

## Track Optimization Algorithm for Automotive Telematics System

<sup>1</sup>Imran Jattala, <sup>1</sup>ShakeelDurani, <sup>1</sup>Junaid Farooqi, <sup>1</sup>Ghalib Janjua, <sup>2</sup>Mohsin Murad

<sup>1</sup>Horizon Technologies, Islamabad, Pakistan

<sup>2</sup>Umm Al-Qura University, Makkah, Saudi Arabia

E-mail: [imran.jattala@gmail.com](mailto:imran.jattala@gmail.com), [shakeel.durrani@gmail.com](mailto:shakeel.durrani@gmail.com), [junaid.farooqi@gmail.com](mailto:junaid.farooqi@gmail.com), [ghalibjanjua@yahoo.com](mailto:ghalibjanjua@yahoo.com), [mohsin\\_murad@yahoo.com](mailto:mohsin_murad@yahoo.com)

### ABSTRACT

GPS track accuracy forms the building block of automotive telematics systems. To enhance track accuracy more track points are required constraining bandwidth and data storage. This paper presents a GPS track optimization algorithm improving GPS track accuracy while maintaining low track point's count. The algorithm employs a three-step approach; wild-point reckoning, adaptive Kalman filter, and adaptive track-point reduction. Wild-point reckoning method truncates huge deviation in geo-points. Adaptive Kalman filter further reduces error covariance within GPS data. Track-point reduction optimizes tracking points in GPS data, based on two variables distance and angle, between trackpoints. The algorithm is adaptive to vehicle speed and precision of the GPS receiver to making it universal applicable. The algorithm enhances the efficiency of tracking/telematics system and simultaneously reducing DB requirement. The algorithm is a part of the device firmware of Secure Automotive Telematics System (SATS).

**Keywords:** GPS, Wild-point reckoning, Adaptive Kalman filter, Moving average filter, Track point reduction.

## 1. INTRODUCTION

Global positioning system (GPS) has now become a household device since its inception in 1973 [1]. GPS is used to obtain geographic location on grid of latitude and longitude around the globe. GPS receivers are readily available and provide accurate location information. GPS receivers in addition also provide GMT time, date and speed information [2]. A majority of GPS receivers update the location data typically at a rate of 1 Hz [3]. Automotive navigation and tracking algorithms make use of this capability of GPS receivers, for the purpose of plotting an accurate track of an automotive on a GIS grid. The accuracy of track plotted on a GIS grid is of great importance especially in urban tracking [4].

Embedded processors used in automotive tracking devices generally come with limited memory and computing resources. Therefore the tracking algorithms used in these devices is simplified versions of the actual tracking algorithms. Most of the tracking algorithms used in GPS based navigation devices and vehicle tracking devices, are either distance travelled or vehicle speed based [5]. Adaptive Kalman filter is used in track simplification for handheld navigational devices [6].

The optimization algorithm for vehicle GPS tracking needs to be highly robust in order to adapt to the varying GPS receiver accuracy and changing vehicle speed. The optimization algorithm for automotive tracking/telematics system has been developed accounting for:

- Optimization of computational intensity of the algorithm for embedded devices,
- Significant data reduction to facilitate fast data transmission and optimize bandwidth usage,
- Capability of real time tracking,
- Optimization of the GPS track plot.

### 1.1 Secure Automotive Telematics System (SATS)

Secure Automotive Telematics System (SATS) is based on Sierra Wireless M2M Processor AirPrime Q2687 [7]. SATS is a vehicle telematics/tracking system with additional functionalities of on-board diagnostics OBD-II interface and secure communication protocols. Track optimization algorithm presented in this paper, is incorporated in the SATS vehicle device.

