Optimal State Estimation via Adaptive Fuzzy Particle Filter

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Abstract: Particle Filters (PF) accomplish nonlinear system estimation and have received high interest from numerous engineering domains over the past decade. The main problem of PF is to degenerate over time due to the loss of particle diversity. One of the essential causes of losing particle diversity is sample impoverishment (most of particle's weights are insignificant) which affects the result from the particle depletion in the resampling stage and unsuitable prior information of process and measurement noise. To address this problem, a new Adaptive Fuzzy Particle Filter (AFPF) is used to improve the precision and efficiency of the state estimation results. The error in AFPF state is avoided from diverging by using Fuzzy logic. This method is called tuning weighting factor (α) as output membership function of fuzzy logic and input memberships function is the mean and the covariance of residual error. When the motion model is noisier than measurement, the performance of the proposed method (AFPF) is compared with the standard method (PF) at various particles number. The performance of the proposed method can be compared by keeping the noise level acceptable and convergence of the particle will be measured by the standard deviation. The simulation experiment findings are discussed and evaluated.

Keywords: mobile robot tracking, adaptive fuzzy particle filter, fuzzy logic, sensor fusion

1. Introduction

Filtering addresses the problem of determining the state of an uncertain dynamic model due to a series of noisy measurements performed on the system. The dynamic model can be expressed using a state-space equations. A transition function represents the dynamics of the system's hidden state, while a measurement equation defines the relationship between the noisy measurement and the unobserved state. To solve the problem of a linear system Kalman filter (KF) can achieve the optimal solution to the state estimation as long as the transition equation and measurement functions are linear functions. The noises are considering Gaussian distributions of known parameters. The Extended Kalman Filter's (EKF) approach is ineffective for dealing with system models with complicated nonlinearities and non-Gaussian distributions. The authors in [1] discussed a new sequential data integration strategy. It is based on Monte Carlo techniques for forecasting error values, which is a superior option to solving the Extended Kalman Filter's (EKF) standard and technically difficult approximation error covariance problems. A novel linear estimator is created and presented in [2]. The estimator, which is based on the idea that a collection of discretely sampled points can be used to characterize mean and covariance, achieves performance comparable to the KF for the linear model while avoiding the linearization stages inquired by the EKF. The particle filters, which are based on Bayesian estimation are used by [3] and are considered a means of tracking stochastic fluctuations in the state vector of a narrowband MIMO wireless link. The authors in [4] proposed a new method for the non-linear online systems and non-Gaussian prediction states. Their approach comprises a particle filter that generates the significance suggestion distribution using an Unscented Kalman Filter UKF. The authors in [5] proposed a new particle filter based on a sequential importance sampling algorithm. They used a bank of unscented filters to obtain the importance proposal distribution. In [6] the optimum filter calculates the posterior probabilistic model of a state in a dynamic model subjected to noisy recordings by iteratively applying prediction steps based on the state's dynamics, and corrective steps based on the observations. The authors in [7] presented a novel

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object-tracking technique based on local structural multivariate learning that implements selective sampling importance resampling (SSIR). A novel contribution in [8] was a Fuzzy Adaptive Unscented Kalman Filter (AUKF), developed to avoid divergence and determine the most suitable trajectory for a space robot. In [9], the authors proposed a novel Unscented Adaptive Kalman Filter (AUKF) to capture an unidentified object with a vision system.

In this work, the new filter is interested in tuning the Fuzzy logic parameters. The Adaptive fuzzy particle filter is proposed to Minimize the noises in R and Q before the resampling step using a suitable gain for Fuzzy logic. The particle numbers are selected depending on percentage errors in the position and rotation angle. The remainder of the paper is organized as follows: Section 2 presents a brief review of the Particle filter and fuzzy logic. Section 3 describes the adaptive fuzzy particle filter tuning methodology, and the results are presented and discussed in Section 4. The paper concludes in Section 5, where our contributions are summarized.

2. Particle filter

Bayesian approaches are often used to solve navigation problems and use Bayes' theory to update the probability for a hypothesis if more data and information becomes available. Sensors are commonly used in non-linear/non-Gaussian dynamic systems, thus a sequential Monte Carlo approach can be used without linearization. Particle filter's main purpose is to estimate the position and observe various constraints as they change over time. In most cases, non-Gaussian and probability density functions are applied. A Particle filtering is defined based on two elements: the state process model, which shows the progression of the hidden state of interest, x_k, through time, $P(x_k \mid x_{k-1})$ and the measurement model, which presents the relationship between the observed variables y_k, and the hidden states x_k at each time step $P(y_k \mid x_k)$

$$x_k = f\left(x_{k-1}\right) + \omega_{k-1} \tag{1}$$

$$y_k = h\left(x_k\right) + \upsilon_k \tag{2}$$

where ω_{k-1} and υ_k are independent Gaussian noise process; $f\left(x_{k-1}\right)$, $h\left(x_k\right)$ are known functions with dimensions, $x_k \in R_n$ is the state vector, $y_k \in R_m$ is the measurement vector.

In the Bayesian framework can define the measurement model as follows,

$$z_k = H_k x_k + \upsilon_k, \quad \upsilon_k \sim N\left(0, R\right) \tag{3}$$

where H_k is the measurement matrix and υ_k is the measurement noise which is a Gaussian white noise with covariance R.

The state is set as shown below,

$$H_k = \left[x_k, y_k, \theta_k\right]^{\mathrm{T}} \tag{4}$$

The dynamics of the state is given as follows,

$$x_k = F_k x_{k-1} + w_k, \quad w_k \sim N\left(0, Q\right) \tag{5}$$

where F_k is a state transition matrix and w_k is a process noise which is Gaussian white noise with covariance Q.

System model

$$x_k = f_k\left(x_{k-1}, \upsilon_k\right) \sim p\left(x_k \mid x_{k-1}\right) \quad (6) \ \textit{Markovian process}$$

Measurement model

$$y_k = h_k\left(x_k, \omega_k\right) \sim p\left(y_k \mid x_k\right), \tag{7}$$

where $p(x_k \mid x_{k-1})$ is the probability state estimate of the system x_k given the previous state x_{k-1} and $p(y_k \mid x_k)$ is the sensor measurement y_k given the state estimation x_k.

