Object Tracking Performance Analysis For Kalman,Extended Kalman,Alpha-Beta filters and LSTM

Presented by:

Bheeshmaraya Bheemasamudra Vruksharaj

7206909

Supervisor: Prof.Dr.Andreas Becker

A research thesis presented for the degree of Master of Engineering

Faculty of Information Technology

Fachhochschule Dortmund

Germany

May 2021

Contents

List of Figures

Chapter 1

Introduction

1.1 Motivation

Object tracking is well studied topic with many different approaches to solve the challenges it poses.With increase in safety and comfort functions added to cars the use of object tracking is increased. It is used in many applications like planning route,avoid collision,surveillance etc,which can be done using information provided by different sensors.

Object tracking can be achieved using camera by change in position of object in consecutive frames,LIDAR point clouds and radar point cloud can also be used as well.In the current work radar point cloud data is used for object tracking.Each of the sensors have there own pros and cons based on their working principal and constraints of operation.To achieve single object tracking, classical approaches of object tracking that is Kalman filter, Extended kalman filter,$\alpha - \beta$ filter is used and later their performance is compared with object tracking by Long short term memory(LSTM).Since there are different possible solutions there is need to understand which of these methods could be used for better performance and scientifically differentiate them and conclude a good approach that fits for vehicle tracking using radar.

1.2 Literature overview

There are many proposed solutions of object tracking previously and some of the relevant are quoted here.The work [6] deals with object tracking and evaluation of performance between the different object tracking methods like Kalman filter, KNN (K nearest Neighbour) and LSTM (Long-Short Term Memory) , the data is based series of image frames from different data set and in [13] the tracking is done by sensor fusion by camera and mmwave radar which uses both of them for more accurate tracking details using LSTM. In [5] there is interesting method to improve extended kalman filter by introducing LSTM for prediction step in pose regularization application.

The work [18] investigates the trajectory tracking problem of a flight vehicle performing complex maneuvers. A learnable Extended Kalman Filtering (L-EKF) method is proposed. First, two recurrent neural networks, named Input Modification Network and Gain Modification Network, are designed to identify the model inaccuracy and compensate for the estimation error of the EKF. Then, the L-EKF algorithm is proposed by embedding the two networks into the EKF algorithm. Then, the proposed L-EKF method is applied to a trajectory tracking problem of a gliding vehicle with complex maneuvers. Another possibility of object tracking using camera is video based which is discussed in [7].Similar to [6] there is a comparison of performance of object tracking between Kalman filter and RNN(Recurrent neural network) in [1].

1.3 Outline

The work is divided into 9 chapters.Chapter one outlines motivation and literature review, gives insight about the problem statement for object tracking. The second,third,fourth and fifth chapter provides an overview of Alpha-beta filter,Kalman filter, Extended kalman filter and the LSTM network implemented for current problem statement.Sixth and seven chapters gives details of data preparation and implementation respectively and finally in last two chapters we discuss about the results,feature scope of the current work.

1.4 Problem statement

Radar based object tracking which can be used in different environment conditions has it advantages and some disadvantages as well when compared to camera based object tracking. Based on the information the radar gives which is range(Distance of the object detected),range rate (relative velocity of detected object) and azimuth angle(Angle of detected object) goal is to estimate the nearest position object in comparison ground truth in Cartesian coordinate system based on available measurements.

The measurements data of radar detection for object tracking and ground truth data is generated by Matlab simulation,we can see the implementation details of it in chapter 6. To give an overview of the data,it is a series of iterations(tracks) each with certain number of points which are noisy (to simulate the real-time measurements).We also have ground truth for similar tracks.The noisy measurements are to be used to predict the next real position of the object which is the ground truth.The data contains tracks of both linear and non-linear object movement.

The linear motion of object can be better estimated by kalman filter.To handle non-linearity in some tracks there is a need for a better method than just a kalman like Extended kalman filter and LSTM based deep neural network.The detailed explanation and analysis is done on all these methods in next chapters.

Chapter 2

Alpha Beta filter

Alpha-Beta filtering algorithm is a simple, easy-to-implement, constant-gain filtering method. This method has been widely used in the design of tracking filters for various systems. The biggest advantage is that the calculation is small. It is a simplified scheme of Kalman tracking filter. Its principal advantage is that it does not require a detailed system model as we see in the kalman filter later.

The basic idea of the Alpha-Beta filtering algorithm is when tracking the target, there will be a target position prediction value and a target position measurement value in the case of the target position. In the case of the target velocity, there will be a target velocity at the previous time and it is assumed that the target is moving at a constant speed.

2.1 Filter equations

There are four state variables that are to be predicted that is position and velocity in two directions of Cartesian coordinate system. The position and velocity is predicted using below equation

$$\hat{X_n} = X_{n-1} + dt * V_{n-1} \tag{2.1}$$

$$\hat{V_n} = V_{n-1} \tag{2.2}$$

dt is the time difference between consecutive measurements.$X_{n-1} and V_{n-1}$ are the position and velocity in previous (n-1) time stamp. The prediction done in eqn 2.1 will have error when compared to measurement and that error is calculated as difference and it used to correct the final estimation using below equations

$$\hat{e_n} = X_n - \hat{X}_n \tag{2.3}$$

Using this error the final estimations are calculated using eqn 2.4 and eqn 2.5

$$X_n = \hat{X}_n + \alpha * \hat{e_n} \tag{2.4}$$

$$V_n = \hat{V}_n + (\beta/dt) * \hat{e_n} \tag{2.5}$$

The corrections can be considered in small steps along an estimate of the gradient direction. As these adjustments accumulate, error in the state estimates is reduced. For convergence and stability, the values of the alpha and beta multipliers should be positive and small.Usually alpha and beta fall in the range $0 < \alpha < 1$ and $0 < \beta < 2$. All the above equations are applied for both x and y Cartesian coordinates.The values for alpha and beta are decided based on experiment trails. Larger values provide good transient changes while tracking a object and smaller values gives reduction in noise of estimates.

