# Efficient Mobility Prediction Techniques in MANETs

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## Motivation & Objective

**Motivation:**

**Applications of Mobility Prediction in MANETs**

-Efficient sensor energy management in sensor networks with mobile sinks.

-Communication scheduling in delay tolerant networks (DTN).

-Prioritizing the communication when there are multiple sinks.

**Objective:**

-Using the past trajectory of a mobile node, predict it's future location.

**Assumptions:**

-Mobile nodes record their own position using location-aided instruments like GPS.

-Uncontrolled mobility.

## Adaptive learning of parameters

-Performance of prediction technique depends on parameters chosen.

**MWA and Holt's LES method:**

-Minimize the sum of the errors over a constant window W of the past history, periodically with time gap $T_m$.

$$E_T = (\hat{X}_T - X_T)^2 + (\hat{Y}_T - Y_T)^2 \qquad \alpha_{opt} = argmin\left(\sum_{T=n*T_m-W}^{n*T_m} E_{T,\alpha}\right), 0 \le \alpha \le 1$$

$$(\alpha_{opt}, \beta_{opt}) = argmin\left(\sum_{T=n*T_m-W}^{n*T_m} E_{T,\alpha,\beta}\right), 0 \le \alpha, \beta \le 1$$

## Prediction Techniques

**Linear Estimation Method(LEM)**:

-Mobile node assumes continues with the same instant velocity that is there at current time($T_C$).

$$\hat{X}_{T_p} = X_{T_c} + (X_{T_c} - X_{T_c - 1}) * (T_p - T_c)$$

**Moving Weighted Average Method(MWA):**

-Future velocity is predicted as weighted average velocity, calculated using history and parameter $\alpha$ .

$$V_{T_c} = \alpha * (X_{T_c} - X_{T_c - 1}) + (1-\alpha) * V_{T_c - 1}$$

$$\hat{X}_{T_p} = X_{T_c} + V_{T_c} * (T_p - T_c)$$

**Holt's Double Exponential Smoothing Technique (Holt's LES)**:

-Calculate the variables, level $\mathbf{L_T}$ and trend $\mathbf{b_T}$ at every instance, with parameters $\alpha$ and $\beta$ .

-It considers the error at previous time instance.

$$L_T = \alpha * X_T + (1-\alpha) * (L_{T-1} + b_{T-1}) \qquad \hat{X}_{T_p} = L_T + b_T * (T_p - T)$$

$$b_T = \beta * (L_T - L_{T-1}) + (1-\beta) * b_{T-1} \qquad X_T = L_{T-1} + b_{T-1} + \varepsilon_T$$

**Kalman Filter**:

-Dynamic model is designed by assigning proper values to parameter,process noise($w_k$) and observation noise($r_k$).

-Predict the location using state space equation with process noise and the variables are updated after knowing the actual value (error).

