily sampled.

The measurement $\mathbf{z}_k$ is used when weight of each particle is set:

$$\omega^i_k \propto p(\mathbf{z}_k|\mathbf{x}^i_k) \tag{12}$$

where index i expresses $i-th$ particle in particle filter.

As it is obvious from the disadvantage of particle filters, the particles start to degenerate after time. There is need to resampling. In this case the Systematic resampling is used [14], also known as universal sampling. It is also very often used algorithm, when one random number from the circle is renerated and the others are with the distance of 1/N (Fig. 2).

1) Robot failure when calculating the position of target: Robot failure in target localization can arise not only from a technical defect of robot, but also from the failure of its particle filter. Those types of failures can be suppressed with joint weighting of partial results. Consider that the most sensors errors increases with distance of measurement. Therefore, robots with estimated longer distance will have less weight in joint calculation.

2) Possible extensions of target localization task: The task which is described here can be extended to the field of terrain exploration, where one or more targets are searching in unknown terrain. The exploration can be carried out according to the algorithm specified in [16]. Another extension of the task may be change from known position of the robot to the known position only within their own measurements, and hence the odometry measurement error will be filtered by another particle filter. In this case, it would be preferable to have an improved model of particle filter, known as the Rao-Blackwell filter.

IV. Experiments and Results

For experiments the Mobile robot programmable toolkit (MRPT) was used [17].

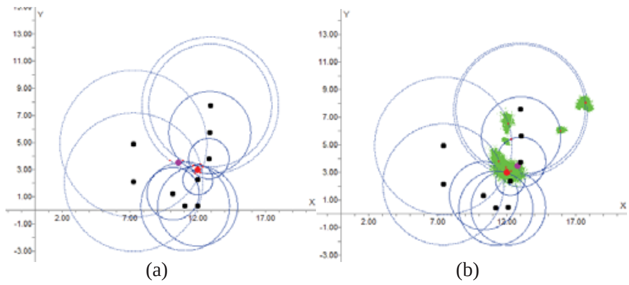

Fig. 3. Simulation of target localization by 10 robots; (a) without filtering, (b) with use of particle filtering

In evaluation the real position of target was used:

$$\mathbf{T}^{real} = (x^{(T^{real})} \quad y^{(T^{real})}). \tag{13}$$

Because the target is static, there is no need to write $\mathbf{T}^{real}$ with time index k.

Error in graph was set as:

$$\begin{aligned} \text{err} &= |\mathbf{T}^{real} - \mathbf{T}^{est}_k| \\ &= \sqrt{\left(x^{(T^{real})} - x^{(T^{est})}_k\right)^2 + \left(y^{(T^{real})} - y^{(T^{est})}_k\right)^2}; \end{aligned} \tag{14}$$

As can be seen from the graphs (a) in Fig. 4, 5 and 6, estimation of the distance slowly converges to the true target position. This process contains many peaks. This is due to the fact that robots are influenced by measurement noise, however,

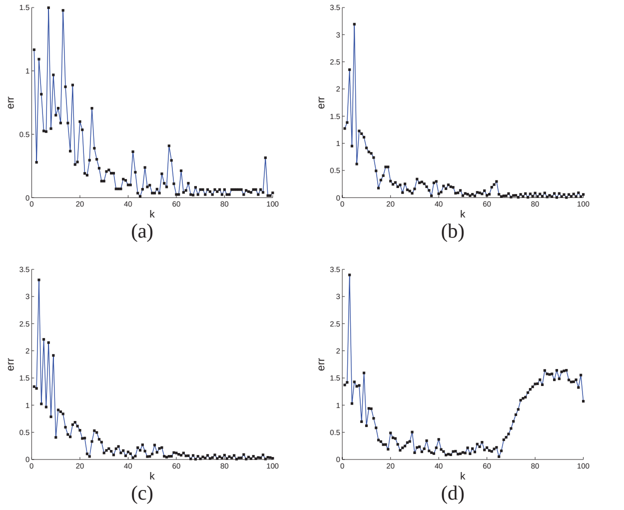

Fig. 4. Error in target position estimation; 10 robots; (a) without filters, (b) with PFs, 5000 particles each, (c) with PFs, 2000 particles each, (d) with PFs, 500 particles each

