Target Tracking Based on Particle and Kalman Filter Combined with Neural Network

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***Abstract*—Wide variations of the maneuvering targets must be track by radar systems. One of the main problems is adaptation of the tracking filter to real behavior of the target. Combining real-time of Kalman filter with robustness of particle filter and neural network, proposes a method for target movement with non-linear motion. The perspective system of adaptive radar data processing for 2D tracking system based on particle filtering is described in this paper. The proposed system has better performance of state estimation (converges to true flight position) then linear Kalman filtering or non-linear adaptive Kalman filtering with Neural Network adaptation. The system can track or estimate object position in environment with interference and noise. The results of simulation show that the method can effectively improve the target tracking process. Final estimated track of object is given by coordinates represented by particles with the highest value of their weights. The modern system of adaptive radar data processing for 2D coordinate system based on particle filtering is designed in this paper.**

Keywords— Target Tracking; Adaptive Radar Data Processing; Kalman filter; Particle filter

I. Introduction

Adaptive filtering in radar data processing is commonly used for target tracking and for prediction of its track, because clutter, interference and noise are part of the environment in which the target is located. Kalman filter and its adaptive upgrades like Extended Kalman filter, Unscented Kalman filter and adaptive Kalman filter based on Neural Network are basic types of filters used for adaptive radar data processing [1]. New approaches in the field of target tracking are about deploying Neural Networks and Particle filters into the modern adaptive radar data processing [2]. Particle filter is a recursive Bayes filter based on the Sequential Monte Carlo method deriving from the set of samples also called particles representing probability density which distribution in the state space and weights determines the probability of each object´s location [3].

The best-known filtration techniques are: α-β filter, filter with fixed weights (in adaptive radar), filter with variable weights (in cognitive radar), Kalman filter, IMM (Interactive Multiple Model) filter [4], Particle filter, etc. [5]. The use of filters with fixed parameters eliminates the need for an iterative calculation of new coefficients for each scan. It significantly reducing the computational load of filter. The first target tracking algorithms were found on this principle and they are still used in practical applications for their simplicity, but their effectiveness and utilization can be low. Filters with variable weights consider the uncertainty in track prediction at various phases (throughout the whole tracking process) and generally they have acceptable efficiency and utilization: profits are preliminary evaluated and stored in the search table, so the calculation requirements remain low. They assume a constant measurement error and a fixed interval during the update. The Kalman filter (the successor of the Wiener filter) is linear filter in which there are also estimates and covariances described by recursive equations. The Kalman filter can be suitably implemented by a feedback scheme that contains a replica of the system model. Weights are evaluated on-line and consider measurement and prediction errors: the derived load is certainly higher than in the previous techniques. Adaptivity to sudden changes in the system model (for example: maneuvers, etc.) is an essential advantage of the filter. It means that it has the ability to provide good noise filtering (which can be achieved by a narrowband filter) and at the same time to ensure the speed at the following sharp maneuvers (wide bandwidth). Adaptivity at this point requires a kind of maneuvering detector to determine the maneuvering time and heuristics for quick adjustment of the filter parameters based on sudden change of the target´s trajectory. The example of random target maneuver simulation and its tracking by radar using measurement and process noise, and by algorithm using particle filtering [6], is shown on Fig. 1.

Signal processing and data processing in cognitive radar is not isolated. The cognitive tracking algorithm is dependent on knowledge and applied rules. If we want to change the processing of the radar signal to both transmitting and receiving, it depends on its targets position in environment and independence of its operation. Basic knowledge is applicable because the progress of the transmitting and the receiving processed signal in response to the change of environment in the knowledgeable status must be changed. The rules or heuristics for determining when and how the processing chain should be changed has been developed. The proven techniques and suggestions have been developed. Future development solution can be based on robotics adaptation. At first, the knowledge-based approach will be built to cooperate with manual human intervention. Thus, it is possible to capture the intervention part of the human system (human-machine interface) and embed this ability to ES. If this approach is proven for multiple sensors operating at the surface-to-air interface, at the air, or even the space, then these sensors can work independent as robots.