Chapter 3

Kalman Filter

Kalman filter is algorithm that uses series of measurements which are observed over time having noise and uncertainties,to estimate more accurate values of certain variables nearer to ground truth.

The steps involved in final estimation is as follows

- Predict current state using previous state and the dynamic equation.
- Calculate Kalman Gain
- Update the current state using prediction step,kalman gain and measurements.

3.1 Prediction

Prediction step is where the state variables are estimated based on dynamic model and in vehicle tracking the dynamic model is $s = s_{n-1} + v_{n-1} * t + 0.5at^2$,Where s and s_{n-1} are current position and previous position respectively, v_{n-1} is previous velocity.t is delta time between 2 consecutive measurements.a is acceleration and the state vector is $X_n = \begin{bmatrix} x & v_x & y & v_y \end{bmatrix}$

where the x,y are position coordinates of object detected and v_x, v_y are the velocity components in x and y coordinates respectively.

The prediction of next state is given by equation

$$\hat{X_n} = A * X_{n-1} + w_n \tag{3.1}$$

A is the transition matrix and it is given by $\begin{bmatrix} 1 & dt & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & dt \\ 0 & 0 & 0 & 1 \end{bmatrix}$

But in reality vehicle does not follow constant velocity because of the acceleration and this factor is added as noise w_n which will be considered in calculation of Q matrix or process noise in eqn 3.2 . X_{n-1} is the previous state vector.

Predicted state error co-variance matrix $\hat{P}_n$ which tells about estimate uncertainties of current state prediction and is given by eqn(3.2).P_{n-1} is previous state error co-variance matrix.Q is called process noise co-variance which is calculated by $B\sigma B^T$.Value of Q decides the level of uncertainty in the dynamic model.

$$\hat{P}_n = AP_{n-1}A^T + Q \tag{3.2}$$

σ is possible co-variance is acceleration in x and y direction i.e $\begin{bmatrix} \sigma_{ax}^2 & 0 \\ 0 & \sigma_{ay}^2 \end{bmatrix}$

B matrix is obtained based on dynamic model that is given as below

$$\begin{bmatrix} 0.5dt^2 & 0 \\ dt & 0 \\ 0 & 0.5dt^2 \\ 0 & dt \end{bmatrix}$$

3.2 Kalman Gain

Kalman gain decides the factor by which prediction and measurement is to be considered for final estimate of data point.It is the relative weight given to the measurements and current state estimate, and can be "tuned" to achieve a particular performance. With a high gain, the filter places more weight on the most recent measurements, and thus follows them more responsively.

Kalman gain is calculated by the below equation

$$KG = \frac{\hat{P}_n H}{H\hat{P}_n H^T + R} \tag{3.3}$$

Here H is observation matrix which transforms state space to measurement space. For example, the digital electric thermometer measures the electric cur-

rent, while the system state is the temperature. There is a need for a transformation of the system state (input) to the measurement (output).In present problem the H is given by **Identity matrix of size 4** which means the measured and required system state are same because radar measurements are converted to Cartesian coordinates in the form of state vector.

R is co-variance matrix of measurement uncertainty which gives the possible error in measurement which can be tuned like Q matrix since we have 4 inputs so the size of the R matrix is 4x4.

3.3 Update step

In this step final estimation is calculated based on prediction done and the measurement obtained including kalman Gain.The update equations for state vector and estimate co-variance is give as below

$$X_n = \hat{X_n} + KG(y - H\hat{X_n}) \tag{3.4}$$

X_n is final current state vector , KG is kalman gain, y is obtained measurement. $\hat{X_n}$ is prediction done in predict step. H is the observation matrix.
The final estimate error co-variance matrix is give by below equation

$$P_n = (1 - KG * H)\hat{P_n} \tag{3.5}$$

Chapter 4

Extended Kalman Filter

When the system has nonlinear dynamic model where it is not able to define either the process model with multiplication of vectors and matrices as in eqn 3.1 .The extended Kalman filter provides a tool for dealing with such nonlinear models in an efficient way.

The extended Kalman filter can be termed as a nonlinear version of the Kalman filter that linearize the models about a current state.

4.1 Prediction

The prediction for state vector is given by 4.1 equation and constant velocity model is followed and change in acceleration will be considered as process noise in eqn 4.2 with state vector being $\begin{bmatrix} x & y & v_x & v_y \end{bmatrix}$

$$\hat{X_n} = f(X_{n-1}) + W_{n-1} = AX_{n-1} + W_{n-1} \tag{4.1}$$

The equations are similar to kalman filter equations with difference in handling of measurements since the relation between measurement and state elements is non-linear. f is a function of non-linear motion model.

A is transition matrix $\begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$

Predicted state error Co-variance matrix is similar to kalman filter and is given by eqn 4.2.

$$\hat{P_n} = AP_{n-1}A^T + Q \tag{4.2}$$

process noise co-variance Q is given by $B\sigma B^T.\sigma$ is possible variance is acceleration in x and y direction i.e $\begin{bmatrix} \sigma_{ax}^2 & 0 \\ 0 & \sigma_{ay}^2 \end{bmatrix}$ and B is given by $\begin{bmatrix} 0.5dt^2 & 0 \\ 0 & 0.5dt^2 \\ dt & 0 \\ 0 & dt \end{bmatrix}$

4.2 Kalman Gain

Kalman gain is calculated using equation 4.3.