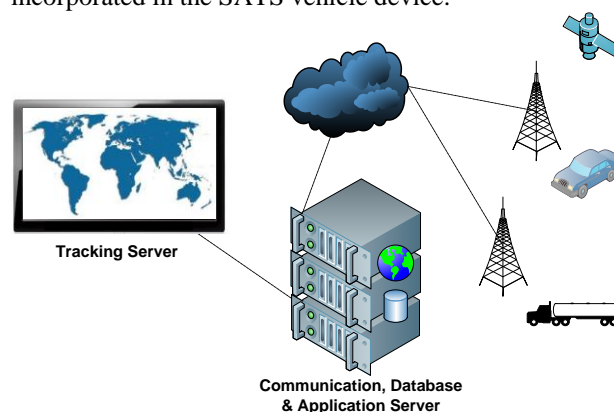


Figure 1: Secure Automotive Telematics System – Architecture.

### 1.2 SATS Device

SATS device is a vehicle telematics unit that provides vehicle position and status data to central server. SATS device acquires position data from GPS and vehicle data from OBD-II interface and transmit this info over GPRS/SMS to the server. The developed SATS device was extensively tested & trialled across Pakistan for GPS track path analysis. The track optimization algorithm running at the heart of SATS device produced optimized track, thus reducing the communication & storage data loads from SATS servers. The SATS device board design is shown in Fig. 2.

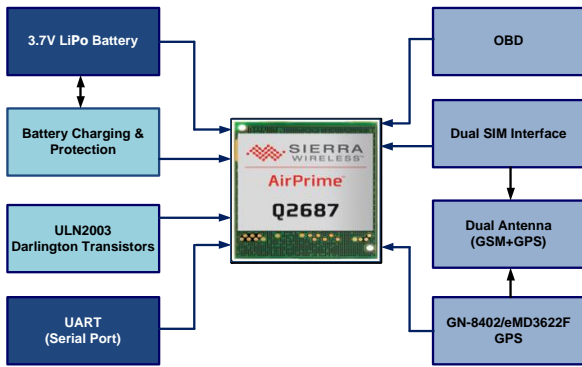


Figure2: SATS Device Board Design & Prototype SATS Device

A plastic casing was developed for SATS prototype. Final SATS product was housed in a ruggedized aluminum case. The SATS prototype device is shown in Fig. 3.

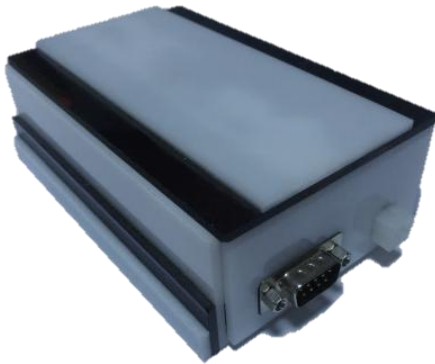


Figure3: SATS Device Board Design & Prototype SATS Device

## 2. DESCRIPTION OF TRACK OPTIMIZATION ALGORITHM

Track optimization algorithm is based on a three-step approach first wild-point reckoning technique, second adaptive Kalman filtering [8], and third track-point reduction technique. The developed algorithm optimizes the GPS track, by intelligently filtering erroneous points while preserving the overall track shape integrity. The algorithm is adaptive to GPS accuracy and vehicle speed. The algorithm reduces the number of points that form the vehicle track.

Wild-point reckoning technique is a novel idea, designed & developed for track optimization algorithm. Wild-point reckoning is used to truncate huge deviation in geo-points present in GPS data. Therefore invalid (wild) points are filtered out before localized GPS errors are smoothed using adaptive Kalman filter. Kalman filter minimizes the errors in GPS data and exact position of vehicle is estimated.

Track point reduction works on the basis of distance and angle between two geographic points. The distance and angle thresholds are adaptively updated on the basis of vehicle speed and bearing. The track point reduction

ratio can reach up to 50% reduced points as compared to the original track depending upon the shape of the track and speed of the vehicle. Flowchart of the Algorithm is presented below in Fig. 4.