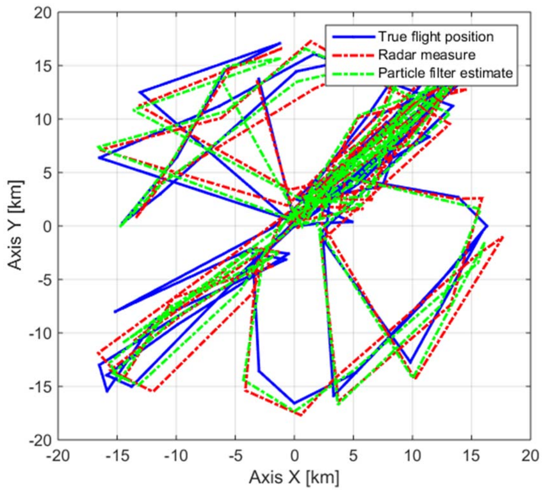

Fig. 1. Rendering of true flight track, Radar measured track and Particle Filtering estimated track

According to the structure and key element of the target tracking model, the cognitive tracking algorithm of the cognitive radar is dynamically formed. Filter algorithms are available, such as α-β-γ filter, Wiener filter, Kalman filter, EKF, MEKF, WMEKF and Particle filter [7], VS-MMPF [8], [9], etc. The cognitive algorithms are designed as hypotheses of the target state and model observations by monitoring the effectiveness of these algorithms during repeated target tracking and feedback learning in environments with clutter.

Research focusing on accurate statistical modelling of noisy echo signals plays an important role. The study organized by MIT-Lincoln Laboratory was probably dealing with the most extensive data collection in relation to ground clutter. The benefit was the remarkable results obtained from data acquisition and data processing with ground clutter caused by local vegetation. Under certain conditions (radar operating at low receiving angles and/or with high resolution/sensitivity) the noisy echoes can be described as spherically invariant random processes that have clearly non-Gaussian character [10]. In this field of study, the big attention is just dedicated to Particle filters for their effective robustness (efficiency/performance) during the tracking in noisy environment [11]. The term VS-IMM in combination with Particle filter technology (PF) leads to an algorithm called VS multiple model PF (VS-MMPF) [8], [9]. These models and simulations realise the efficiency increasing by using clutter-map data and the ability to predictively evaluate and choose which model is the best.

The issue of target tracking by adaptive radars was mainly elaborated by M.C. Wicks, A. Farina, J.R. Guerci, R.M. Guerci, G.T. Capraro and C.T. Capraro in various monographs and articles published at world conferences. The knowledge about the target tracking by cognitive radars and the theory about the adaptive processing of radar data in a data processor were used from these publications. The first chapter is about the current trends in adaptive and cognitive radars. The second chapter is dedicated to the theory about radar data and information processing by the method of Kalman filtration, Adaptive Kalman filtration with the use of Neural Networks, and Particle filtration. The experimental part dealing with the problem of adaptive processing of target tracking by Kalman filtration, Particle filtration and Adaptive Kalman filtration with the use of Neural Networks is in the main part of the article in the third chapter. The fourth and the fifth chapter is about aims and methods, it justifies the results of the filtration methods used and it´s about advantages and disadvantages of used filters.

II. Particle Filter

The dynamic system designed for the target tracking area forms an equation of state and observation with respect to the noise, interference and estimation error caused by manoeuvring target. The purpose of the system is to estimate the state based on all available observations and rules. The target in complex situations represents dynamically non-linear model and its parameters, which are available. Based on this, the concept of dynamic system area can be defined by the state equation and the observation equation written below:

$$X(k+1) = f[X(k), W(k)] \tag{1}$$

$$Z(k) = h[X(k), V(k)] \tag{2}$$

where $X(k)$, $Z(k)$ represent the state of the vector and observation vector, $W(k)$, $V(k)$ are noise and tracking noise models in order, f and h are linear or nonlinear functions. State dynamic and observation dynamic parameters are stable or variable.

It´s recommended to integrate the information about the evaluation of target status by radar and to form an effective evaluation of target status by radar characteristics with typical targets. Characteristic features are the number of active models operating at any time, and dynamics of states varying according to the current state and circumstance. Due to the possible kinematics of the target, corresponding variations of the algorithms correspond to the different models. How is used the decision-making algorithm of the filter bank, which includes the α-β-γ filter, Wiener filter, Kalman filter, EKF, MEKF, WMEKF and Particle filter, VS-MMPF, and so on [11] is an essential feature of a cognitive tracking algorithm.

For the formulation of mathematical models belonging more to the real environment in which a continuous training and on-line learning radar operates, the radar is defined as a radar with cognitive tracking algorithm. Of course, this is not isolated, and it depends on the processing software unit or any radar correlation information.