The objective of filtering is to estimate the posterior density of the states using the previous measurements $p(x_k \mid y_{1:k})$ [13]. The key idea is to represent the required posterior density function by a set of random particles with associated weights and then calculate estimates states based on these particles and their weights as follows [8]:

$$\left\{x_{0:k}^i, w_k^i\right\}_{i=1}^N \tag{8}$$

where $\left\{x_{0:k}^i, i = 0, \ldots, N\right\}$ is a set of support points with associated weights, $\left\{w_k^i, i = 1, \ldots, N\right\}$ and $x_{0:k} = \left\{x_j, j = 0, \ldots, k\right\}$ is the set of all states up to time step k. In [14] the associated importance weight of the particle is defined as follows:

$$w_k^i = \frac{p\left(x_{0:k}^i \mid y_{1:k}\right)}{q\left(x_{0:k}^i \mid y_{1:k}\right)} \tag{9}$$

where $p\left(x_{0:k}^i \mid y_{1:k}\right)$ is the target distribution and $q\left(x_{0:k}^i \mid y_{1:k}\right)$ is the proposal distribution which can be represented by a recursive form as:

$$q\left(x_{0:k}^i \mid y_{1:k}\right) = q\left(x_k^i \mid x_{k-1}^i, y_{1:k}\right) q\left(x_{k-1}^i \mid y_{1:k}\right) \tag{10}$$

Samples can be obtained using $x_k^i \sim q\left(x_{0:k}^i \mid y_{1:k}\right)$ by augmenting each of the exiting samples $x_{k-1}^i \sim q\left(x_{0:k}^i \mid y_{1:k-1}\right)$ with the new state $x_k^i \sim q\left(x_{0:k}^i \mid X_{k-1}, y_{1:k}\right)$. Similarly, the posterior can also be given by a recursive form using Bayes rule as follows:

$$p\left(x_{0:k}^i \mid y_{1:k}\right) = \frac{p\left(y_k \mid x_k^i\right) p\left(x_k^i \mid x_{k-1}^i\right)}{p\left(y_k \mid y_{1:k-1}\right)} p\left(x_{k-1}^i \mid y_{1:k-1}\right)$$

$$\propto p\left(y_k \mid x_k^i, y_{1:k-1}\right) p\left(x_k^i \mid x_{k-1}^i\right) p\left(x_{k-1}^i \mid y_{1:k-1}\right) \tag{11}$$

$$w_k^i \propto \frac{p\left(x_{0:k}^i \mid y_{1:k-1}\right)}{q\left(x_k^i \mid x_{k-1}^i, y_{1:k-1}\right) q\left(x_{k-1}^i \mid y_{1:k-1}\right)} \tag{12}$$

$$w_k^i = \frac{p\left(y_k \mid x_{0:k}^i\right) p\left(x_{0:k}^i \mid x_{0:k-1}^i\right) p\left(x_{0:k-1}^i \mid y_{1:k-1}\right)}{q\left(x_{0:k}^i \mid x_{0:k-1}^i, y_{1:k-1}\right) q\left(x_{0:k-1}^i \mid y_{1:k-1}\right)} \tag{13}$$

$$w_k^i = w_{k-1}^i \frac{p\left(y_k \mid x_{0:k}^i\right) p\left(x_{0:k}^i \mid x_{0:k-1}^i\right)}{q\left(x_{0:k}^i \mid x_{0:k-1}^i, y_{1:k}\right)} \tag{14}$$

The weights are normalized such that:

$$w_k^i = \frac{w_k^i}{\sum_{i=1}^N w_k^i} \tag{15}$$

$$\sum_{i=1}^N w_k^i = 1$$

The posterior density can then be estimated:

$$p\left(x_{0:k} \mid y_{1:k}\right) \cong \sum_{i=1}^{N} w_k^i \delta\left(x_{0:k} - x_k^i\right) \tag{16}$$

where $\delta\left(x_{0:k} - x_k^i\right)$ is Dirac's delta function [11], and N is the number of particles. Unluckily, the $p\left(x_{0:k} \mid y_{1:k}\right)$ is often unknown, it is impossible to sample directly from the $p\left(x_{0:k} \mid y_{1:k}\right)$. In general, the steps of particle filter are: Propagate set of particles, Calculate state estimation, Compute particle weight (likelihood) and Re-sampling.

3. Particle fuzzy filter tuning

Many scientific challenges need to estimate the state of a system as it changes over time based on a series of noisy sensor readings taken on the system. A particle filter has the drawback of degenerating with time, which means that most particles would be negligible after a certain number of steps. The fuzzy logic approach is one of the methods used to address this problem with particle filter's performance. In order to analyze and make inference about a dynamic system, at least two models are required: First, a model describing the evolution of the state with time (System Model) and, a model relating the noisy measurements to the state (Measurement Model) [15].

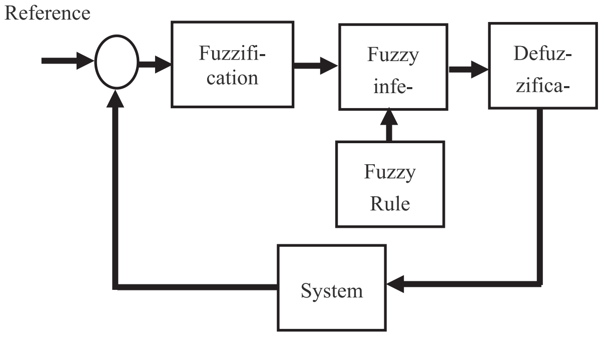

Fig. 1. Fuzzy logic schematic
Rys. 1. Schemat logiki rozmytej

The general Fuzzy Logic architecture consists of four stages of handling: fuzzification, a knowledge base, inferences of the rules, and defuzzification as shown in fig. 1. To get more accurate estimation results of the robot pose, particle fuzzy filter has been used to reduce the effects of the noise in the measurement data. While particle filter is suitable to estimating the state of mobile robot kinematic model. A new method based on fuzzy logic is developed to enhance the state of mobile robots. This filter is called Adaptive fuzzy particle filter (AFPF). It is a scheme to reduce or prevent the result from divergence based on Fuzzy Logic. As mentioned above, about reduced the degree of divergence (DOD) for states. Two parameters are created for measuring the mean and covariance of residual error (υ) for states as shown in fig. 2 and 3. These parameters $(\mu,\ \xi)$ are considered as the input membership of fuzzy logic to get the output membership (α) illustrated in fig. 4 [9].