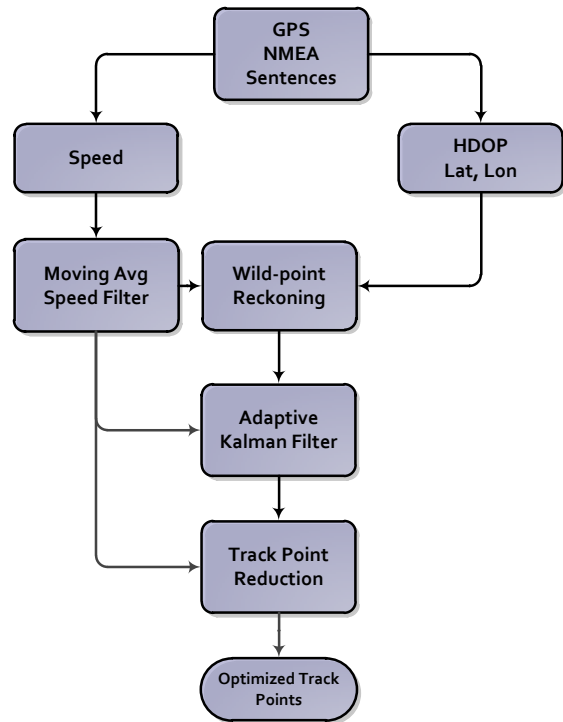


Figure 4: Track Optimization Algorithm.

### 2.1 Wild-Point Reckoning

The accuracy of a GPS receiver is highly dependent on the number of satellites visible and received signal strength. Horizontal dilution of precision (HDOP) is a measure of the accuracy of the GPS receiver [9]. We have estimated (through experimentation) the value of HDOP for vehicular application to be less than 3.50. The distance travelled by a vehicle at a speed of 200 Km/hr (maximum speed bound set for computation simplicity) in one second is 55.55 meters. To achieve GPS accuracy in a radius of 55.55 meters, error coefficient  $E_0$  value of 10 is used.

$$E_0 = 10, \quad (1)$$

$$E_n = E_0 * HDOP \quad (2)$$

Where  $E_n$ , is the acceptable precision radius in meters, of GPS points. Generated GPS points are only accepted if  $E_n$  is less than 55.55. The new point in the track is admitted on the basis of vehicle speed. Algorithm is adaptive to the vehicle speed for the admission of a new point into the track. The vehicle speed values are filtered in order to remove spikes from the data. Algorithm implements a three point moving averages filter to obtain a smooth speed value [10].

Moving average filter is a low-pass filter, employed for filtering the speed fluctuations. The transfer function

(H(z)) of the second order moving average filter is given by:

$$H(z) = \frac{1}{3} * \left( \frac{z^2 + z + 1}{z^2} \right) \quad (3)$$

The  $\hat{V}_n$ , moving averages filtered speed is given by:

$$\hat{V}_n = \frac{(X[n] + X[n-1] + X[n-2])}{3} \quad (4)$$

The most critical error in GPS data is “wild” points. These points occur at very low GPS precision (low HDOP) or when tracking satellites are switching at very high rate. The algorithm ensures complete filtration of such points which degrade the quality of the GPS track. A wild-point reckoning technique is proposed & developed. The wild-point reckoning technique effectively tracks the position of new GPS point included in the track, and reckons a wayward point within a radius  $R_w$  and angle  $\alpha_w$ . The reckoning radius and angle computed on the basis of vehicle speed and angle of the course traversed by that vehicle [11].

The algorithm is designed for vehicle tracking and a GPS point is assumed “wild” which occur outside the radius of 55.55 meters from last valid GPS point assuming maximum speed of 200 km/h. The algorithm instead of filtering a wild-point out of the track, reckons it into a valid track point based on a point-distance-angle calculation. Wild-point dead reckoning calculation is:

$$R_w = 55.55 \text{ Meters} \quad (5)$$

Where,  $R_w$  is the radius of the threshold distance to detect an expected wild-point. If point  $P_2$  is detected as wild-point, than that point will be replaced with the reckoned point. The dead reckoned point distance and angle are computed as

$$d_w = d_2 + (d_2 - d_1) \quad (6)$$

$$\alpha_w = \alpha_2 + (\alpha_2 - \alpha_1) \quad (7)$$

Where  $d_1$  is the distance between point  $P_0$  and  $P_1$ ,  $d_2$  is the distance between point  $P_1$  and  $P_2$ , and  $d_w$  is the reckoned wild-point distance. And  $\alpha_1$  is the bearing of point  $P_1$ ,  $\alpha_2$  is the bearing of  $P_2$ , and  $\alpha_w$  is the reckoned wild-point bearing.