Particle Filtering (PF) is a recursive Bayesian filter based on the Monte Carlo method also called Sequential Monte Carlo (SMC). In this method, the probability density is the set of samples whose distribution in the state space and the weight determine the probability of the individual positions of the object. PF is able to process non-linear data obtained from sensor measurements and non-Gaussian noise by distribution represented by a plurality of samples (particles). The complexity of calculating such a filter increases with increasing number of points of interest [13]. As a result, this filtration is used to solve the object localization and tracking problems, while also combining with other methods or using the so-called filter banks [14], [15]. Each sample (particle) is a hypothesis about the association of its data with a certain probability. The algorithm consists of the process of generating particles (samples) and resampling. Its complexity is logarithmic. The more samples (particles), the longer time is needed for a more complicated calculation, which is difficult to define because it is difficult to define what is the enough particles (samples) for a sufficient correct calculation [16].

A common problem with a Particle filter is the phenomenon of degeneration [17]. After several iterations, one particle will have a negligible weight. It means that a large computational effort is being made to update the particles whose share of $p(X_k|Z_{1:k},\theta_{1:k})$ is almost zero.

Therefore, this issue can be solved in the following ways:

1.) using NN technology, this non-linear model can become comparable to several common models for designing a cognitive radar tracking filter algorithm;

2.) in particle resampling process, each particle can be considered as a node of the network and identify key nodes based on NN technology.

The target status and the mathematical model of measurement in complex situations is nonlinear and each state of the random variable is very continuous. The Elman NN technology application model for analyzing relative data that is sampled and dispersed allows us to recognize, distinguish and produce the type of space and the type of time. We can decide about the network structure and approximately replace nonlinear functions in the dynamic target model and mathematical measurement models with the mathematically expressive model in networks, and thus solve the design of a cognitive algorithm for a single radar tracking filter.

The structural characteristics of the Elman network combination allow access to any function of any accuracy whatsoever during a limited radar tracking time and data filtration process (see formulas below).

$$X_0(k+1) = W_1 Z_c(k+1) + WX(k) + \theta_1 \qquad (3)$$

$$Z_c(k) = o(k-1) = f\big(X_0(k-1)\big) \qquad (4)$$

$$Z(k) = W_2 o(k) + \theta_2 \qquad (5)$$

Analysis of the current review in the field of adaptive processing of radar data in the data processor suggests that an adaptive filtration method, particle filtering and neural networks, is appropriate to improve data processing. The following objectives and tasks are presented in the practical part:

1.) To analyze data in a data processing system for 2D target tracking.

2.) To analyze the proposed algorithms and methods using real off-line radar data.

3.) To statistically compare and analyze the results achieved and draw conclusions for practice.

By analyzing the proposed algorithm and method of adaptive data processing, real radar data will be subjected to off-line analysis. From this analysis we will draw the results of the experiment based on statistical evaluation. Gist of work will propose such filtration that the adaptive data processing system will be enough capable for predicting the track of the target. Therefore, statistical methods of experimental data processing, statistical filtrations and estimation theory methods will be used.

The goal of the analysis is to compare the methods of data filtration in the process of their processing in order to accurately track the targets, predict their tracks and compare them in terms of computation.

The computer technology using interactive program environment with library of programs was used for creating models, realizing simulations and analyzing results.

III. Target Tracking Model

In this study, Particle Filtering for 2D space is created.

Real target position measured by radar (longitude and latitude) was loaded to program for data processing. The variables were initialized for the simulation. The period of measurement in seconds is set by the period of radar measuring. Noise covariance in the measurement (i.e. the aircraft creates complex of deceptions on its track), the number of particles that the system generates (Better approximation is represented by larger number, but more computation is needed.) and prior particle distribution as a Gaussian around the first measured initial value were initialized. The variance of the initial estimate and the vector of particles were defined. The randomly generated particles from the initial prior Gaussian

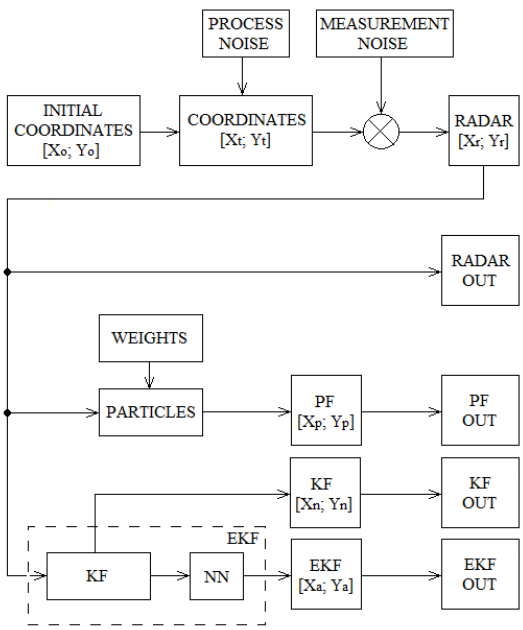

Fig. 2. Target tracking system model [6]

distribution were made and saved as vector of particles x_P and y_p separately for two axises. We made the particles distribution around each initial value of measured aircraft position in x and y axis gathered from the radar (Fig. 2).

