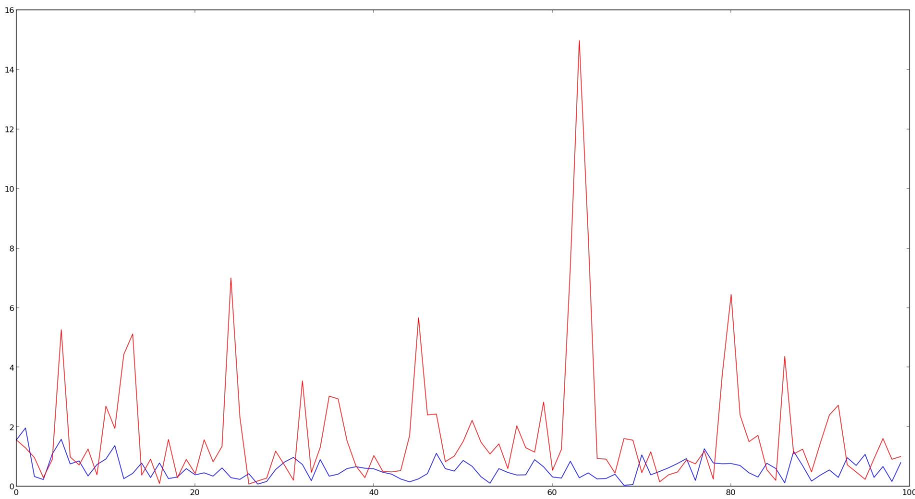
Figure 1: σ_{D_d}=0.05 $\sigma^*_{D_d}$ = 0.2 Sensor Noise= 2.0



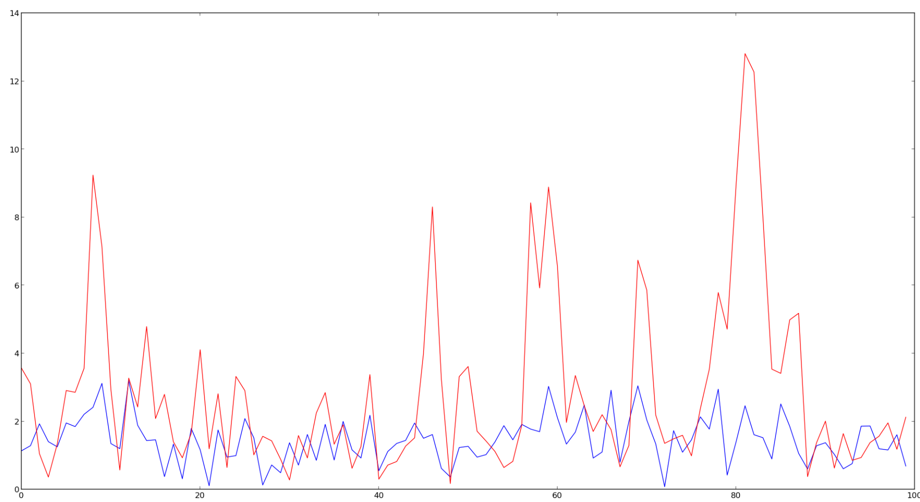
We use a simulation to demonstarte the effictivnes of learning the motion model. The simulation mainly consists of particle filter SLAM. We use a motion model described in the above chapters. The sensor model basically measures the distance from the four static landmarks defined at the start of the experiment. The experiment runs over 100 time steps and at every 5^{th} time step we change the paramters of the motion model. As described in the above chapters the parameters that we intendend to learn are $\sigma^2_{D_d}$,$\sigma^2_{T_d}$,$\sigma^2_{D_1}$, $\sigma^2_{D_r}$,$\sigma^2_{T_r}$,$\sigma^2_{D_1}$,$\sigma^2_{T_1}$. In the first stage of the experiment at every 5^{th} timestep we change $\sigma^2_{D_d}$ or $\sigma^2_{T_r}$in our motion model. The following table and plots describes the five experiments that were conducted in the simulation.

No.	σ_{D_d}	σ_{T_r}	$\sigma^*_{D_d}$	$\sigma^*_{T_r}$	Sensor Noise
1	0.05	0.05	0.2	0.05	2.0
2	0.05	0.05	0.2	0.05	5.0
4	0.05	0.05	0.5	0.05	2.0
5	0.05	0.05	0.5	0.05	5.0
6	0.05	0.05	0.05	0.2	5.0
7	0.05	0.05	0.05	0.5	5.0

σ_{D_d},σ_{T_r} are the parameters values that the motion model was initalized. These values are altered in order to simulate a change in the motion model and they are descibed by $\sigma^*_{D_d}$,$\sigma^*_{T_r}$. The sensor noise can be descibed as the confidence the robot has in its sensor model . The impact of the noise on the locilization error can be seen in the following plots.

Figure 1 and Figure 2 are plots of the locilization error with different sensor

Figure 2: σ_{D_d}=0.05 $\sigma^*_{D_d}$ = 0.2 Sensor Noise= 5.0



noises. We can see in both the cases the learned motion model performed better than the static motion model. Another important point is that the average error is less when the sensor noise is 2.0 as compared to the second case. This can be accounted for the fact that our locilization algorithm is more confident on the sensor model as compared to the motion model.

As we can see in Figure 3 and Figure 4 at 5^{th} time step the error shooting up but the learned motion model brings back the error whereas the static motion model takes time to recover back depending upon the sensor noise. In both the figures we can see that the error is pretty static in the learned motion model whereas in the static motion model there is a lot of fluctulation.