$$\mu = \frac{1}{n}\sum_{1}^{n} v_i \tag{17}$$

$$\xi = \frac{v_i^{\mathrm{T}} v_i}{n} \tag{18}$$

where, the number of measurements is represented by n while, an innovation is v_i

$$v_i = z_i - \hat{z}_i \tag{19}$$

The DOD is observed by fuzzy logic, which is used to control the softening factor according to fuzzy logic principles as mentioned in table 1. The softening factor is calculated through trial and error. The model [10] of the weighted noise covariance is:

$$R_i = R\alpha^{-2(I+1)} \tag{20}$$

$$Q_i = Q\alpha^{-2(I+1)} \tag{21}$$

where $\alpha \geq 1$, and the constant matrices are Q and R. It's important to note that raising k causes the R and Q matrices to reduce, indicating that the most important measurement gets more trusted.

Table. 1. The fuzzy rules
Tabela. 1. Rozmyte zasady

μ/ξ	**Z**	**S**	**L**
Z	S	Z	L
S	Z	L	M
L	Z	M	S

S: small Z: zero L: large M: medium

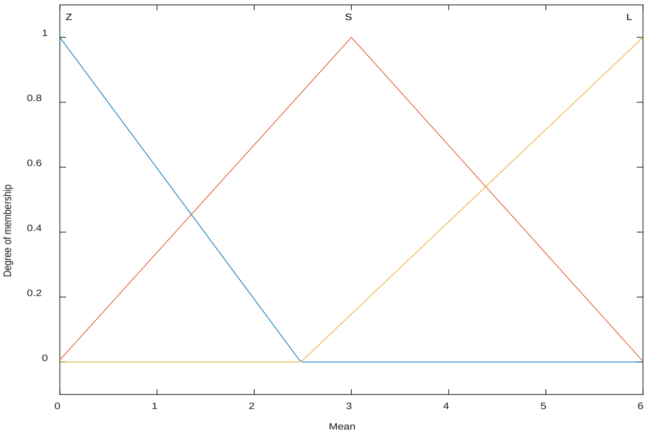

Fig. 2. Membership function of Covariance (ξ)
Rys. 2. Funkcja przynależności kowariancji (ξ)

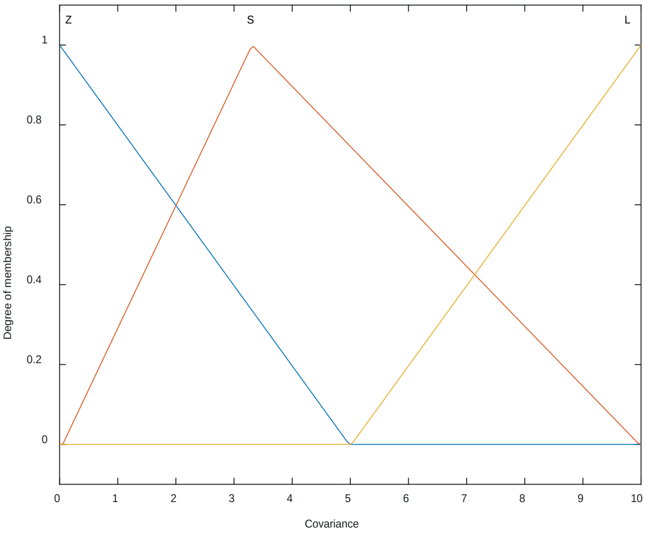

Fig. 3. Membership Function of Mean (μ)
Rys. 3. Funkcja przynależności średniej (μ)

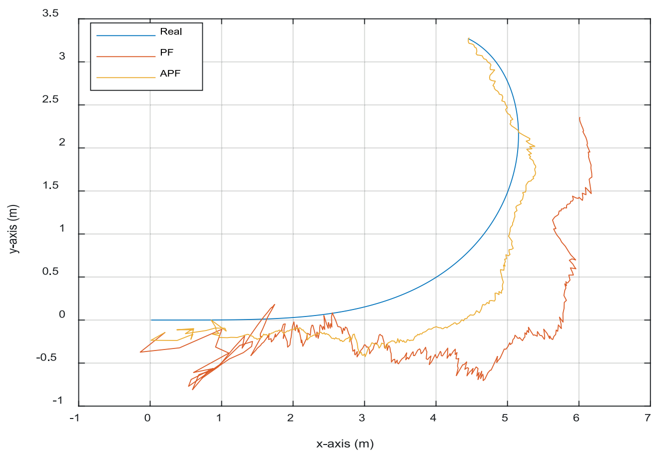

Fig. 5. The trajectory of mobile robot applied 15 particles
Rys. 5. Trajektoria ruchu robota mobilnego nałożonego na 15 cząstek