The data from radar are many times in other coordinates like it´s necessary for the system computation. That´s why, they need to be converted. After the measured data were converted, particle filtering was built and applied. Given the prior set of particles, each of these particles was run through the state update model to make a new set of transitioned particles. With these new updated particle locations, the observations were updated for each of these particles.

The weights for each of these particles were generated. The weights are based upon the probability of the given observation for a particle, given the actual observation. If we observe a tracked location, and we know our observation error is Gaussian with noise variance in the measurement x_R and y_R, then the probability of detected given tracked location centered at that actual measurement is (from the equation of a Gaussian):

$$P_{wx} = \frac{1}{\sqrt{2\pi x_R^2}} . e^{-\frac{(x_{RADAR}-x_P)^2}{2x_R^2}} \quad (6)$$

$$P_{wy} = \frac{1}{\sqrt{2\pi y_R^2}} . e^{-\frac{(y_{RADAR}-y_P)^2}{2y_R^2}} \quad (7)$$

Probability distribution was normalized to form (i.e. sum to 1) and resampling was made (From this new distribution, we randomly sampled from it to generate our new estimate particles.). What this code or function in program exactly does is randomly, uniformly, sample from the cumulative distribution of the probability distribution generated by the vector P_{wx} and P_{wy}. If we sample randomly over this distribution, we will select values based upon the statistical probability, and thus, on average, pick values with the higher weights (i.e. high probability of being correct given the observation x_{RADAR} and y_{RADAR}) store this new value to the new estimate which will go back into the next iteration. The codes are:

x_P=$x_{Pupdate}$(find(rand<=cumsum(P_{wx}),1));

y_P=$y_{Pupdate}$(find(rand<=cumsum(P_{wy}),1));

The final estimate is some metric of these final resampling, such as the mean value or variance [16].

Then we used Kalman Filtering and Adaptive Kalman Filtering [18]. We compared those three methods of filtering. We evaluated results based on advantages and disadvantages of the filtering system.

IV. Simulation Results

There are dashed lines used for discrete measured or estimated track in these next eight figures. We can see in Fig. 3, that measured track by Radar is compared with predicted track by Particle filter. In Fig. 4, it´s zoomed to critical part of maneuver.

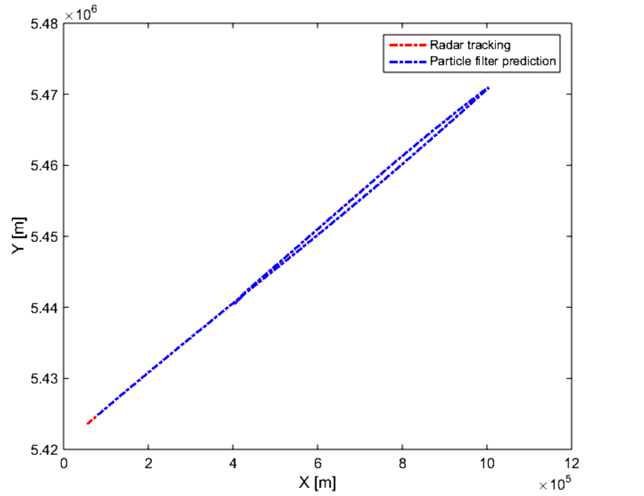

Fig. 3. Rendering of Radar measured track and Particle filter predicted track in XY (Cartesian coordinates)

Fig. 4 shows error when PF is used in this simulation for the most critical target maneuver. Fig. 7 and 8 shows how the Particle filtering absolute error in axises X and Y approximate to 0.