Figure 5 and Figure 6 describe the errors when the robot rotational motion is much more than the translational motion. We can clearly see that the learned motion model quickly adapts to the changes whereas the static motion model struggles to get the error down.

In all the cases it was very clear that we could see the adaptive motion model performing better than the static. The sensor noise had its imapct on the overall error. Robot calibration is important to process in mobile robotics. The proposed algoirhtm is an automated process which can help us in better navigation of the robots and can be used for any motion model.

Figure 3: σ_{D_d}=0.05 $\sigma^*_{D_d} = 0.5$ Sensor Noise= 2.0

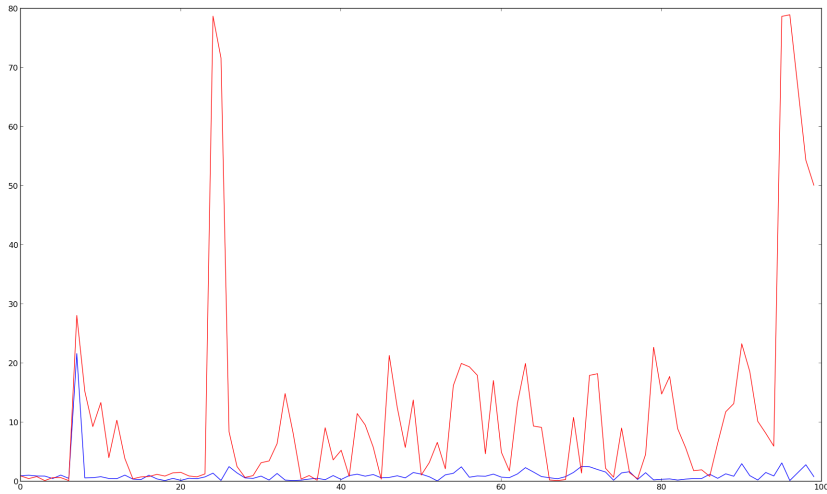


Figure 4: σ_{D_d}=0.05 $\sigma^*_{D_d} = 0.5$ Sensor Noise= 5.0

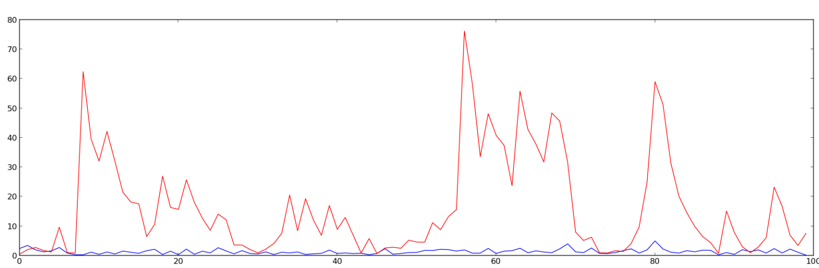


Figure 5: σ_{T_r}=0.05 $\sigma^*_{T_r}$ = 0.2 Sensor Noise= 5.0

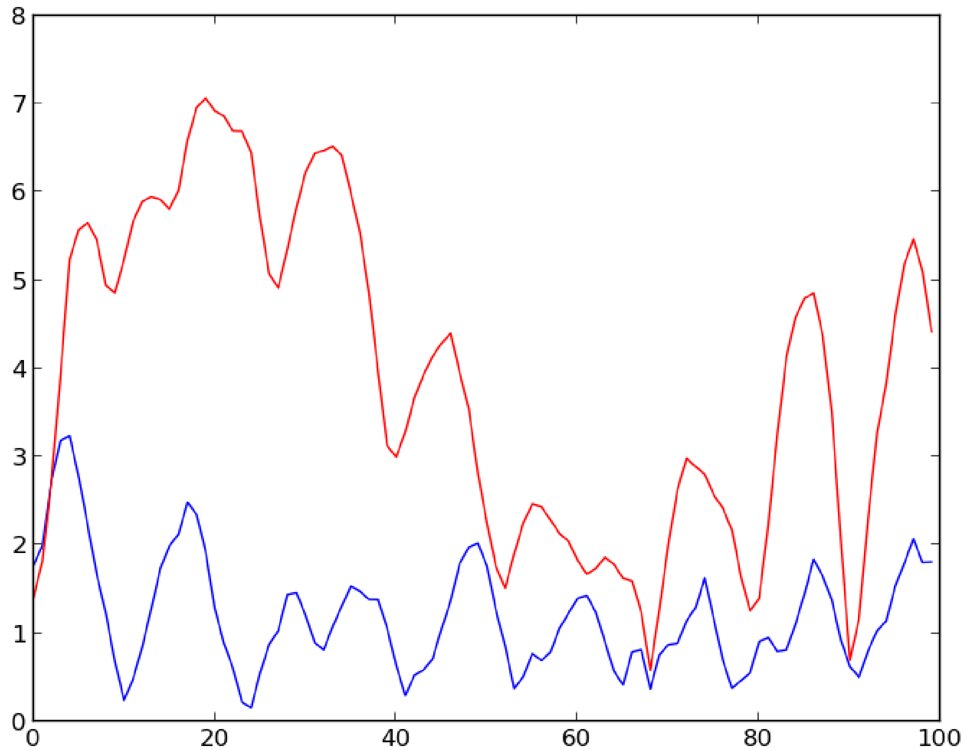


Figure 6: σ_{T_r}=0.05 $\sigma^*_{T_r}$ = 0.5 Sensor Noise= 5.0