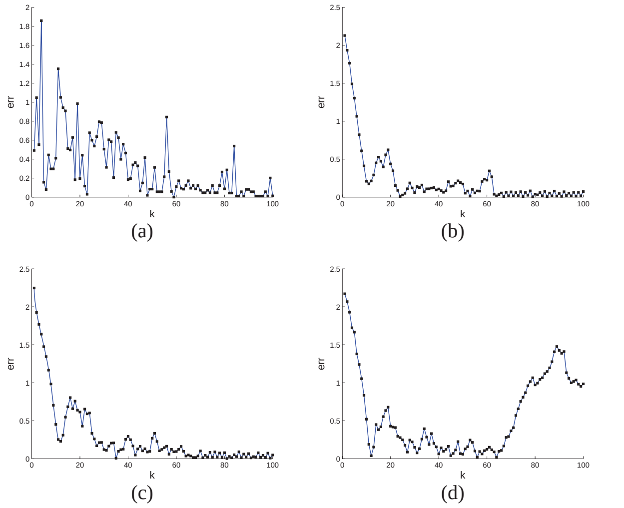

Fig. 5. Error in target position estimation; 4 robots; (a) without filters, (b) with PFs, 5000 particles each, (c) with PFs, 2000 particles each, (d) with PFs, 500 particles each

after a time steps as the robot is closer to the target the measurement error decreases. This means that although the measurement error was not filtered by particle filter, the erros is suppressed by joint estimation.

As was written, the other inaccuracies can be removed by the filter and the graph line will be smoother. This can be seen in other graphs of Fig. 4, 5 and 6. While using particle filter, a number of particles were changed equally for each robot. The fact that a small number of particles can give bad results is clear from graphs (d) in Figures 4, 5. In these cases, after a certain number of steps in the calculation, the result began to degrade and system started to estimate wrong position. It is good to note that this problem of graph line rising was not present with using MRS without particle filters. With this degradation also weighting of robots has problem. This can be partially solved with re-weighting of robots.

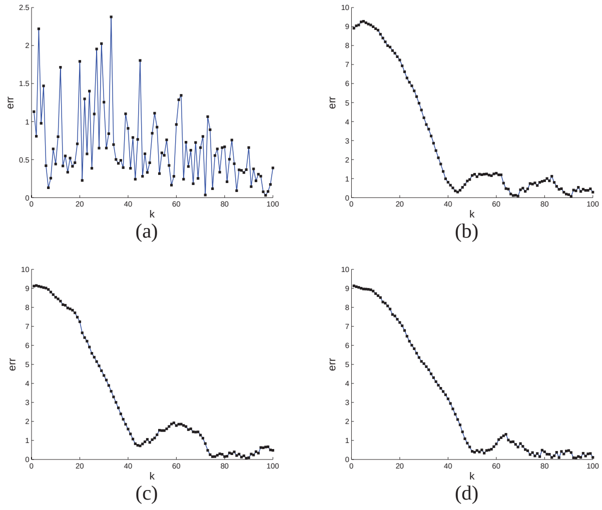

Fig. 6. Error in target position estimation; 1 robot; (a) without filters, (b) with PF, 5000 particles, (c) with PF, 2000 particles, (d) with PF, 500 particles

Other graph lines which need to note are the progresses of one robot estimation (Fig. 6). Compared with the estimation of MRS, it is clear that the accuracy of the estimate is made faster by group of robots. In progresses tested on one robot is also other importance. Other remarkable fact is, that the graph lines increase and decrease in time. Each of these increases was due to resampling the particles. It is one of the shortcomings of particle filter, but without resampling the result would have not been useful at all. Note, that the resampling was made also in the case of a large number of robots but using a sufficient number of particles the resampling error is suppressed by cooperation in joint position estimation.

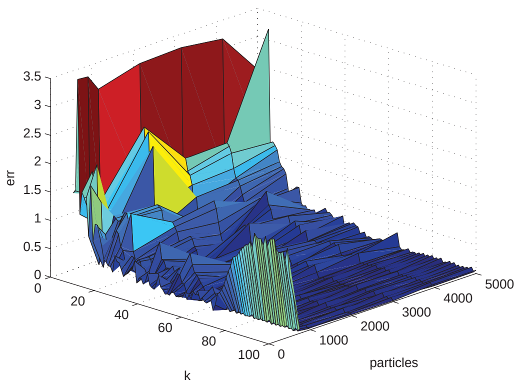

Fig. 7. Error in target position estimation by 10 robots with use of particle filtering

Comparison of system behavior by changing the number of particles in used particle filter is shown in Fig. 7. It is clear that when the number of particles drop down after some level, the result begins to degrade. In other cases, the measurement error decreases.