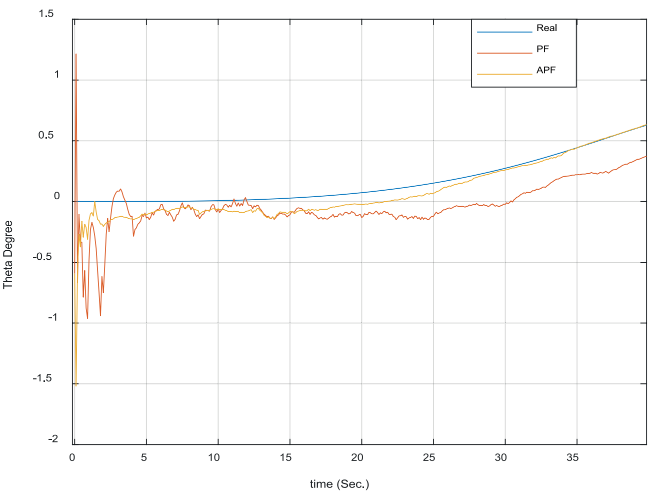

Fig. 8. Estimation Theta Degree of mobile robot applied 15 particles
Rys. 8. Oszacowanie stopnia Theta robota mobilnego nałożonego na 15 cząstek

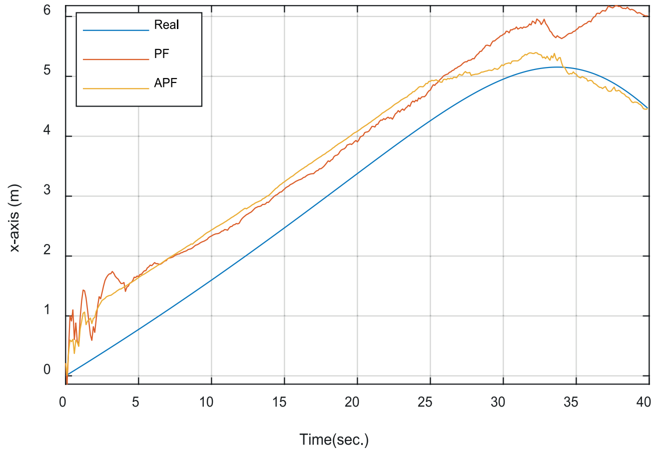

Fig. 6. Estimation position in x-axis of mobile robot applied 15 particles
Rys. 6. Szacowanie położenia w osi x robota mobilnego nałożonego 15 cząstek

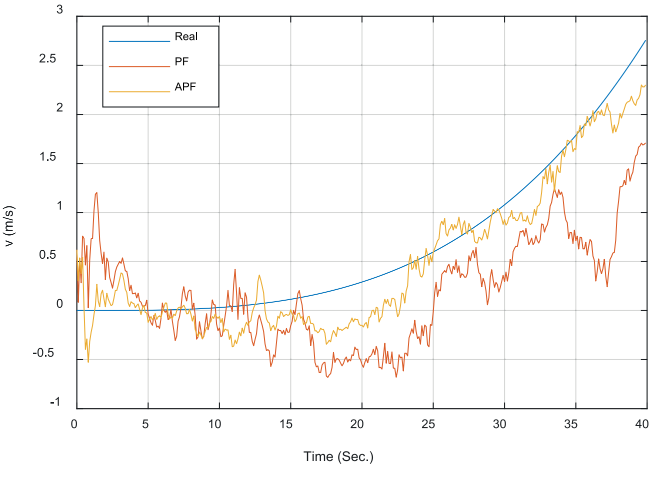

Fig. 9. Velocity of mobile robot applied 15 particles
Rys. 9. Prędkość robota mobilnego nałożonego na 15 cząstek

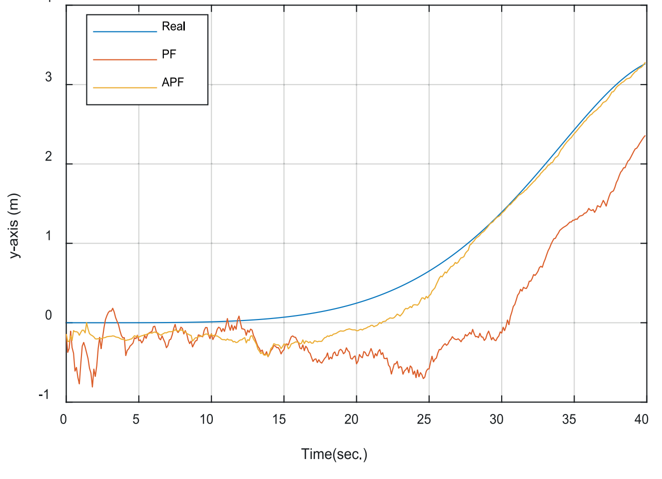

Fig. 7. Estimation position in y-axis of mobile robot applied 15 particles
Rys. 7. Szacowanie położenia w osi y robota mobilnego nałożonego na 15 cząstek

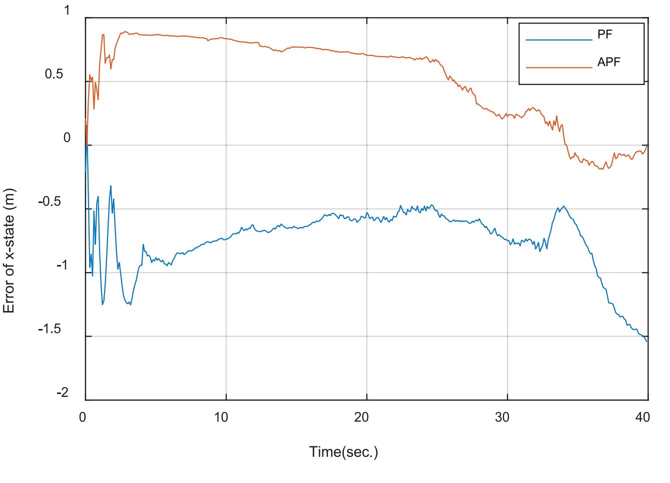

Fig. 10. Error estimation of position in x-axis of mobile robot applied 15 particles
Rys. 10. Błąd oszacowania położenia w osi x robota mobilnego nałożonego 15 cząstek

4. Experimental and results

The measurement data are collected from previous work in [12] with the camera and odometry sensors that is applied to the mobile robot. In these experimental results, various values of number of particles applied 15, 100, 500, and 1500 particles. Figures 5, 11 and 17, 23 represented the 2D trajectory estimated by using PF and AFPF comparing with a real trajectory for the mobile robot with 15, 100, 500 and 1500 particles respectively. It was noticed that the AFPF results are better than traditional particle filter results when compared with real