$$KG = \frac{\hat{P_n}H}{H\hat{P_n}H^T + R} \tag{4.3}$$

The measurements here are in the form of range(ρ) , azimuth angle (ϕ) and range rate ($\dot{\rho}$) ,are in non-linear form of state variables as shown in below

$$h(x) = \begin{bmatrix} (\rho) \\ (\phi) \\ (\dot{\rho}) \end{bmatrix} = \begin{bmatrix} \sqrt{x^2+y^2} \\ arctan(x/y) \\ \frac{xv_x+yv_y}{\sqrt{x^2+y^2}} \end{bmatrix} \tag{4.4}$$

The H matrix in equation 4.3 is the Jacobian of matrix $h(x)$ which is given by the eqn 4.5

$$\begin{bmatrix} \frac{\partial\rho}{\partial x} & \frac{\partial\rho}{\partial y} & \frac{\partial\rho}{\partial v_x} & \frac{\partial\rho}{\partial v_y} \\ \frac{\partial\phi}{\partial x} & \frac{\partial\phi}{\partial y} & \frac{\partial\phi}{\partial v_x} & \frac{\partial\phi}{\partial v_y} \\ \frac{\partial\dot{\rho}}{\partial x} & \frac{\partial\dot{\rho}}{\partial y} & \frac{\partial\dot{\rho}}{\partial v_x} & \frac{\partial\dot{\rho}}{\partial v_y} \end{bmatrix} \tag{4.5}$$

$$\begin{bmatrix} \frac{x}{\sqrt{x^2+y^2}} & \frac{y}{\sqrt{x^2+y^2}} & 0 & 0 \\ \frac{-y}{\sqrt{x^2+y^2}} & \frac{x}{\sqrt{x^2+y^2}} & 0 & 0 \\ \frac{y(v_xy-v_yx)}{(x^2+y^2)^{3/2}} & \frac{x(v_yx-v_xy)}{(x^2+y^2)^{3/2}} & \frac{x}{\sqrt{x^2+y^2}} & \frac{y}{\sqrt{x^2+y^2}} \end{bmatrix} \tag{4.6}$$

In Eqn 4.3 R is the measurement noise co-variance matrix which tells the possible variance in error of the range(ρ),azimuth angle(ϕ) and in range rate($\dot{\rho}$) measurements and is supplied usually by radar supplier.Here it is 3x3 matrix.It

is calculated manually for our data and tuned for better performance.

4.3 Update Step

In update step using kalman gain, prediction and measurement the final posterior of state vector is calculated as in by Eqn 4.7

$$X_n = \hat{X}_n + KG(y - h(x)) \tag{4.7}$$

As seen earlier h(x) is raw measurements in polar coordinate form.

The final estimate covariance matrix remains as in Eqn 4.2

$$P_n = (1 - KG * H)\hat{P}_n \tag{4.8}$$

Here H is jacobian as in Eqn 4.6.

Chapter 5

Long short-term Memory

5.1 Introduction

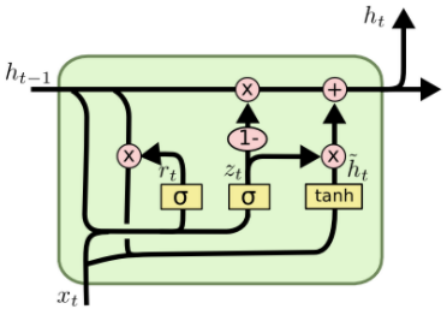
The LSTM performance is evaluated for the single object tracking.Unlike Kalman filter LSTMs make no assumption about motion model of the objects but try to learn motion model from the data given in terms of tracks.In essence it should work for both linear and non-linear motion.Because of recurrent nature LSTM can use the window of previous history to get to know future position. LSTM network is a type of recurrent neural network capable of learning order dependence in sequence prediction problems.LSTMs are majorly used in machine translation,speech recognition where data is sequence dependent. In current approach a sequence of positions is passed from noisy measurement to LSTM network,on which future position is predicted and compared with ground truth by LSTM.All recurrent neural networks have the form of chain of repeating models of neural network.

5.2 LSTM basics

Since LSTM is advanced version of RNN it also has repeating model like structure instead of having one neural network layer,it has multiple layers as shown in fig 5.1

The important point in LSTM is the cell state which runs from input to output with some minor linear interactions.The LSTM does have ability to

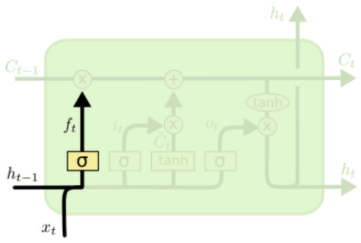
Figure 5.1: LSTM unit with 3 gates [3]



remove or add information to cell based on controls called gates.

To decide what to remove from cell state forget gate is used as shown in the fig 5.2

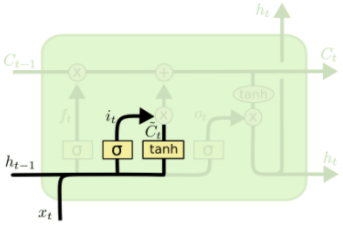
Figure 5.2: LSTM unit forget gate [3]



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

Next step is to decide what information is to be stored in the cell state, it has two parts first is sigmoid layer which is "input gate" ,it decides which values needs to updated.Next is tanh layer which creates a vector of new candidates(fig 5.3).And eventually these two combined to update the cell state.

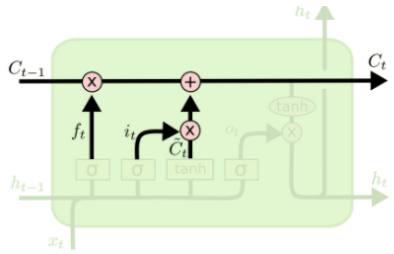
Figure 5.3: LSTM unit input gate [3]



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Once values to be updated are ready, the task is to remove old and update with new values which is shown in 5.4.Old state is multiplied by forget gate and new state is stored in cell state.