**Predict**

$$\hat{X}_{k+1/k} = F\hat{X}_{k/k} + Bu_k + w_k$$

$$P_{k+1/k} = FP_{k/k}F^T + Q_k$$

**Update**

$$\hat{y}_{k+1} = z_{k+1} - H_{k+1}\hat{X}_{k+1/k}$$

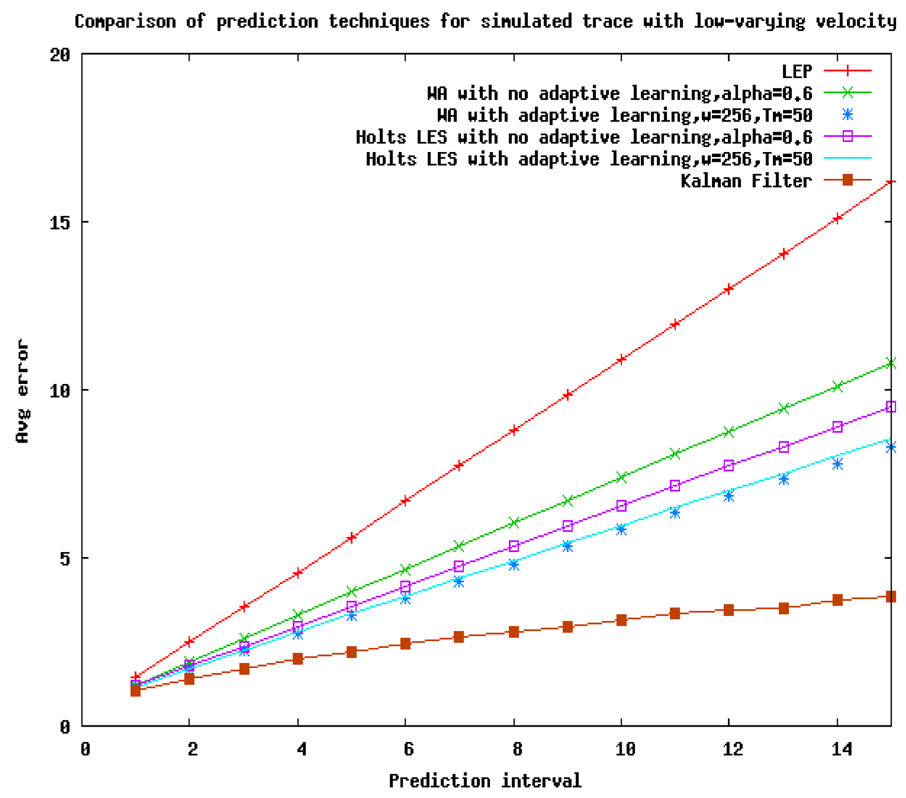
$$S_{k+1} = H_{k+1}P_{k+1/k}H_{k+1}^T + R_{k+1}$$

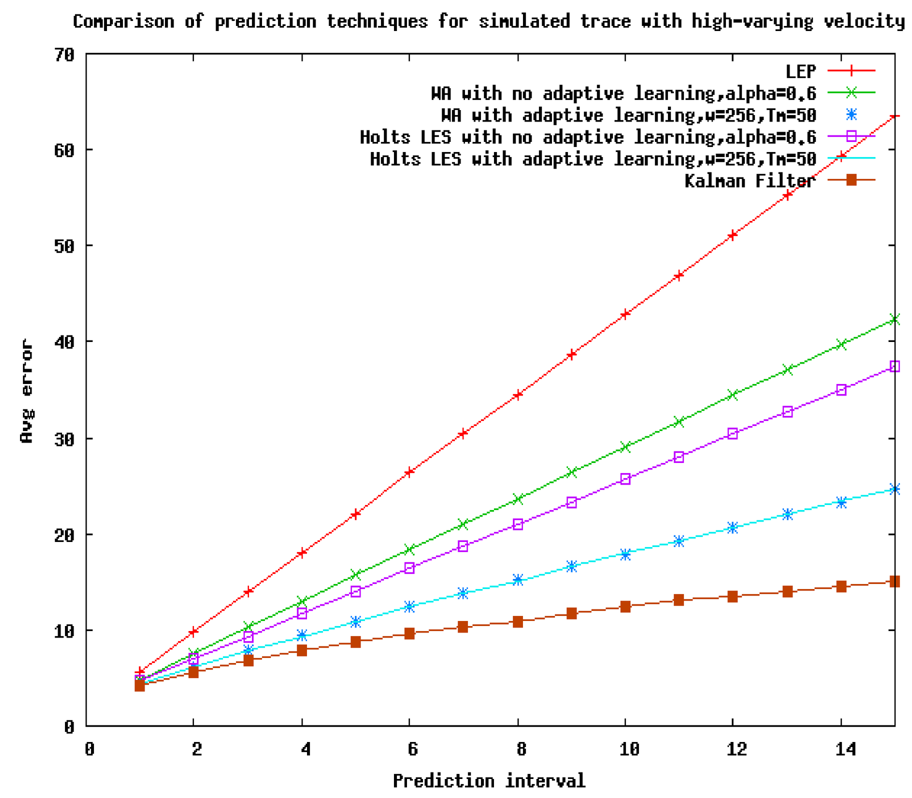
$$K_{k+1} = P_{k+1/k}H_{k+1}^T S_{k+1}^{-1}$$