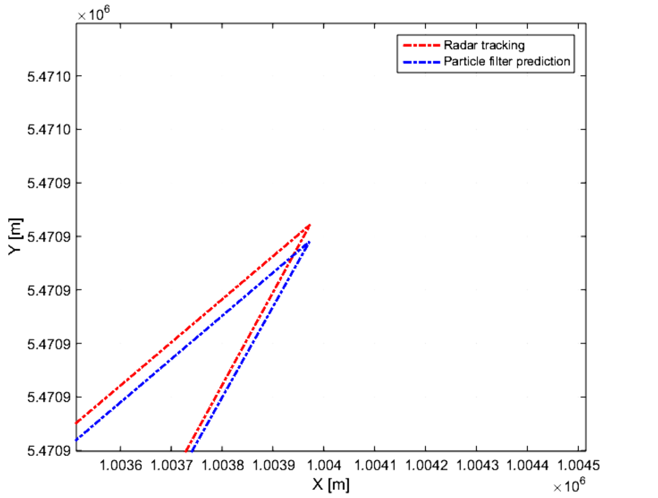

Fig. 4. Detailed view on comparison

The target track prediction by Particle Filtering is accurate to radar measured track as we can see in Fig. 3. On the other hand, as we can see in Fig. 3, the Particle Filtering has significant absolute error at the beginning of plane maneuver. The second serious absolute error occurs when the target suddenly changes its flight track (Fig. 4) [16]. On Fig. 5 are randomly generated particles (red dots) around the known position of the target (blue dot) gathered from radar. Particle filter algorithm assigns weight to each particle and chooses only one particle with highest value as the next probable position of a target. On Fig. 6 is shown probable track of a target created based on the previous known position from the radar. Despite all of that, in case off enough particles

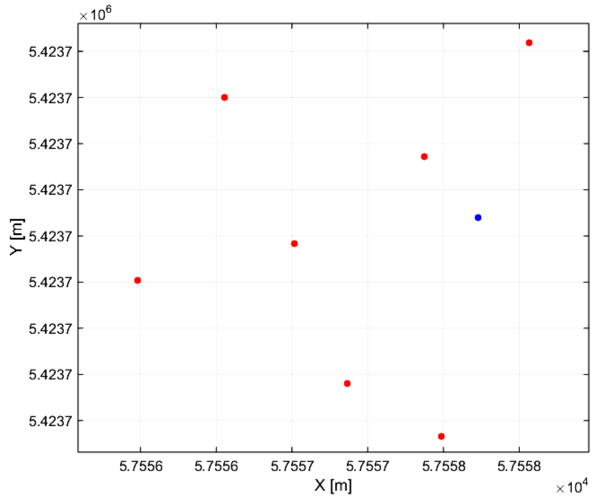

Fig. 5. Example of generated particles (red dots) around Radar measured position of a target (blue dot)

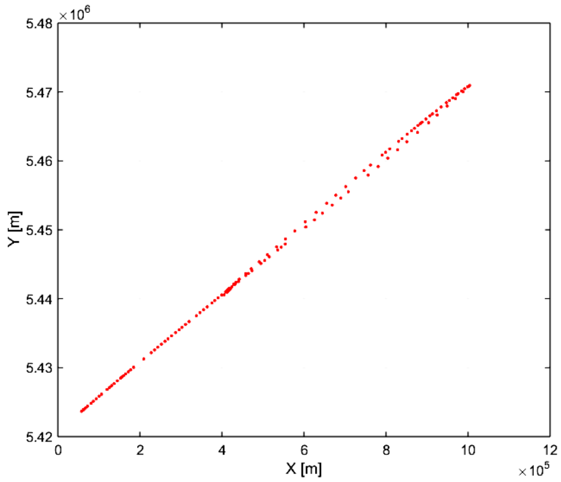

Fig. 6. The target track created by generated particles using particle filtering algorithm