V. Conclusion and Future Work

The use of multiple robots in target localization task brings not only necessary redundancy in case of failure of some robots, but also shortens the calculation time and increases accuracy. As was verified by experiments, it is possible to achieve accuracy without the use of filtering, because some filtration is created through cooperation in joint estimation of target position. To speed up the convergence and smooth the error progress the particle filter was used in this case. It was verified that the correct functioning of the filter is when the filter consists of appropriate number of particles and the combination of MRS and particle filter is suitable for target localization task.

In the future, an algorithm will be improved to use only cooperation of robots in order to smooth the error progress without using of particle filter.

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References

[1] J. E. Handschin and D. Q. Mayne, "Monte Carlo Techniques to Estimate the Conditional Expectation in Multi-stage Non-linear Filtering," *International Journal of Control 9(5)*, pp. 547-559, 1969.
[2] N. J. Gordon, D. J. Salmond and A. F. M. Smith, "Novel Approach to Nonlinear/non-Gaussian Bayesian State Estimation," *IEEE Proc.-F*, vol. 140, no. 2, pp. 107-113, 1993.
[3] A. Doucet, J. F. G. Freitas and N. Gordon, *Sequential Monte Carlo Methods In Practice*. New York: Springer-Verlag, 2001.
[4] M. S. Arulampalam, S. Maskell, N. Gordon, "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking," *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174-188, February 2002.
[5] M. Kulich and M. Saska, *Vybraná témata z mobilní robotiky*. 2011.
[6] P. Ševčík and O. Kovář, "Very efficient exploitation of FPGA block RAM memories in the complex digital system design," *Journal of information, control and management systems*, vol. 8, no. 4 spec. iss., pp. 403-414, 2010.
[7] P. G. Jayasekara, L. Palafox, T. Sasaki, H. Hashimoto and B. H. Lee, "Simultaneous localization assistance for multiple mobile robots using particle filter based target tracking," *5th International Conference on Information and Automation for Sustainability (ICIAFs)*, pp. 469-474, 2010.
[8] A. Howard, "Multi-robot Simultaneous Localization and Mapping using Particle Filters," *Robotics: Science and Systems Conference*, pp. 201-208, 2005.
[9] R. Havangi, M. A. Nekoui and M. Teshnehlab, "A Multi Swarm Particle Filter for Mobile Robot Localization," *IJCSI International Journal of Computer Science Issues*, vol. 7, Issue 3, no. 2, pp. 15-22, May 2010.
[10] S. Thrun, D. Fox, W. Burgard and F. Dellaert, "Robust monte carlo localization for mobile robots," *Artificial Intelligence*, 128(1-2), 2000.
[11] L. Carlone, M. K. Ng, J. Du, B. Bona and M. Indri, "Rao-Blackwellized article Filters Multi Robot SLAM with Unknown Initial Correspondences and Limited Communication," *IEEE International Conference on Robotics and Automation*, Alaska, USA, pp. 243-249, May 2010.
[12] D. Schulz, W. Burgard D. Fox and A. B. Cremers, "Tracking Multiple Moving Targets with a Mobile Robot using Particle Filters and Statistical Data Association," *Proceedings of the 2001 IEEE International Conference on Robotics and Automation*, Seoul, Korea, May 2001.
[13] M. K. Pitt and N. Shephard, "Filtering via Simulation: Auxiliary Particle Filters," *Journal of the American Statistical Association*, vol. 94, No. 446., pp. 590-599, 1999.
[14] J. L. Blanco-Claraco, *Contributions to Localization, Mapping and Navigation in Mobile Robotics*. PhD Thesis, 2009.
[15] B. Ristic, S. Arulampalm and N. Gordon, *Beyond the Kalman filter: particle filters for tracking applications*. Boston, Ma., London: Artech House, 2004.
[16] J. Púchyová, "Exploration algorithm with shortened return for group of mobile robots," *MEMSTECH 2012: Perspective technologies and methods in MEMS design*, pp. 77-80, 2012.
[17] http://mrpt.org/

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