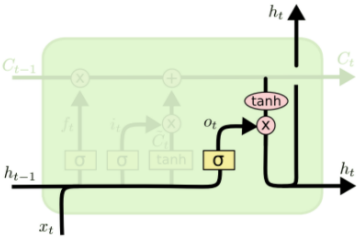
Figure 5.4: LSTM update state [3]



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Finally the output is to be decided which is based on the cell state.And final output is given as in Fig 5.5. In current model 16 such LSTM units were used and sequence length of 5 is used. These are hyper parameters which can change according model and data.

Figure 5.5: LSTM output state [3]



$$o_t = \sigma\left(W_o\ [\,h_{t-1}, x_t]\ +\ b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

The details of symbols used in the equation are explained below:

$i_t \rightarrow$ *represents input gate*

$f_t \rightarrow$ *represents forget gate*

$o_t \rightarrow$ *represents output gate*

$\sigma \rightarrow$ *represents sigmoid function*

$W_x \rightarrow$ *represents weight of respective gate(*x*) neurons*

$h_{t-1} \rightarrow$ *represents output from previous LSTM blocks (at time stamp (t-1)*

$x_t \rightarrow$ *represents input at current time-stamp*

$b_x \rightarrow$ *represents biases of respective(*x*) gates*

$C_t \rightarrow$ *represents the cell state*

$C_{t-1} \rightarrow$ *represents the previous cell state (at time stamp (t-1)*

$\tilde{C}_t \rightarrow$ *represents the new cell state candidate)*

Chapter 6

Data preparation

For the performance analysis of object tracking radar point cloud data is used.The data is generated from Matlab script, which gives multiple tracks or iterations and each track consist of 101 points which simulates position of single vehicle in time.

The matlab script gives the measurement and ground truth values for range, azimuth angle, range rate and corresponding Cartesian coordinate values that is position in x direction,position in y direction ,velocity in x direction and velocity in y direction.So the .csv file generated will contain 14 values in total for each point generated in a track or iteration.

6.1 Matlab script for data generation

The script is available in matlab file called 'targetSimulation.m'.'targetSimulation' class has various methods to generate the required tracks and possibility to set required parameters like number of points in each iteration,time interval between 2 points generated,randomness in values for ground truth and measurement for range, range rate, azimuth angle and acceleration of target. *getData()* function in *targetSimulation.m* does the work of generating ground-truth and measurements.

The *getData()* function using the number of points per iteration as decided above generates the ground-truth using *getGroundtruth()* function.This function makes sure it generates increasing ,decreasing and no acceleration values

within a iteration of 101 points.To control randomness a parameter *sigma_gt_a* is used as show below. As seen for 3 different types of acceleration generated *sigma_gt_a* is multiplied to random number generated there by controlling the non-linearity in the tracks.

```
obj.groundTruth.a(obj.t < P(1)*obj.Tmax) = 0.2;
obj.groundTruth.a(obj.t > P(2)*obj.Tmax) = -0.2;
obj.groundTruth.a(obj.t > P(3)*obj.Tmax) = 0;

obj.groundTruth.a = obj.groundTruth.a + randn(size(obj.t))*obj.settings.sigma_gt_a;
```

With the acceleration values, the range rate is calculated by just integrating with respect to time and again integrating range rate ,the range is obtained.Azimuth angle is generated similarly to acceleration which in-turn is used to get position and velocities in Cartesian form using sine and cosine angles as shown in below code snippet:

```
obj.groundTruth.phidotdot(obj.t < P(1)*obj.Tmax) = 0.0001;
obj.groundTruth.phidotdot(obj.t > P(2)*obj.Tmax) = -0.0001;
obj.groundTruth.phidotdot(obj.t > P(3)*obj.Tmax) = 0;
obj.groundTruth.phidotdot = obj.groundTruth.phidotdot ...
    + randn(size(obj.t))*obj.settings.sigma_gt_phi_dot_dot;
obj.groundTruth.phidot = cumsum(obj.groundTruth.phidotdot)*obj.dt;

obj.groundTruth.phi = cumsum(obj.groundTruth.phidot)*obj.dt;
obj.groundTruth.x = obj.groundTruth.r .* cos(obj.groundTruth.phi);
obj.groundTruth.y = obj.groundTruth.r .* sin(obj.groundTruth.phi);
obj.groundTruth.dx = obj.groundTruth.rr .* cos(obj.groundTruth.phi);
obj.groundTruth.dy = obj.groundTruth.rr .* sin(obj.groundTruth.phi);
```

For generating measurements a white noise is added for ground truth range, range rate, acceleration and azimuth angle.And using these Cartesian coordinates are generated.The randomness is controlled by parameters of each of them as shown below in *getMeasurements()* function of the *targetSimulation* class.

```
function obj = getMeasurement(obj)
       obj.measurement.r  = obj.groundTruth.r  + randn(size(obj.groundTruth.r))*obj.settings.sigma_m_r;
       obj.measurement.rr = obj.groundTruth.rr + randn(size(obj.groundTruth.rr))*obj.settings.sigma_m_rr;
       obj.measurement.a  = obj.groundTruth.a  + randn(size(obj.groundTruth.a))*obj.settings.sigma_m_a;
       obj.measurement.phi = obj.groundTruth.phi  + randn(size(obj.groundTruth.phi))*obj.settings.sigma_m_phi;
       obj.measurement.x  = (obj.measurement.r.*cos(obj.measurement.phi));
       obj.measurement.y  = (obj.measurement.r.*sin(obj.measurement.phi));
       obj.measurement.dx = (obj.measurement.rr.*cos(obj.measurement.phi));
       obj.measurement.dy = (obj.measurement.rr.*sin(obj.measurement.phi));
```

