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Tracking Multi-Mobile Targets using Kalman Particle Filtering and K-means

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Abstract—**Tracking a mobile target in cellular networks is a constraint problem that depends on the motion and the required accuracy. A GPS system can get the coordinates of a mobile user through a system of satellites. However, GPS cannot track an indoor mobile target or a target that changes suddenly its acceleration. Kalman Particle Filtering has been used to solve such problem. The main idea consists to deploy a set of particles to predict the trajectory of mobile targetand the signal strength received from some base stations will be measured to update the prediction. Tracking multi-mobile targets is a challenging problem especially when the targets follow the same motion model. Our paper solves such problem by deploying a set of particles and applying a K-means clustering process such that each subset of particles will track one target by avoiding high computation. Our simulation results have been obtained via Matlab and show that the error between the estimated and the real trajectory is small and the performance is good once the noise value is small.**

Keywords—Cellular Networks, Tracking, Kalman Particle Filtering, Clustering, K-means, Matlab.

I. INTRODUCTION

A cellular network is a radio based network which divides an area into cells. Each cell is served by one or more base stations (BSs). Each BS provides services to the users on its own cell. Cellular networks provide roaming feature which allow users to move from one location to another and from a country to another one. The BSs must communicate with each other in order to provide services to the users and to determine their locations [1]. By another hand, some social, military and scientific applications need to track the mobility pattern of a mobile target that moves in a cellular network (figure 1). GPS is a technique to get the coordinates of users through a system of 24 satellites that are spaced in six orbital planes. The GPS receiver receives transmitted signals from GPS satellites. The receivers do not transmit. They only receive satellite signals. The atomic clocks on board the satellites provide accurate time reference and the GPS operations depends on it. The GPS satellite transmitsdata that shows its location and its current time. The problem is that the GPS receivers require a clear view of the sky, and at least 4 satellites in line of sight. So, GPS systems cannot be used in an indoor environment. Another approach exists in the literature and estimates the trajectory of a mobile target based on some data [2,3]. By training a Hidden Markov Model (HMM), we extract the movementpattern of a mobile object. This method may predict a long path from observed sequences and also uses successive sequences of observed data to train its learning parameters to enhance prediction's accuracy. Kalman Particle Filtering is a real time trackingmethod which is faster than HMMs. It tracks the location and the dynamic motion of a mobile target in cellular networks. It uses pilot signal strengths from neighboring base-stations (BS). [4]

Tracking the position and the velocity of multi-mobile targets is a challenging problem. Tracking multi-targets using Kalman Particle Filtering requires a joint multi-target probability density (JMPD) which is used to produce a recursive filtering process. [5]

Another approach is used in sensor networks and applies a fuzzy data fusion of sensed data which is related to mobile targets.

[6] Proposed to use an acoustic sensor network and a Gaussian Mixture Probability Hypothesis Density (GM-PHD) filter to track the positions and velocities of ground targets.

[7] Use a sensor network to track multi-mobile targets. The proposed method optimizes the estimation of the trajectories through a set of ants that generate an estimation by applying Interval analysis.

Different from the above approaches, our method requires less computation and concerns a cellular network. It generates a sufficient number of particles, applies clustering to assign each particle to a cluster that should be responsible for tracking one object using traditional Kalman Particle Filtering.

This paper s is organized as follow: section 2 explains Kalman particle filtering. Then, section 3 outlines K-means. In section 4, our proposed method is explained. Finally, section 5 illustrates the obtained results followed by a conclusion and future works.

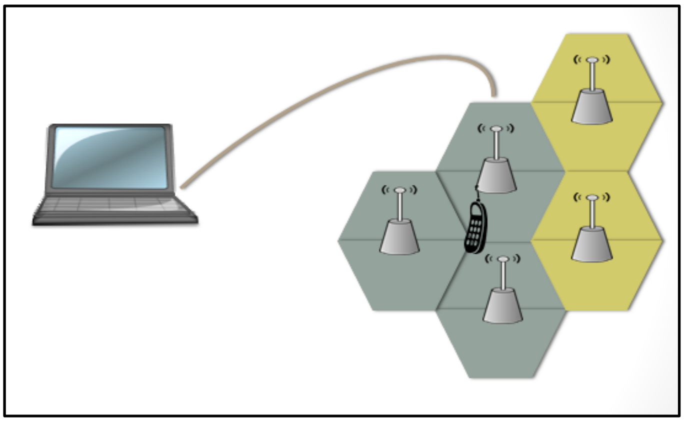

Figure 1 . Tracking in Cellular Networks.