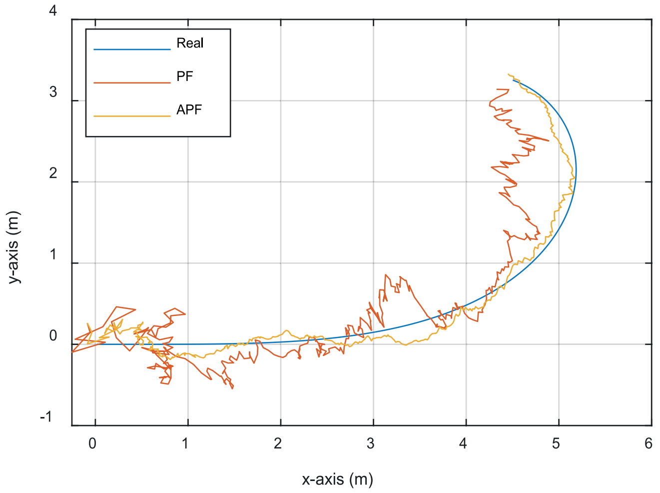

Fig. 11. Trajectory of mobile robot with 100 particles applied
Rys. 11. Trajektoria ruchu robota mobilnego z zastosowaniem 100 cząstek

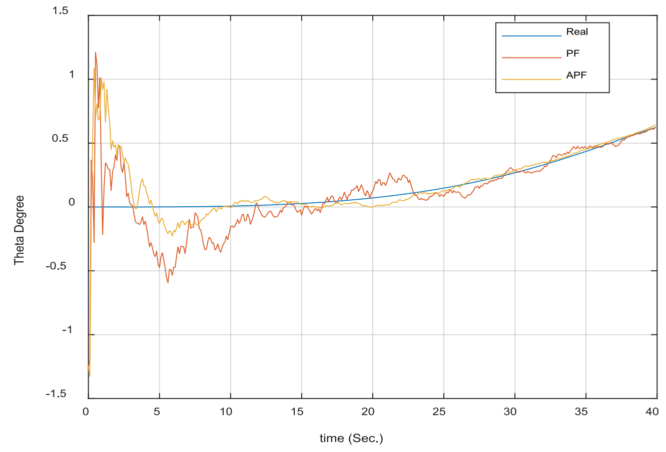

Fig. 14. Estimation of theta of mobile robot with 100 particles applied
Rys. 14. Estymacja theta robota mobilnego z zastosowaniem 100 cząstek

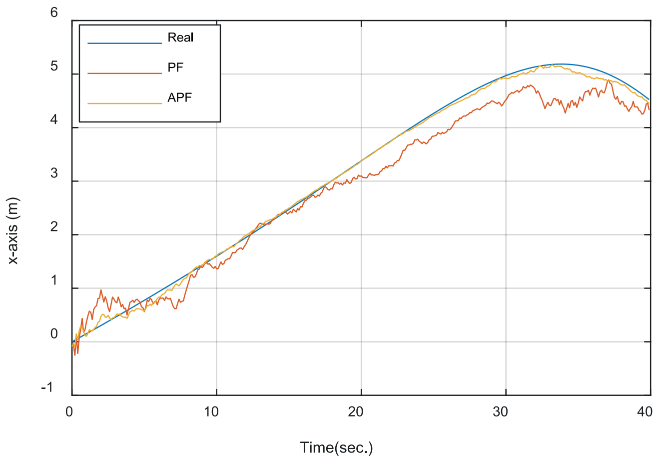

Fig. 12. Position estimation in x-axis of mobile robot with 100 particles applied
Rys. 12. Estymacja pozycji robota mobilnego w osi x z zastosowaniem 100 cząstek

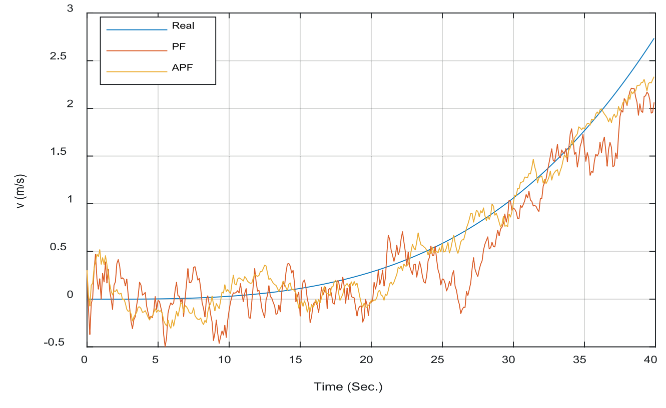

Fig. 15. Velocity estimation of mobile robot with 100 particles applied
Rys. 15. Estymacja prędkości robota mobilnego z zastosowaniem 100 cząstek

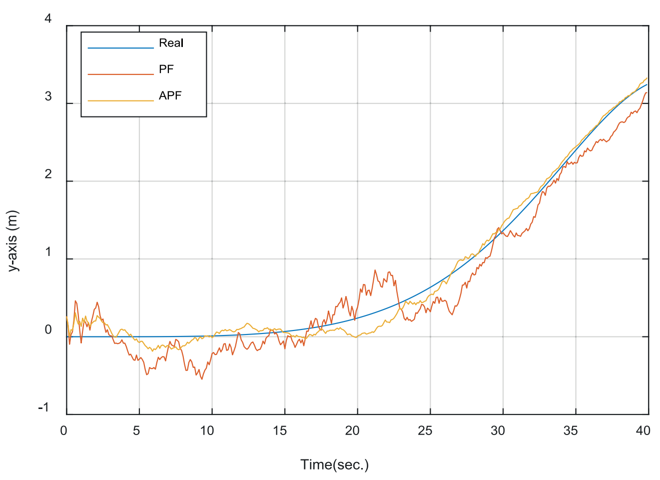

Fig. 13. Position estimation in y-axis for mobile robot with 100 particles applied
Rys. 13. Estymacja położenia robota mobilnego w osi y z zastosowaniem 100 cząstek