Many tracks with required randomness for linear and non-linear motion of vehicle can be simulated.An example of track with ground truth and corresponding measurements simulated from matlab is show figures 6.1 and 6.2

Figure 6.1: Example1 track generated from matlab

A track with more maneuvers(non-linear)

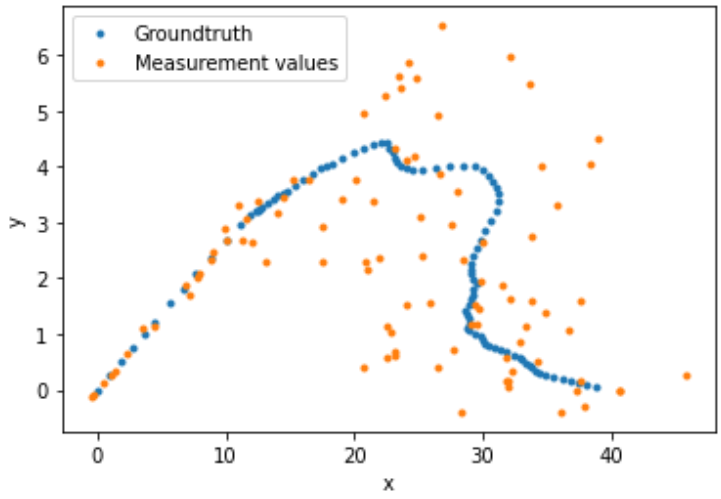
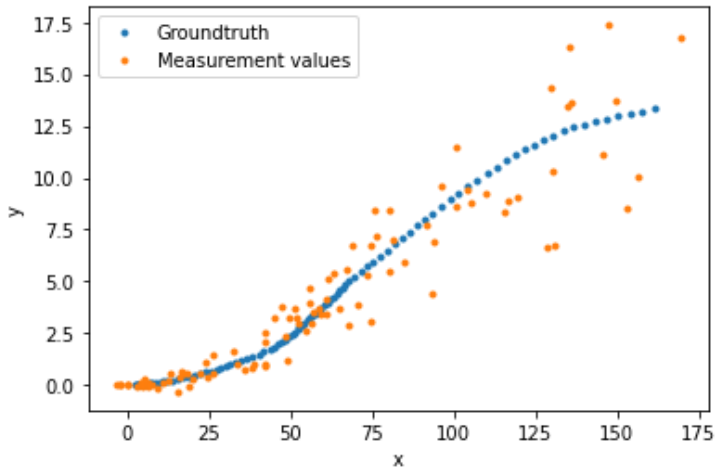


Figure 6.2: Example2 track generated from matlab

A track with less maneuvers



Chapter 7

Implementation

In this chapter the implementation details of Alphabeta filter, Kalman filter ,extended kalman filter and LSTM model is explained with evaluation criteria.Python language with version 3 is used for implementing all the four approaches and LSTM model is implemented using Keras library with Tensorflow backend.

7.1 Alpha beta filter

Alpha beta filter is implemented in *alpha_beta* file. The file contains a AlphaBetaFilter class with all required methods for estimation.From the data generated from matlab in data.csv file only the required columns x,y of measurements and ground truth are used. Ground truth is used in RMSE calculation for performance evaltuation.

The estimation is done for individual tracks or iterations which has 101 points.Since our final goal is to compare with LSTM performance and LSTM uses first 5 measurements to predict sixth data point and compare it to ground truth.So only 96 points are considered.

Since the estimation for data points depends on the previous value of position and velocity the first estimation would be same as measurement for all state variable the is x,y,v_x,v_y.

Eqn 2.1 is implemented in *predictions()* method and other Eqns from 2.2 to 2.5 are implemented in *add_sample()* method of *AlphaBetaFilter* class.Plotting

and RMSE calculation on estimation, ground truth and measurements functions are available in same file.

7.2 Kalman filter

Kalman filter implementation can be seen in *kalman_filter.py* in *kalman_filter* folder. The file has all required functions to estimate the position on an object based on measurements.From the "data.csv" file only required columns of measurements in carestain coordinate system i.e x(position in x direction),y(position in x direction),dx(velocity in x direction) ,dy(velocity in y direction) and for ground truth only x and y positions are used.

For estimation of each point in a track the python function *kalman_estimation()* is used with measurements. This function in-turn calls all other functions and for the first estimation the first measurement itself is the final estimation.Prediction error Co-variance matrix P being an identity matrix for first estimation of a point in a track.

Having initial values after first estimation of a point in the track, prediction is carried out for the 2nd point in the track and further points of track using equation 3.1 and is implemented in *prediction_State_Vector()* function which returns the prediction of state vector i.e x, y, v_x, v_y. The prediction error co-variance matrix prediction is calculated using eqn 3.2 in the *prediction_process_covariance()* function.The process noise Q is calculated as mentioned in section 3.1 and is implemented in the same function.

The kalman gain calculation is implemented using eqn 3.3. Measurement error co-variance matrix R is usually provided by the measuring device supplier.In present case since we know the measurement and ground truth its easy to get the R matrix. It is variance of error between ground truth and the measurement of all state variables x, y, v_x, v_y for each iteration or track which is tuned after multiple trails.So that R is not calculated for each track separately.

The kalman gain is calculated *kalman _gain()* function and is used in the update step as in equation 3.4 .y in the equation is the real measurement that is sent out by radar for all state variables.Similarly update of prediction error co-variance matrix P of estimation error of state variables is also calculated.The

measurement matrix Hin eqn 3.3 is identity matrix of size 4 because we have 4 states in our state vector and there is no conversion needed between measurement equipment and estimating function which makes it an identity matrix.