The reckoned point latitude, longitude is computed as:

$$Lon_w = Lon_2 + d_w * COS(\alpha_w) \quad (8)$$

$$Lat_w = Lat_2 + d_w * SIN(\alpha_w) \quad (9)$$

Where,  $(Lon_2, Lat_2)$  are the coordinates of last valid point, and  $(Lon_w, Lat_w)$  are the coordinates of the reckoned wild-point. Thus, the wild point will be replaced by point  $(Lon_w, Lat_w)$ . The wild-point reckoning technique is represented in Fig.5. The technique ensures that every new GPS point admitted into the track is valid or reckoned close to valid point.

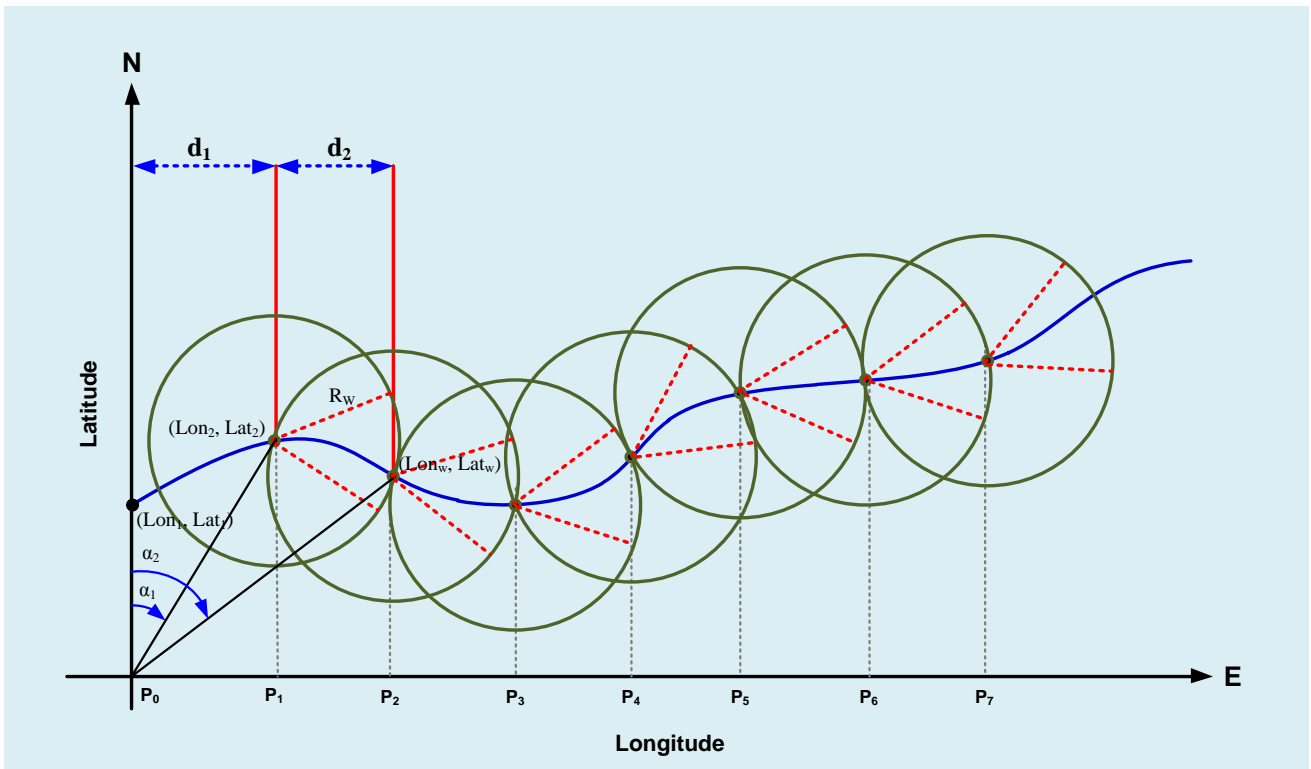


Figure5: Wild-point Reckoning Technique.