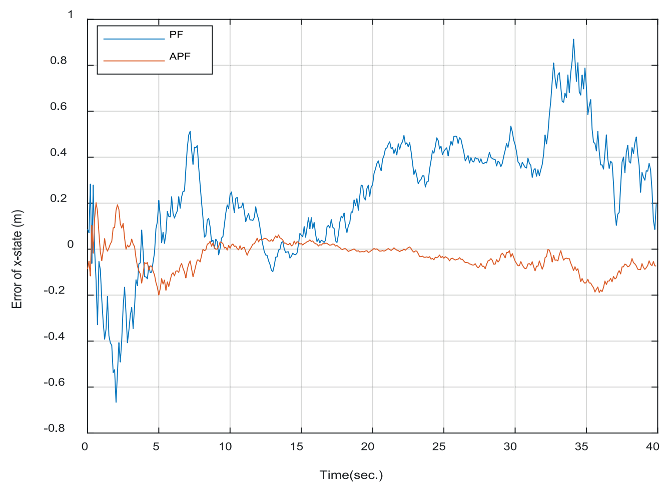

Fig. 16. Error estimation in x-axis with 100 particles applieds
Rys. 16. Estymacja błędu położenia robota mobilnego w osi y z zastosowaniem 100 cząstek

trajectory with respect to the x-position estimation for 15, 100, 500 and 1500 particles as shown in Figures 6, 12, 18, 24. The same estimation results are getting for y-position and rotation angles as the same number of particles which is illustrated in Figures 7, 8, 13, 14, 19, 20, 25, 26. In Figures 9, 15, 21, 27 represented for the velocity estimate by AFPF and PF.

It is noticed that the velocity estimation by proposed method becomes better and close to the real velocity compared to the traditional filter. The error in the estimation results become smallest at AFPF than PF as illustrated in Figures 10, 16, 22, 28.

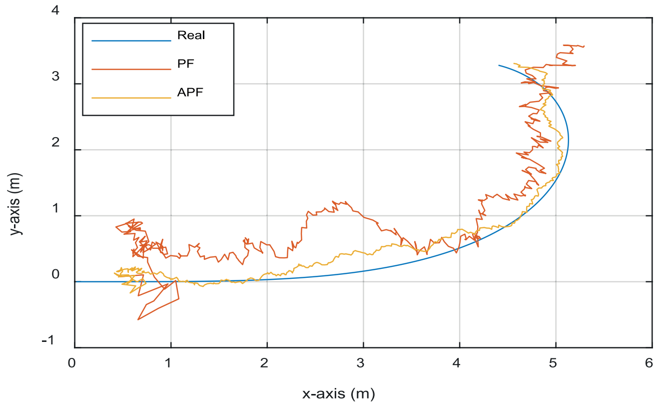

Fig. 17. The trajectory of mobile robot applied 500 particles
Rys. 17. Trajektoria ruchu robota mobilnego aplikowała 500 cząstek

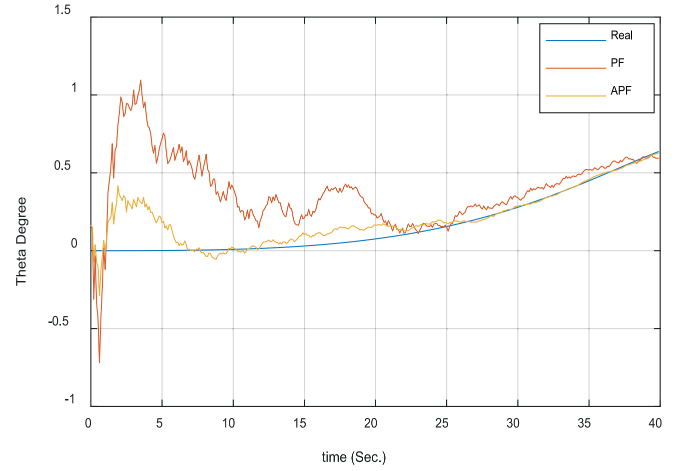

Fig. 20. Estimation of theta of mobile robot applied 500 particles
Rys. 20. Oszacowanie theta robota mobilnego nałożonego na 500 cząstek

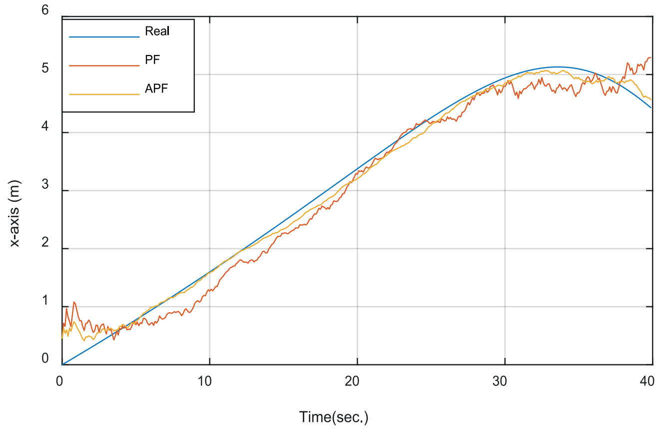

Fig. 18. Estimation position in x-axis of mobile robot applied 500 particles
Rys. 18. Szacowanie położenia w osi x robota mobilnego nałożonego na 500 cząstek