II. KALMAN PARTICLE FILTERING

The Kalman filter is a real time tracking method that uses pilot signal strengths from neighboring base stations for the measurements. This filter supports the estimation of past, present, and future states. Its prediction of the future depends on the state of the present (position, velocity, acceleration, etc). [8]

The steps below show how Kalman filter works:

1. Build a model:

$$x_k = Ax_{k-1} + Bu_k + w_{k-1} \quad (1)$$

$$Z_k = Hx_k + v_k \quad (2)$$

xk (Signal values) :linear combination of its previous value plus a control signal uk and a noise process. A is the transition matrix.

Zk(Measurement value) :linear combination of the signal value and the measurement noise.

2. Prediction process:

Time Update (prediction)	Measurement Update (correction)
$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k$	$K_k = P_k^- H^T(HP_k^- H^T + R)^{-1}$
$P_k^- = AP_{k-1}A^T + Q$	$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$
	$P_k = (I - K_k H)P_k^-$

$\hat{x}^-{}_k$ (prior estimate): the state estimation before the measurement update correction.
p_k^-**:** prior error covariance

Q : estimated process error covariance.
$\hat{x}_k$: estimation of **x** at time **k.**
P_k**:** necessary for the future estimation, together with$\hat{x}_k$**.**

K_k: (Kalman gain): it's a hidden and the most important part of this set of equations.

R: estimated measurement error covariance.

Then, we need to repeat our estimation after gathering the information and starting the process.

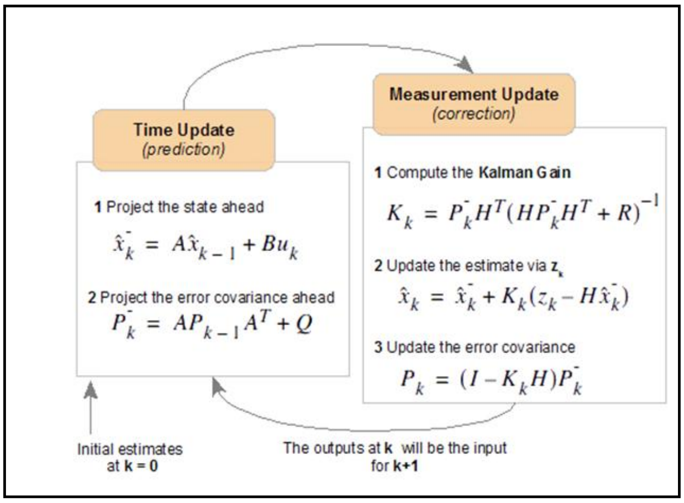

Figure 2. Steps of Kalman Filtering.

Kalman Particle Filtering solves such equations by generating a set of particles to estimate the current location of a mobile target. It is based on the following steps:

1. Initialization: Generate x_0^i. Each sample of the state vector is referred to as a particle.
2. Measurement update : Update the weights by the likelihood function (more generally , any importance function) and normalize:

$$w_{t=}^i w_{t-1}^i = \mathrm{p}(y_t | x_t^i) = w_{t-1}^i p_{et}\ (y_t - \mathrm{h}(x_t^i)) \quad (3)$$

$$w_t^i := w_t^i / \textstyle\sum_i \quad w_t^i \quad (4)$$

3. The approximation of the estimation is:

$$\hat{x} \quad {}_t = \textstyle\sum_i^n \quad w_t^i x_t^i \quad (5)$$

4. Prediction :choose $f_t^i p_f$ and simulate:

$$x_{t+1}^i = \mathrm{A}x_t^i + B_u U_t + B_f f_t^i\ ,\ i \quad = 1,2,\ldots\ldots,\mathrm{N} \quad (6)$$

5. Let t:= t+1 and iterate to step 2.

III. K-MEANS CLUSTERING ALGORITHM

Clustering is the process of organizing a collection of K-dimensional vectors intogroups whose members share similar features in some way. In order to partitionan initial input space, a wide range of clustering algorithms has been suggested in theliterature. Each of them exhibits some advantages and problems Clusteringalgorithms fall into two groups: supervised algorithms and unsupervised ones. Anotherclassification distinguishes hierarchical and non-hierarchical clustering techniques [9].

Partitioning techniques choose the number of clusters before the actual process andfrequently refer to the K-means algorithm. The goal of this algorithm is to minimize the measure between the centroid of the cluster and the observation by moving the observation form one cluster to another to find the lowest distance measure. It will terminate once the lowest measured distance is achieved.