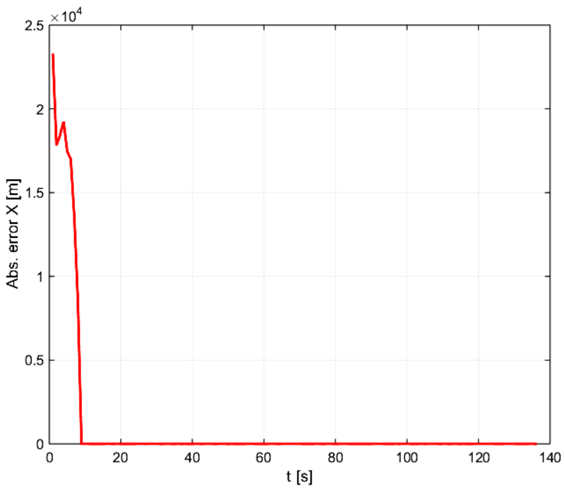

Fig. 7. Particle filtering absolute error X

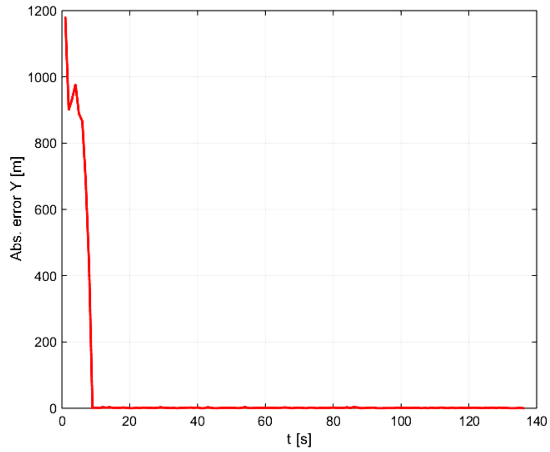

Fig. 8. Particle filtering absolute error Y

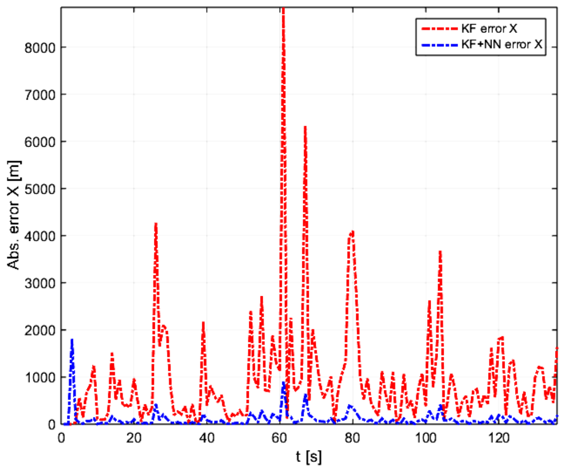

Fig. 9. Kalman filtering and KF+NN absolute error X

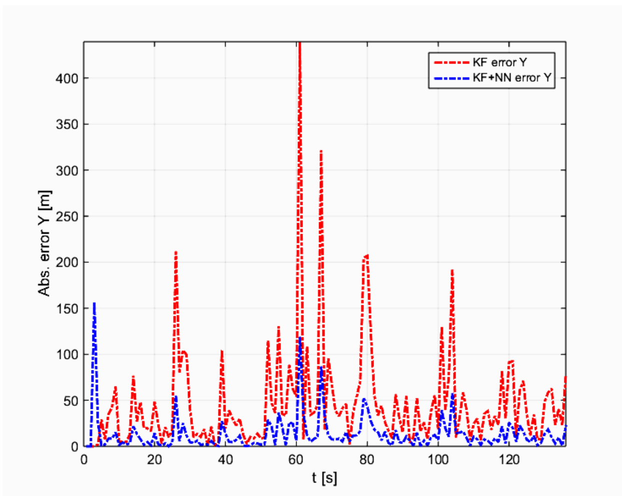

Fig. 10. Kalman filtering and KF+NN absolute error Y

depending on the time it takes to calculate, the result is accurate with better results in comparison of absolute errors both Particle and standard Kalman Filtering (Fig. 7, 8, 9 and 10).

Fig. 9 and 10 informatively show absolute error when KF and NN in KF is used. The KF+NN is more accurate and better than classic KF, but in some cases it is not enough.

V. Conclusion

The Particle Filter was created for 2D radar positioning system with real data acquired from the test flight of a target for its flight prediction. One Particle Filter was used for both longitude and latitude separately. PF is better in many cases than the classic Kalman Filter regarding to results. After ten seconds of target tracking, the error was less than five meters. The more particles we used in Particle Filtering, the more precise the Particle Filtering was, but we needed more time for difficult computation. The problem was that the Particle Filter sometimes made wrong decisions based on Probability Distribution Functions and their weights. Particle filtering estimate flight track based on previous estimated positions. It causes an issue in some cases: when we have wrong estimated positions of a target; when the target suddenly changes its positions. The Probability Distribution Functions are messy, and weights are outdated. On the other hand, the more particles we used, the smaller variation was, and the quicker filtering adaptation was. It caused quicker limitation of estimated value to true flight position. Future investigation should be focused on research of particles number in relation to absolute error, type of target because its maneuverability and calculation time needed for optimization of PF. We recommend using PF in a filter bank in many variations with different number of particles and use it in a combination with another filters. In our simulation is recommended to use KF for the first five seconds and for the next five seconds KF+NN. After ten seconds, the best performance has PF, when it´s adapted to target tracking.

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