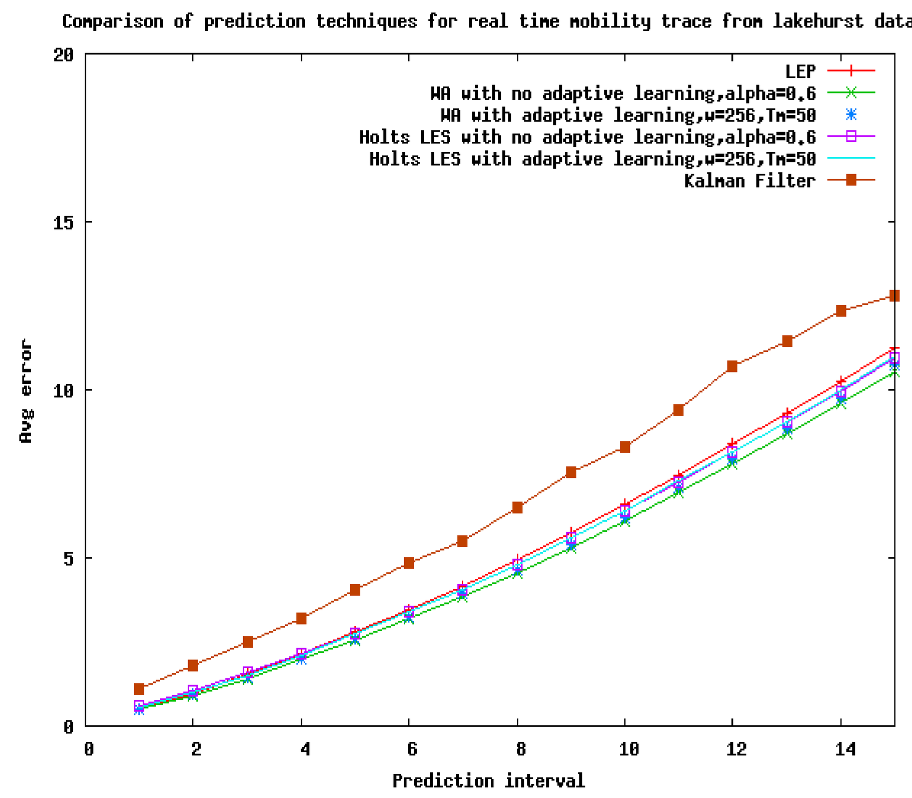
$$\hat{X}_{k+1/k+1} = \hat{X}_{k+1/k} + K_{k+1}\hat{y}_{k+1}$$

$$P_{k+1/k+1} = (I - K_{k+1}H_{k+1})P_{k+1/k}$$

## Simulation and Results




- Simulated mobility trace by random walk model
  - -Low-varying velocity-- speed(12-14), angle(45-60)
  - -High-varying velocity--speed(10-20), angle(45-90)
- Empirical mobility trace (Lakehurst data)
  - -Consists of long pause time intervals in between the motion.
- We ran all the traces for t=5001s, and used different prediction intervals (T=1 to 15 s)
- Performance metric: Average error of predicted location over time at different prediction intervals

## References

**[1]** Lynwood A. Johnson, Douglas C.Montgomery, and John S. Gardiner. *Forecasting and Time Series Analysis*. McGraw-Hill Inc 2nd edition, 1990.

**[2]** Robert R. Andrawis and Amir F. Atiya. A New Bayesian Formulation for Holt's Exponential smoothing. *Journal of forecasting*, 2009.

**[3]** Ka-Veng Yuen, Ka-In Hoi and Kai-Meng Mok. Selection of noise parameters for Kalman filter. *In Journal of Earthquake Engineering and engineering vibration*, 2007.

**[4]** K. A. Meyers and B. D.Tapley. Adaptive Sequential Estimation with unknown noise statistics. *In IEEE Tran. Automatic control*, 1976.

## Ongoing Work

**Multi-State Mobility Prediction Model**:

-Different mobile characteristics need different set of parameters to optimize the performance of prediction technique .

-Design a multi-state model by assigning a particular feature of mobile characteristics to each state.

-Each state can implement its own prediction technique and maintain its own history.

**Different methods for adaptive learning of parameters:**

- **Kalman Filter**

**Adaptive sequential estimation:**

-Noise parameters are estimated using approximated parameter values of the past [4].

**Bayesian estimation:**

-Given measurements $Y_n$ from time 0 to n. Lets say the parameter set is $\theta$. According to Bayes theorem,

$$p(\theta / Y_n) \propto p(Y_n / \theta)\, p(\theta)$$

-Select the appropriate value of $\theta$ using maximum likelihood method [3].

-This method can be extended for Holt's LES as well [2].

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