In particular, K-means proceeds as follow: [10]

1. Initialize K clusters and the observations are randomly assigned to the clusters.
2. Assign each observation to its closest cluster center by calculating the distance between the observation and the centroids of the clusters. If the sample is closest to its own cluster then leave it, else select another cluster.
3. Repeat steps 1 and 2 until the observations are not moving from one cluster to another.

There are three common types of distance metrics: Euclidean distance, Euclidean squared distance and Manhattan distance. The fastest and widely used is Euclidean squared distance.

IV. PROPOSED METHOD

The aim of the proposal method is to track k mobile targets. So, k clusters of particles are generated and updated. Each cluster is responsible to track one mobile target. We assume that the targets have a linear movement. In addition the signal strength received from three base stations will be used to update the predictions.

More specifically, figure 3 illustrates our flowchart. It initializes a set of particles that are represented as vectors. Each vector includes the coordinates of its particle. We also initialize a random weight for each particle. The user selects a set of centroids such that their numbers equals the number of mobile targets. Then, K-means classifies the particles according to their distance to the centroids. Next, each particle updates its position by following a linear model. The received signal strength from three base station will be used to update the weight of each particle. The new estimated state of each mobile target depends on the weight of all particles that belong to its cluster and their previous states. At the end, the error between the previous and the new estimated state is calculated and used to decide if we still need more iterations.

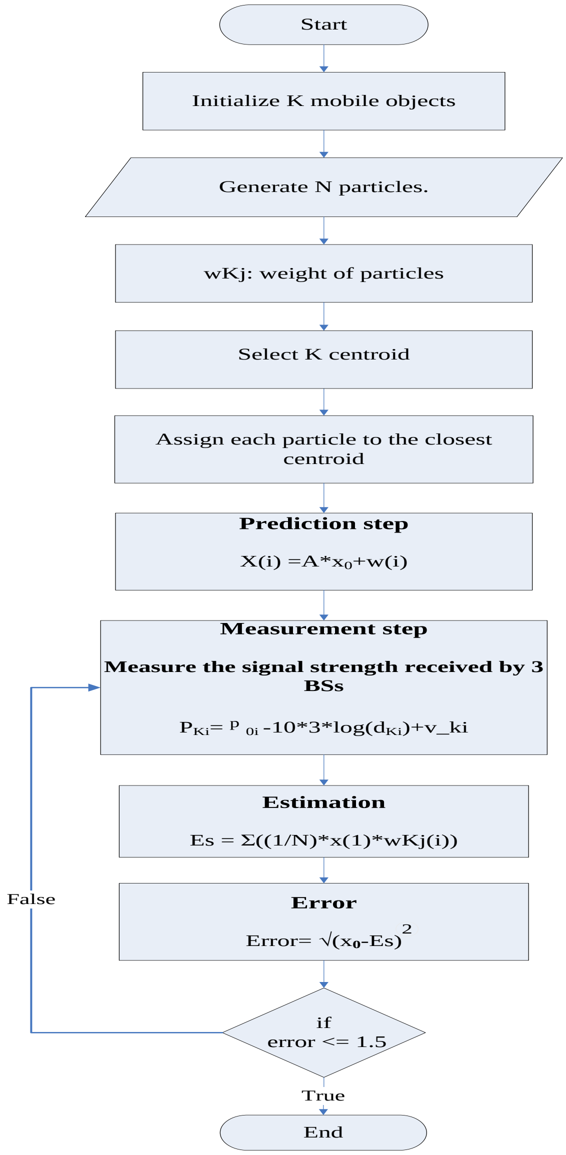

Figure3. Flowchart of our proposed method.

V. SIMULATION RESULTS

This section illustrates the simulation results obtained via Matlab that includes mathematical tools for our simulation requirements. The input of our simulation is a map, a set of particles, the noise value, the number of clusters, and a set of base stations. The outputs are the estimated trajectories of the mobile targets. Picture 4 shows the estimated trajectories for a noise value that equals 0.1. The number of base stations is 3, the number of mobile targets is 4, and the number of particles is 100. It is clear that the estimated trajectories does not fit exactly true ones.