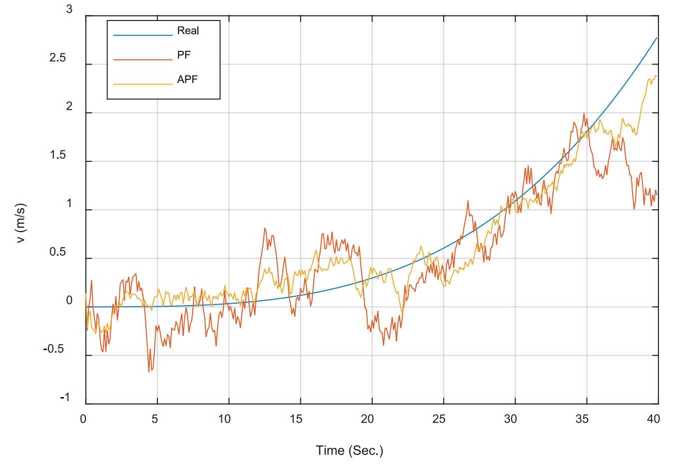

Fig. 21. Estimation of Velocity of mobile robot applied 500 particles
Rys. 21. Oszacowanie prędkości robota mobilnego nałożonego na 500 cząstek

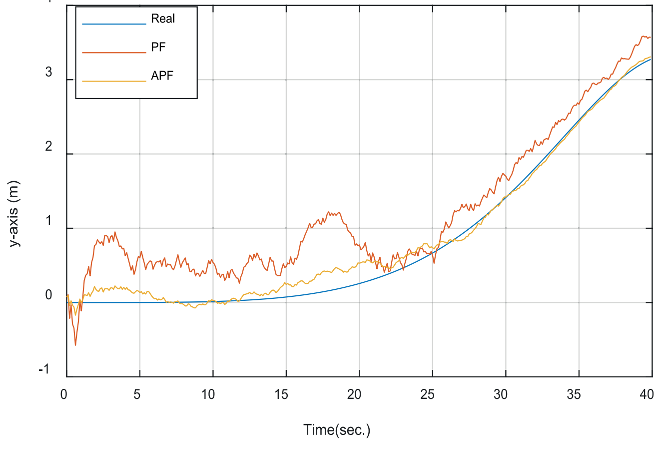

Fig. 19. Estimation position in y-axis of mobile robot applied 500 particles
Rys. 19. Szacowanie położenia w osi y robota mobilnego nałożonego na 500 cząstek

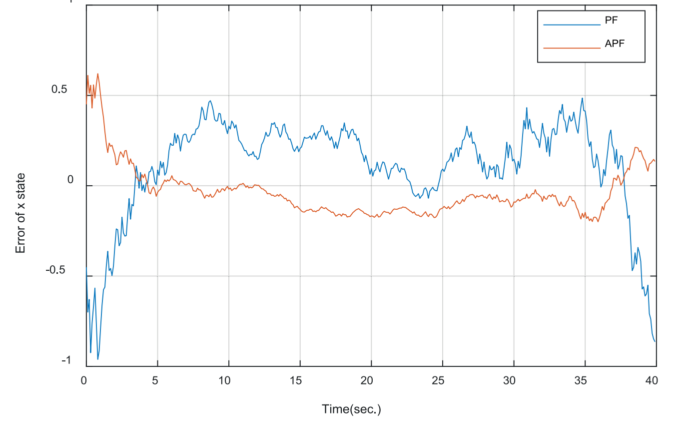

Fig. 22. Error estimation of position in x-axis of mobile robot applied 500 particles
Rys. 22. Błąd oszacowania położenia w osi x robota mobilnego nałożonego 500 cząstek

5. Conclusions

The measurement data were obtained from preliminary work on camera and odometry sensors applied to mobile robots. In these experimental results, various values of the number of particles applied are 15, 100, 500 and 1500 particles. Figures 5, 11,17 and 23 represented the 2D trajectory estimates when using a Particle Filter (PF) and an Adaptive Fuzzy Particle Filter (AFPF), when compared with a real trajectory for a mobile robot with 15, 100, 500, and 1500 particles. It is clear that the AFPF results are better than the traditional