## 2.2 Adaptive Kalman Filter

Kalman filter provides a best estimate of the system state variable from a given discrete linear system and its noisy state variable measurements. Kalman filter assumes that the current state of a system is derived from previous state of system in discrete step intervals. This predictor-estimator is optimal in the sense that it minimizes the estimated error covariance. The adaptive Kalman filter implemented is more accurate vehicle positioning method than the conventional used methods [12].

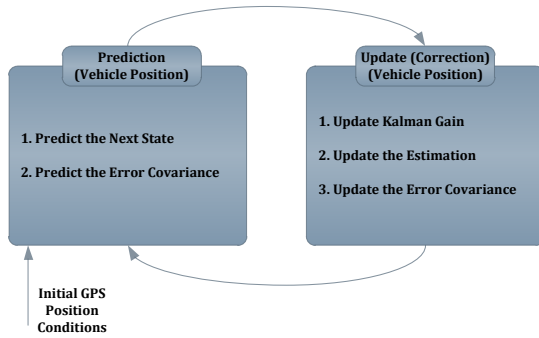


Figure 6: Kalman Filter – Flowchart.

In automotive telematics/tracking systems one of the main sources of error in GPS data is due to transition from fix-GPS state to unfix-GPS state and vice versa. This type of error in GPS position data (latitude & longitude) can be minimized by filtering data through an adaptive Kalman filter. The filter is adaptive to noise variance  $r$  with limits  $(r_{\min}, r_{\max})$  in GPS data [13]. The value of  $r$  is computed adaptively depending on the vehicle speed:

$$\Delta V_n = \text{floor}(\hat{V}_n / 4) \quad (10)$$

$$r_n = r_{\min} \text{ if } \hat{V}_n > 70 \text{ km/h} \quad (11)$$

$$r_n = r_{\max} - ((r_{\max} - r_{\min}) / 4) \text{ otherwise} \quad (12)$$

The value of  $r$  is computed again only if there is variation in speed and:

$$\Delta V_n \neq \Delta V_{n-1} \quad (13)$$

The Kalman filter equations are listed below.  
Initialization:

$$P_0 = 0, P_0^- = 1.0, K_0 = 0, \hat{x}_0 = z_0, \quad (14)$$

$$r = r_{\min}, \hat{X}_0^- = z_0, q = 1.0, \quad (15)$$

Prediction (Estimation):

$$\hat{X}_k^- = \hat{X}_{k-1}, P_k^- = P_{k-1} + q \quad (16)$$

Update (Correction):

$$K_k = \left( \frac{P_k^-}{(P_k^- + r)} \right) \quad (17)$$

$$\hat{X}_k = \hat{X}_k^- + K_k (z_k - \hat{X}_k^-) \quad (18)$$

$$P_k = (1 - K_k) * P_k^- \quad (19)$$

Where priori state estimate of the system is  $\hat{X}_0^-$  at time step  $k$ , and posteriori state estimate of the system is  $\hat{X}_k$  at time step  $k$ .  $P_k$  is priori estimate error covariance matrix and posteriori estimate error covariance matrix is  $P_k^-$  at time step  $k$ .  $Z_k$  is measured GPS position data,  $K_k$  is Kalman filter gain, and  $q$  is noise variance of the system.

The Kalman filter minimizes the error covariance in GPS position data and a fine track path is obtained [14]. The quality enhancement of a GPS track path is a big value addition to the telematics/tracking system.

## 2.3 Track-Point Reduction

Optimization of the memory in embedded controllers used in automotive telematics/tracking systems is of primary importance thus reduction in track points also plays a critical role to achieve this objective. To realize this goal track point reduction method is implemented in this algorithm that works on the basis of straight path distance traveled and the curve angles traversed [15].