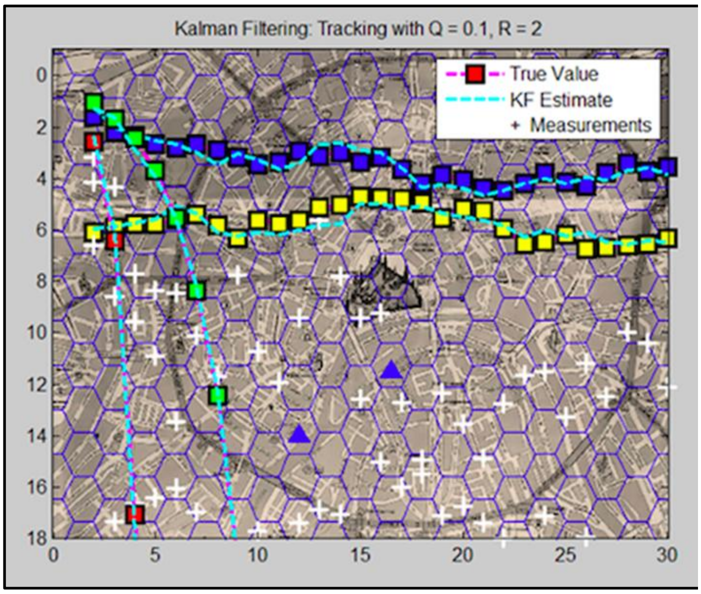

Figure4. Prediction results (Q= 0.1).

Fugure 5illustates the Kalman gain which equals 0.2 and shows also the covariance between the prior and the posterior states. The Kalman gain depends jointly on the measuremenst and the current estimation.

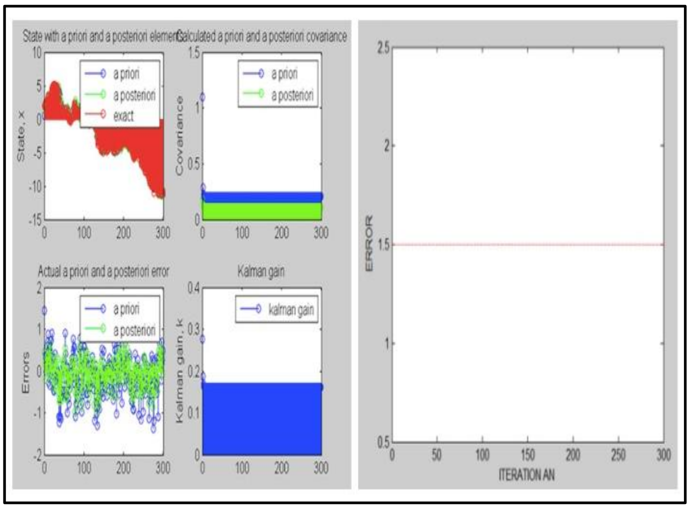

Figure5. Analysis of the prior and posterior states (Q= 0.1).

We conducted several tests. We reduced the noise value and it is clear from figures 6 and 7that the prediction result is good and that the value for Kalman gain decreased. This means that the filter follows the model prediction instead of giving more importance to the measurements.

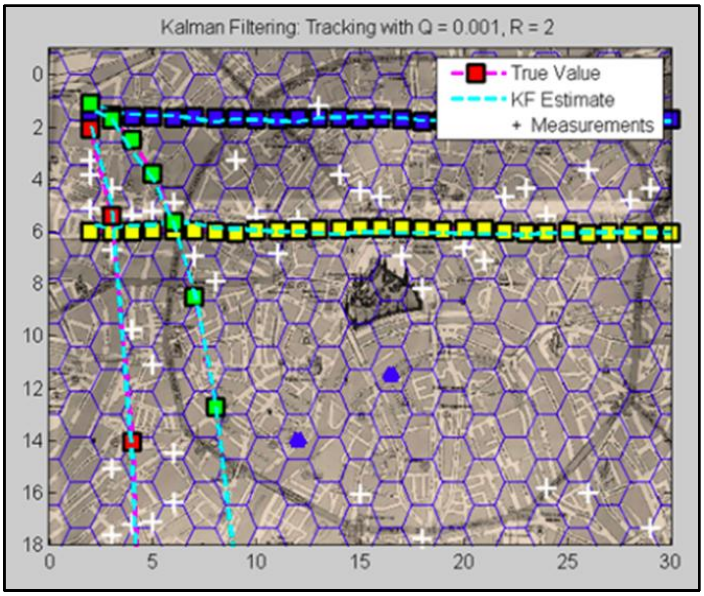

Figure 6. Prediction results (Q= 0.001).