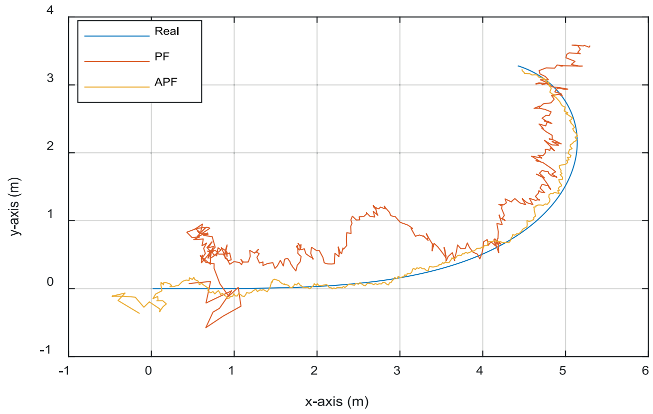

Fig. 23. The trajectory of mobile robot applied 1500 particles

Rys. 23. Trajektoria ruchu robota mobilnego nałożyła 1500 cząstek

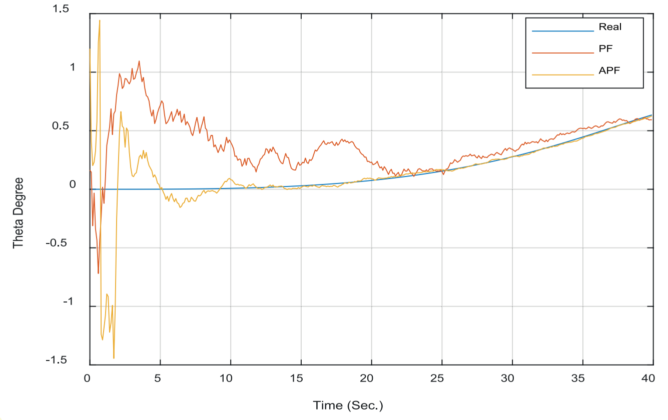

Fig. 26. Estimation of theta of mobile robot applied 1500 particles

Rys. 26. Oszacowanie theta robota mobilnego nałożonego na 1500 cząstek

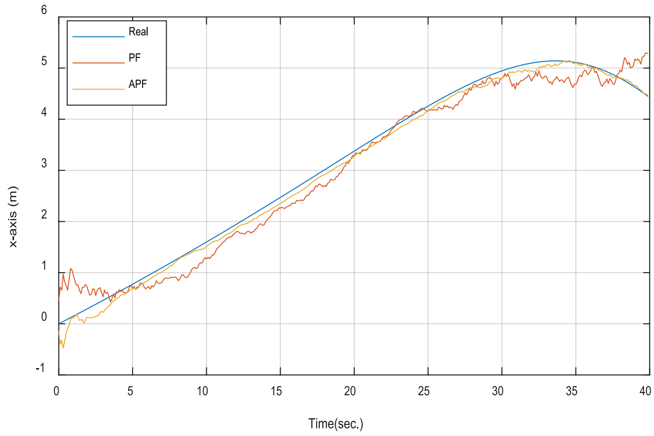

Fig. 24. Estimation position in x-axis of mobile robot applied 1500 particles

Rys. 24. Oszacowanie położenia w osi X robota mobilnego nałożyło 1500 cząstek

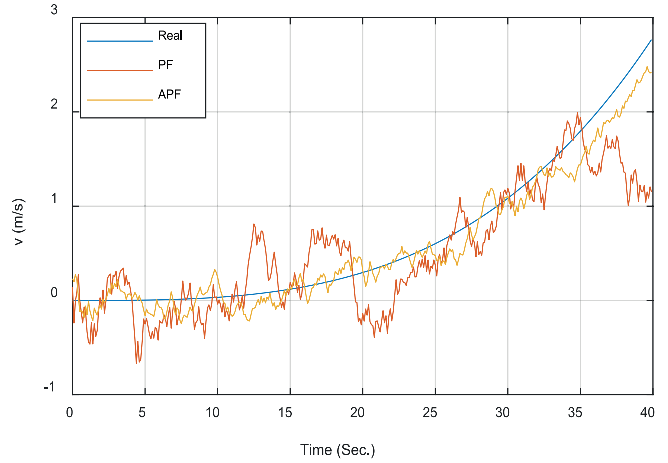

Fig. 27. Estimation of Velocity of mobile robot applied 1500 particles

Rys. 27. Oszacowanie prędkości robota mobilnego nałożonego 1500 cząstek

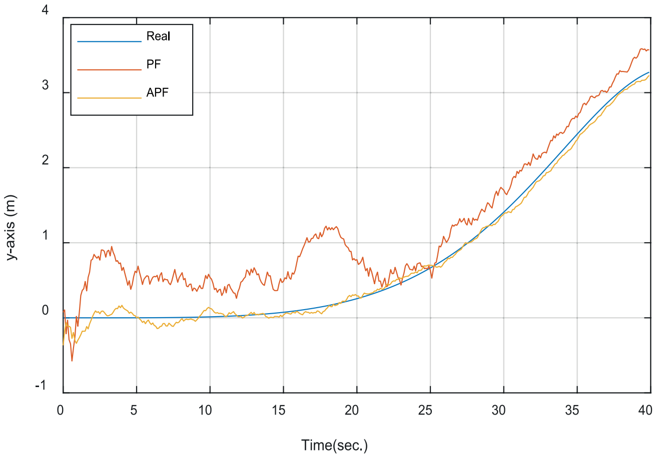

Fig. 25. Estimation position in y-axis of mobile robot applied 1500 particles

Rys. 25. Oszacowanie położenia w osi y robota mobilnego nałożyło 1500 cząstek

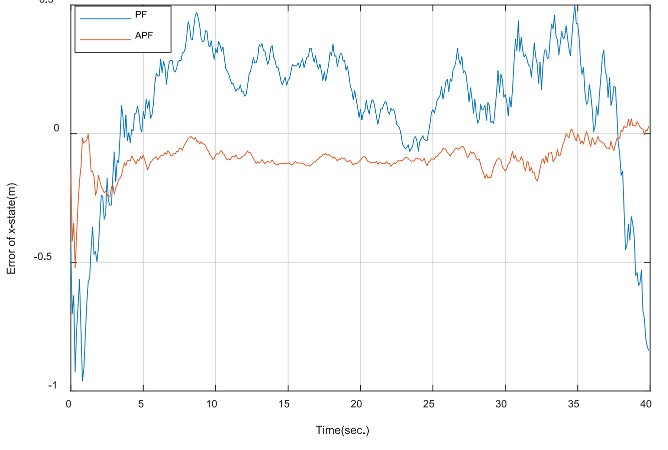

Fig. 28. Error estimation of position in x-axis of mobile robot applied 1500 particles

Rys. 28. Błąd oszacowania położenia w osi x robota mobilnego nałożonego 1500 cząstek

particle filter results when compared to real trajectories with respect to the x-position estimation for 15, 100, 500 and 1500 particles, as indicated in Figures 6, 12, 18 and 24. The same estimate results are obtained for the y-position and rotation angle as the same number of particles illustrated in Figures 7, 8, 13, 14, 19, and 20. Figures 9, 15, 21 and 27 represent the velocity estimates of PF and AFPF. It is apparent that the proposed method provides better velocity estimation results than the traditional filter. The error in the estimation results is less with the AFPF than with PF, as illustrated in Figures 10, 16, 22 and 28.

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Optymalne szacowanie stanu za pomocą adaptacyjnego filtra cząstek rozmytych

Streszczenie: Adaptacyjny filtr cząstek rozmytych (AFPF) służy do poprawy precyzji i wydajności wyników szacowania stanu. Metoda ta nazywana jest dostrajaniem współczynnika ważenia (α), ponieważ wyjściowa funkcja przynależności logiki rozmytej, a wejściowa funkcja przynależności jest średnią i kowariancją błędu resztowego. Wydajność proponowanej metody jest porównywana przez utrzymanie dopuszczalnego poziomu hałasu, a zbieżność cząstki będzie mierzona przez odchylenie standardowe. Wyniki eksperymentu symulacyjnego są omawiane i oceniane.

Słowa kluczowe: śledzenie robotów mobilnych, adaptacyjny filtr cząstek rozmytych, logika rozmyta, fuzja czujników

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