Based on the Kalman gain calculation next step is to update the state vector as in eqn 3.4 and that is calculated in *Update_State_Vector()* function. The updated process co-variance matrix P is implemented in *Update_Process_Covar()* function.

Each iteration is of 101 points of radar point cloud but only 96 points are considered leaving the first 5 points since the LSTM gives its first prediction after a sequence of 5 points. So in order to evaluate performance in each iteration(track) first 5 points are not considered in Kalman filter.

The evaluation is based on Root mean square error(RMSE) between the prediction and the ground truth in each iteration.Similarly the RMSE is calculated between measurements and ground truth.Implementation to calculate RMSE is in *calculate_rmse()* function.

7.3 Extended Kalman Filter

In further to discussion of extended kalman filter(EKF) in chapter 4 in this section the implementation details would be discussed.The complete implementation of EKF is split in 5 files and they are *main.py*, *Extended_kf.py*, *Kalmanfilter.py* , *DataSample.py* and *Toolkit.py*. The data preparation explained in chapter 6 is still valid for EKF as well. Here also radar point cloud information of the tracks or iterations of 96 points are sent to EKF to get the filtered estimations.

Going through details of implementation ,*main.py* has required functions for processing data ,estimation related functions and plotting functions to visualize data.*Parse_data()* function needs the path for data file in folder where script is present. First initialization for prediction error co-variance matrix P is a Identity matrix of 4x4 and measurement noise co-variance is tuned for better performance based on the error between measurement and the ground truth.The transition matrix (A) and process noise(Q) are initialized to identity matrix and *get_estimations()* is a function which sends measurement to get the estimate of

state variables using EKF.

There are 2 types of data first is the one which is raw data from radar in polar form and another is the ground truth of position and velocity of object in Cartesian form.In *DataSample* class of *DataSample.py* file each data point is processed based on if it is radar measurement or ground truth for further comparison of EKF performance and usage.In the *Toolkit.py* there are functions for polar to Cartesian and vice versa conversions and to calculate Jacobian of h(x) as in eqn 4.6 matrix is here.

When a data point of radar point cloud is passed to estimate the filtered position in *main.py* in *get_estimations()* function it uses *process()* from *Extended_kf* class.If it is the first estimation then final estimation would be same as measurement. From second estimation the *update()* function is called which takes care of updating the transition matrix A and Q matrix based on the time difference between the consecutive measurements as in 4.1 and 4.2 respectively for calculating the prediction of state vectors.But here the measurements are available at equal intervals making these matrix constants after first computation.With required information the Jacobian is calculated for the obtained raw measurements. Having all these the final step is to calculate the posterior and that is done using *update()* method of *Kalmanfilter* class.

The above process is applied to all the remaining data points of a particular iteration.And finally the RMSE is calculated in calculated using the *combined_RMSE()* function in *main.py* for each iteration of 96 data points.

7.4 LSTM

The LSTM model and data preparation is available in *LSTM_object_tracking.ipynb* file in LSTM folder.The LSTM model was implemented using Keras library using Tensorflow back-end.The tensor flow version used is 2.4.1. And other python libraries like sklearn , numpy and other generic libraries were used.

The data is generated from matlab is available in .csv format. The .csv file contains iteration number,point number in the iteration,range,range rate,azimuth angle,x, y, v_x, v_y for both measurement and ground truth.For training LSTM model Cartesian coordinates of measurements is used.For training and valida-

tion a set of around 970 iterations(tracks) are used of which 75 percent is used for training an LSTM model and 25 percent was used for validation from *training_data*.The data set with window size of 5 was prepared where in 6th is predicted by LSTM and label for that is 6th element in the Ground truth.Testing was done on separate data set.Similar data set for testing is prepared from another *testing_data.csv* file having many iterations.

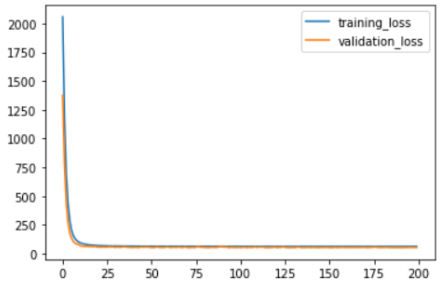
To train a model, some training or hyper parameters are used and they are usually decided randomly in beginning and tuned based on data used to train the model.The training parameters are :

- *LSTM Units*: It is the number of LSTM units in each layer of the model.
- *Window size*: It the length of sequence based on which the next prediction is calculated in sequence.
- *Hidden layers*:It the number of hidden layers between the input layer and the output layer in neural network.
- *Batch size* : This is number Number of samples considered at a time for training for each forward and backward propagation.
- *learning rate*:It decided the rate of gradient descent.
- *Number of epochs* : Number of iterations of training.
- *Optimizer*: Algorithms used to change the attributes of the neural network such as weights and learning rate to reduce the losses.
- *Train-Test split*:It is the ratio to randomly split the entire data set as training and test/validation samples.

Parameter	*Value*
Batch size	32
Learning Rate	0.001
Number of Epochs	200
Train-Test split	0.25
Optimizer	RMSprop
Hidden layers	1
Window size	5

A learning curve plots the optimal value of a model's loss function for a training set against this loss function evaluated on a validation data set with same parameters as produced the optimal function and it is as shown figure 6.1

Figure 7.1: Learning Curve



Performance for object tracking is evaluated based on RMSE as it was used in Kalman filter also.The RMSE is calculated between the prediction of LSTM model with ground truth and Measurement with ground truth for each iteration or track.