The developed point reduction computation technique is based on the straight line distance travelled and heading angle (from north) between the last three successive GPS points. Point  $P_1$  is the last point entered in the track, than the angle traversed by the vehicle while travelling from point  $P_0$  to  $P_2$  is  $\gamma = |\alpha_2 - \alpha_1|$  [16]. If  $\gamma \geq \gamma_{TH}$  than the point belongs to the track.  $\gamma_{TH}$  updated adaptively depending upon the vehicle speed by the equation :

$$\gamma_{TH} = \gamma_{\min} \text{ if } \hat{V}_n > 45 \text{ km/h} \quad (20)$$

If Vehicle speed is greater than 45 km/h the angle threshold is re-computed as:

$$\gamma_{TH} = \gamma_{\max} - ((\gamma_{\max} - \gamma_{\min}) / 45) * \hat{V}_n \quad (21)$$

On a straight path in a track if the distance travelled is greater than  $d_{Th}$  the point is included in the track regardless of the angle traversed, thus reducing the number of points on a straight track. The value of distance threshold  $d_{Th}$  is adaptively updated on the basis of vehicle speed along the path.

$$d_{TH} = d_{\min} \text{ if } \hat{V}_n > 40 \text{ km/h} \quad (22)$$

If Vehicle speed is greater than 45 km/h the distance threshold is re-computed as:

$$d_{TH} = d_{\max} - ((d_{\max} - d_{\min}) / 40) * \hat{V}_n \quad (23)$$

The track point reduction technique is adaptive to the vehicle speed and a degree of point reduction is achieved on vehicle speeds greater than 40 km/h. The track-point reduction technique is shown in Fig. 7. The track-point reduction technique removes redundant points from the GPS track on the basis of distance & angle threshold.

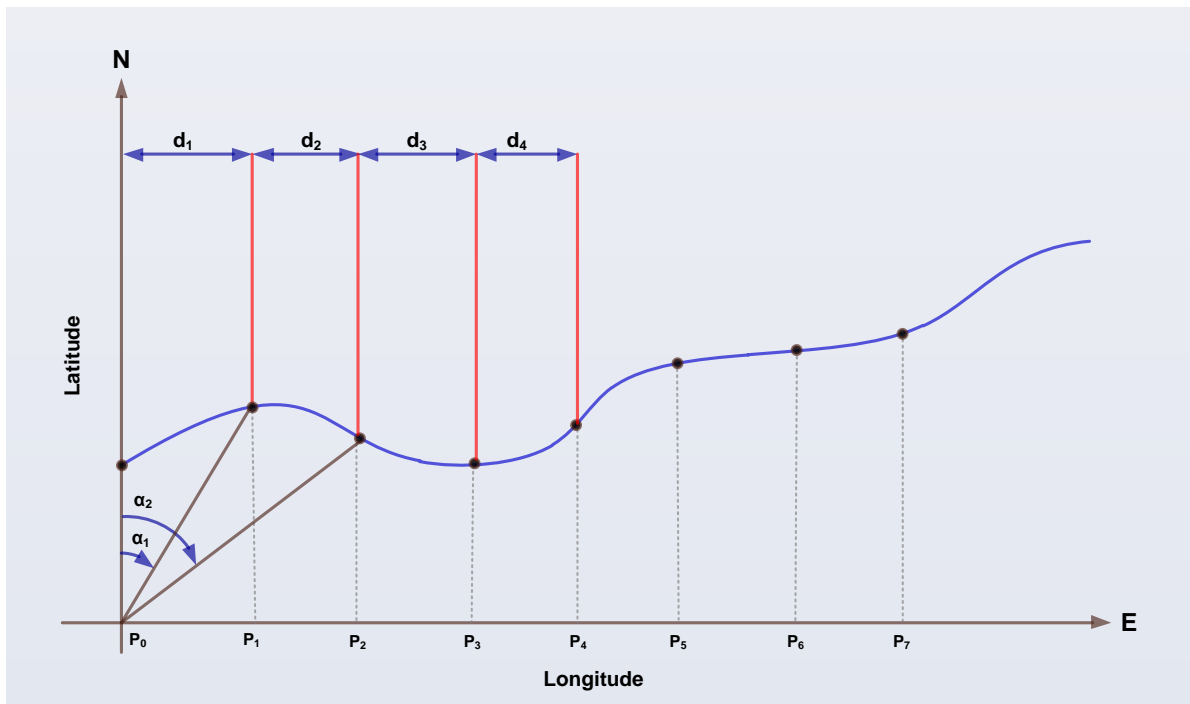


Figure7: Track-point Reduction Technique.