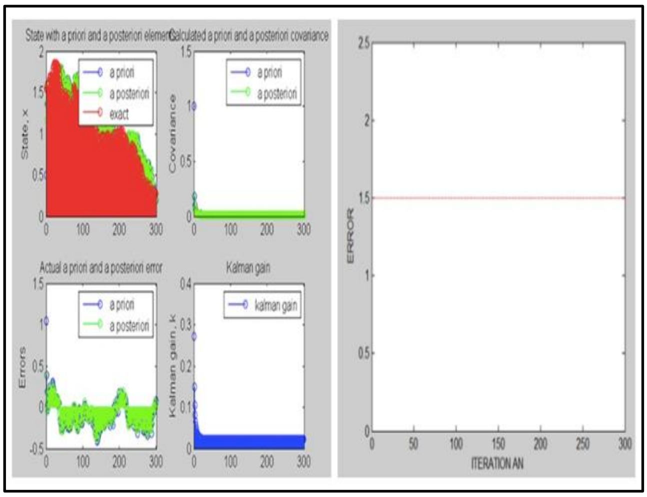

Figure7. Analysis of the prior and posterior states (Q= 0.001).

We tested the impact of the number of particles on the simulation results. We added 200 particles. Figures 8 and 9 show that adding more particles did not improve the simulation results.We need to mention that we conducted many simulation testing to see the impact of the number of particles, the noise, and the number of base stations on the results and this paper shows the most significant results.

VI. Conclusion and Future Works

The simulation results of this paper prove that we are able to track multi-mobile objects using Kalman filtering to avoid the complexity of defining a joint probability density function. We created four clusters of random particles in order to track the trajectory of the mobile targets. The trajectory is updated. Thus, the estimation of the updated trajectory shows that it's approximately close to the exact trajectory once the noise value is small. In addition, the simulation shows that the posterior and the prior states are close to the exact trajectory which doesn't vary in an abnormally way out of the object trajectory. The covariance seems to be changing slightly at the beginning but it remains constant through the whole simulation and the same situation concerns Kalman gain. The error seems to be swinging between the 0 and 1.5 values. So, our scheme shows good results according to the above parameters.

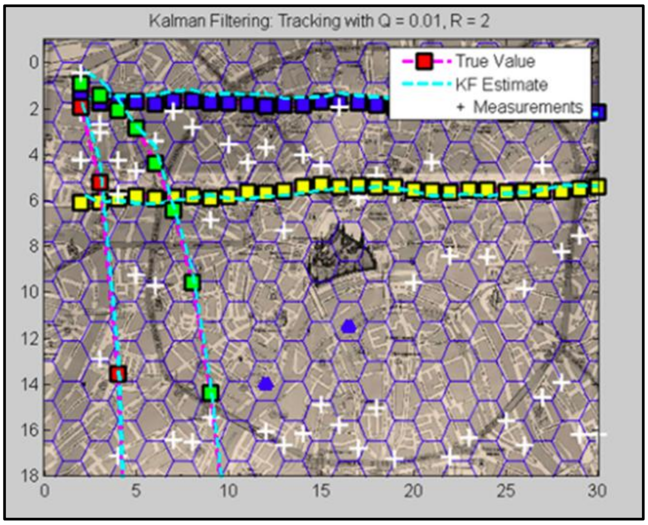

Figure 8. Analysis of the prior and posterior states (Q= 0.001).

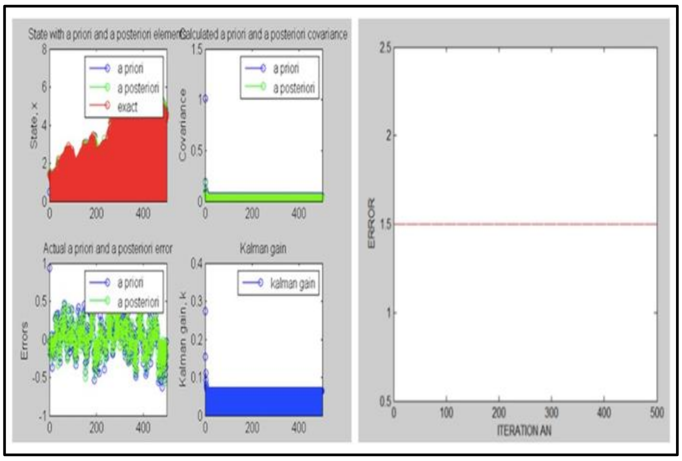

Figure 9. Analysis of the prior and the posterior states after adding 200 particles.

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