Chapter 8

Results

Performance analysis for single object tracking using radar point cloud data was done for 4 possible approaches Alphabeta filter Kalman filter, Extended kalman filter and tracking based on Long short term memory.The project explains the details about object tracking and 4 possible approaches for single object tracking quoting details of equations used in all the approaches.The radar point cloud data was simulated using the Matlab script.The evaluation was done based on Root mean square error between the predictions done by each one of them with respect to ground truth and RMSE between the Measurement and ground truth.Most of the iterations in each of them had better RMSE when compared to measurement to ground truth RMSE.

The basic idea is to compare the RMSE between the prediction-ground truth of all the approaches individually and measurement-ground truth.To consider estimation method to be good the RMSE for prediction-ground truth should be less than measurement-ground truth.

The Kalman filter is usually designed for linear motion models and it was proved that it performs better in linear motion of vehicle and performance decreases in case of non-linear motion i.e when there are more maneuvers in vehicle.

The LSTM performs better than Kalman filter in non-linear cases,it does not depend on whether the motion is linear or non-linear so basically it learns the motion model irrespective of the type of motion of vehicle.It turns out that

LSTM performance is less than kalman filter in linear cases.

Extended kalman filter performs better for both linear and non-linear motions and its is even better than LSTM for the data set it was tested on.To understand the performance we use some symbols like P_{rmse} which is RMSE between the prediction done by estimation method to ground truth.And the M_{rmse} is the RMSE between the track measurement and ground truth.

8.1 Performance analysis for less maneuvers tracks

From the fig 8.1(a) and fig 8.1(d) tracks with less maneuvers, RMSE of Alphabeta filter estimation to ground truth is more than RMSE of LSTM prediction to ground truth by using same measurements.It indicates the LSTM has better performance than Alphbeta filter.

From the fig 8.1(b) and fig 8.1(d) tracks with less maneuvers,RMSE of kalman filter estimation to ground truth is less than RMSE of LSTM prediction to ground truth by using same measurements.It indicates the kalman filter has better performance than LSTM in less maneuvers. EKF performance is better for less maneuvers as seen in fig 8.1(c) when compared to Kalman filter and LSTM. Since it linearizes small non-linearities and performs better.

8.2 Performance analysis for more maneuvers tracks

From fig 8.2(a) and fig 8.2(d) it can be seen that LSTM performs better than Alphabeta filter in tracks with more maneuvers. And also Alphbeta performs better than kalman in more maneuvers as seen in fig 8.2(a) and 8.2(b)

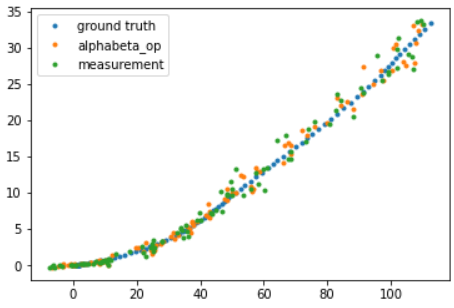
From fig 8.2(b) and 8.2(d) it can be seen that LSTM performs better than Kalman filter in tracks with more maneuvers.Kalman filter performance decreases since it cannot adjust its update step to the sudden change in the direction of travelling or longitudinal acceleration of vehicle,it takes some measurement data points to correct its kalman gain and estimate updated values nearer to ground truth.On the other hand LSTM makes its decision based on the previous measurements and predict the next nearest position in comparison

with ground truth.

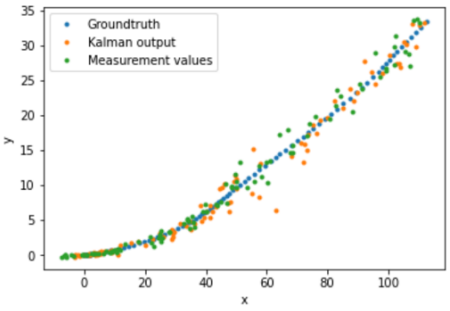
EKF performs better than kalman filter as seen in fig 8.2(c) and 8.2(b) as expected since it depends on Jacobian for update step of estimation and takes care of non-linear motions of vehicle.

EKF also performs better than LSTM as seen in as fig 8.2(c) and fig 8.2(d) this might be because the LSTM could not completely learn the variance in track so that it can outperforms the EKF.

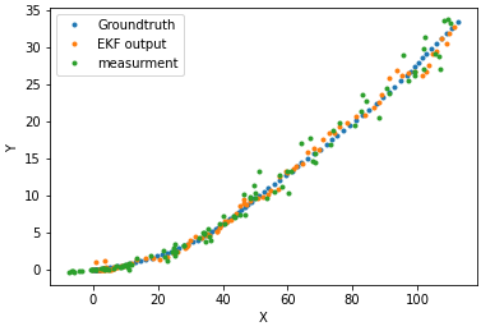
To summarize LSTM outperforms Kalman filter in tracks having more maneuvers and LSTM performs better than kalman filter when the track is not having too much of variance and value ranges.But EKF performs better than LSTM at-least for the data set tested on.Still LSTM is good approach too and can be relied on for all sought of tracks to get optimum RMSE but not the best RMSE .