### 3. TEST & TRIAL RESULTS

The track optimization algorithm (TOA) was modelled in Matlab. A testing track was selected in Islamabad, Pakistan for TOA testing and evaluation. The selected track is along a curved path on the Margalla Hills of Islamabad. GPS data points at a frequency of 1Hz were logged for the testing track. The GPS used for data logging was eMD3622F from eRide. The GPS track data was fed into Matlab and a virtual testing environment was created for the development & testing of track optimization algorithm for telematics system. The speed of the vehicle along the track was extracted. The track selected for the testing is shown Fig. 8.

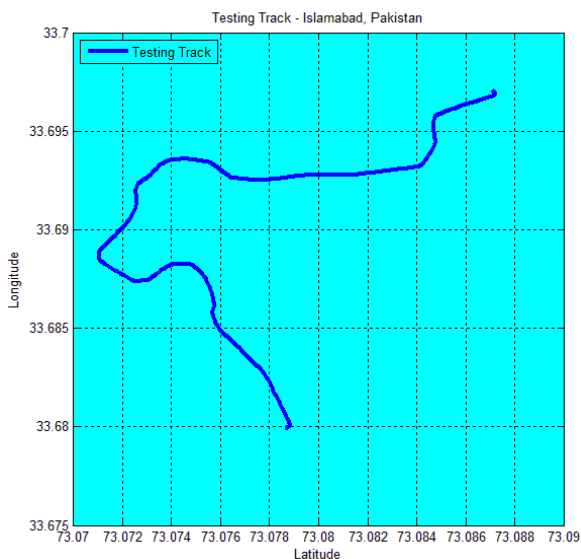


Figure8:Track Optimization Algorithm Testing Track.

The HDOP values for complete track were extracted and number of satellites in view was also analyzed for possible causes of errors in GPS data. The number of GPS satellites in view varied along the testing track but the GPS fix state was maintained by GPS receiver. The variation in the GPS Speed values were smoothed by moving averages filter. Moving averaged speed data along with HDOP filtered position data was fed to Kalman filter.

The spikes in the speed data can lead to invalid calculations. The percentage speed variation is shown in the Fig. 8. There can be spikes of up to 50% of the values of the speed. This type of data should be filtered before using it for some deterministic calculations.

A three point moving averages filter is applied to the speed values to smoothen the speed curve. Moving average filter filters abrupt acceleration & deceleration variations in the speed data, reducing the error covariance and enhancing the performance margin for next stage filter i.e. the Kalman Filter.

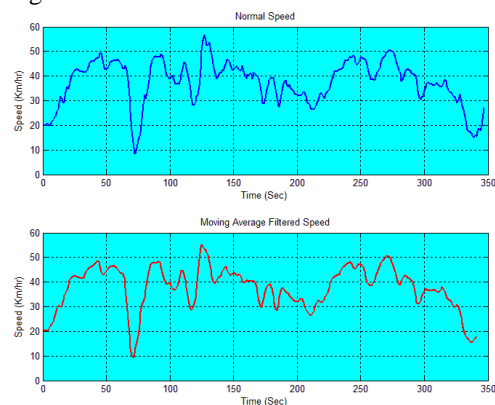


Figure9: Moving Average Filtered Speed.



©2012-13 International Journal of Information Technology and Electrical Engineering

The moving averages filtered data has reduced variation in the speed values as shown in Fig. 10.

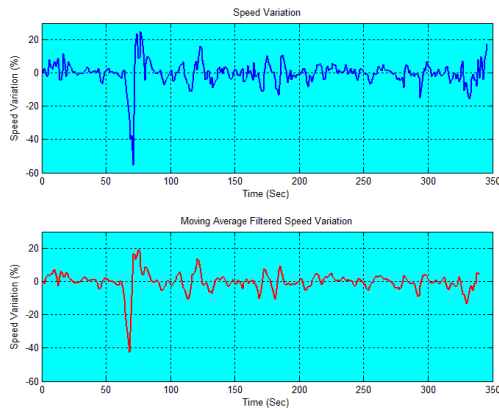


Figure 10: Speed Variation on the Testing Track.