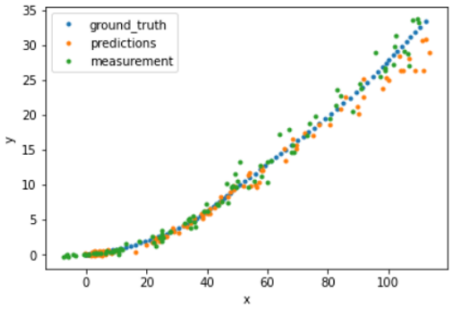
(a) Alphabeta Filter $P_{rmse} = 3.10$



(b) Kalman filter $P_{rmse} = 2.07$

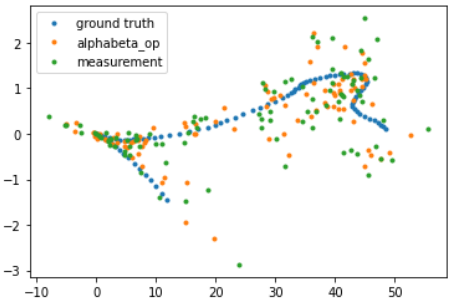


(c) Extended Kalman filter $P_{rmse} = 1.37$

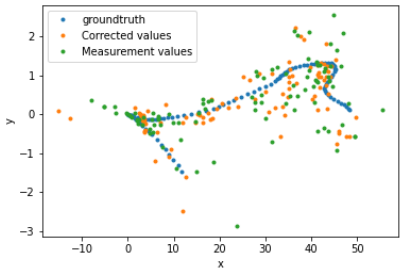


(d) LSTM $P_{rmse} = 2.56$

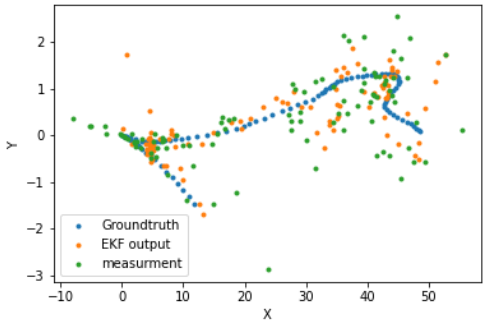
Figure 8.1: Track of less Maneuvers with $M_{rmse} = 3.64$



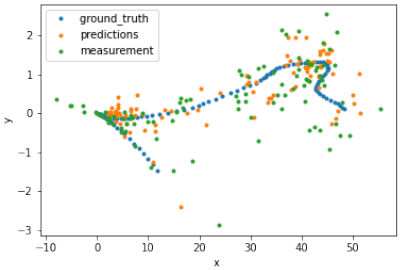
(a) Alphabeta Filter $P_{rmse} = 2.74$



(b) Kalman filter $P_{rmse} = 3.57$



(c) Extended Kalman filter $P_{rmse} = 1.17$



(d) LSTM $P_{rmse} = 2.04$

Figure 8.2: Track of more Maneuvers with $M_{rmse} = 3.51$

Chapter 9

Future scope

The single object tracking using kalman filter,extended kalman filter are already been proven as an effective means to estimate position of vehicle and LSTM is comparatively new approach using radar point cloud data.With the analysis LSTM also proves to provide optimum estimation.There were many impediments faced while implementing this project. While most of those were resolved within the scope of this research thesis, solutions to some of the unresolved complications are mentioned as a future scope of this project.

The data that was used was simulated data using matlab and always there is difference in results for real case scenarios ,so there is possibility to get real data using any of possible mmwave radars to get radar point cloud data and perform analysis on it. The data generation can also be done on simulated platforms like Carla, AirSim which can also be used to get data more nearer to real-time data and performance analysis.There are still more advanced filters like adaptive kalman filter , Unscented kalman filter on which performance analysis can be carried out.The approach followed can be extended to multiple object tracking using clustering and data association and perform analysis on these different approaches and along with other filters quoted earlier.Object tracking using sensor fusion can be done which increase accuracy and acts as back up in failure of any one of them.Along with radar, camera can be used which tracks objects by consecutive image frames.

The LSTM network can be used to learn the more nonlinear motion mod-

els for which getting a dynamic motion model is difficult and try to increase accuracy of the extended kalman filter.

We faced difficulty in getting labelled radar data, and the dataset which we found had very less frames by which it was difficult to train the neural network.To develop and test more number of applications using deep learning based on the radar there is necessity to lot of open source labelled radar data like how we have for camera.

Bibliography

[1] RajaGopalReddy B et al. *State Estimation and Tracking using Recurrent Neural Networks.*

[2] Alex Becker. *https://www.kalmanfilter.net/default.aspx.*

[3] Jason Brownlee. *https://machinelearningmastery.com/multivariate-time-series-forecasting-lstms-keras/.*

[4] Jason Brownlee. *https://machinelearningmastery.com/tune-lstm-hyperparameters-keras-time-series-forecasting/.*

[5] Huseyin Coskun, Felix Achilles, and Robert DiPietro. *Long Short-Term Memory Kalman Filters Recurrent Neural Estimators for Pose Regularization.*

[6] Dan Iter, Jonathan Kuck, and Philip Zhuang. *Target Tracking with Kalman Filtering, KNN and LSTMs.*

[7] Ming xin Jiang et al. *Multiobject Tracking in Videos Based on LSTM and Deep Reinforcement Learning.*

[8] Keras. *https://keras.io/api/layers/recurrent$_l$ayers/lstm/.*

[9] Keras. *https://keras.io/api/optimizers.*

[10] Intech Open. *https://www.intechopen.com/books/introduction-and-implementations-of-the-kalman-filter/introduction-to-kalman-filter-and-its-applications.*

[11] Maria Isabel Ribeiro. *Kalman and Extended Kalman Filters: Concept, Derivation and Properties.*

[12] towards data science. *https://towardsdatascience.com/alpha-beta-filter-21d3276cf35e.*

[13] Arindam Sengupta, Feng Jin, and Siyang Cao. *A DNN-LSTM based Target Tracking Approach using mmWave Radar and Camera Sensor Fusion.*

[14] Gabriel A. Terejanu. *https://www.cse.sc.edu/ terejanu/files/tutorialEKF.pdf.*

[15] Udacity. *https://www.udacity.com/course/self-driving-car-engineer-nanodegree–nd013.*

[16] wiki. *https://en.wikipedia.org/wiki/Alpha$_b$eta$_f$ilter.*

[17] Christian Wolff. *https://www.radartutorial.eu/index.en.html.*

[18] Tianyu Zheng et al. *An RNN-based Learnable Extended Kalman Filter Design and Application.*