Adaptive Kalman extracts actual position values from measured erroneous values and initial state conditions. Adaptive Kalman produces a track plot conforming very closely to the actual location of the vehicle on the road. A smooth track plot is achieved as a result of the Adaptive Kalman filter. The Kalman filtered GPS track points are shown in the Fig. 11.

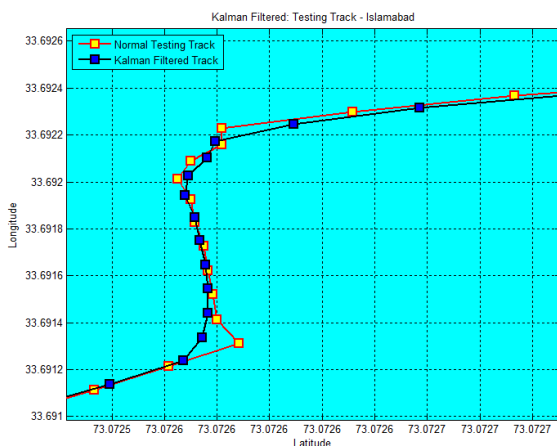


Figure 11: Normal & Kalman Filtered Testing Track

Finally point reduction is applied to reduce the data points while maintaining the original shape of the track. The distance travelled along a straight path produces redundant points without improving the quality of the GPS track. Therefore a distance threshold is computed in Point reduction technique to filter the redundant track points. Similarly Point reduction technique computes an angle threshold to filter track points not required at curves part of the GPS track.

The testing track selected has most of its part along a curved path; therefore angle threshold played a leading role in the application of Point reduction technique on this track. The track point reduction technique is based on the distance and angle thresholds and employ's Haversine Formula for this computation [17]. The track point reduction results in reduction of communication

bandwidth and DB storage requirements. The track Point reduction technique resulted in GPS track, similar in shaped to the testing track with a benefit of 26% reduction in track points. The track point reduction technique is shown in Fig. 12.

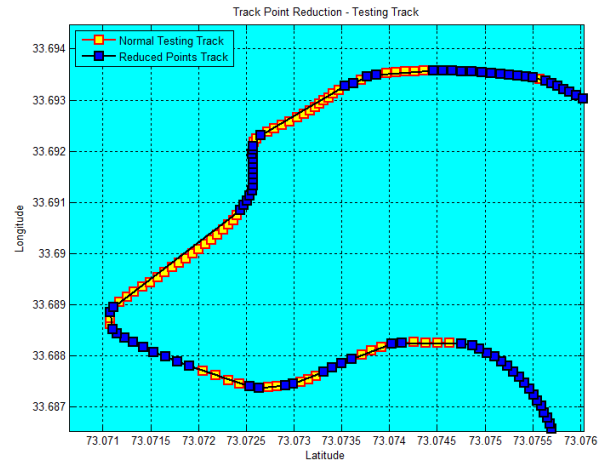


Figure 12: Point Reduction in Test Track.

The track optimization algorithm was incorporated in a Secure Automotive Telematics System (SATS) and a resultant Google Maps based GPS track is shown in Fig. 13.

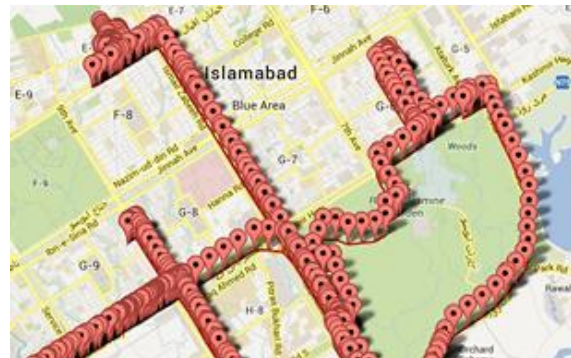


Figure 13: Google Maps plot of SATS with TOA.

#### 4. CONCLUSION

The paper describes a new approach in handling wild points improving the quality of a GPS track. The algorithm not only filters invalid values but also reckons the wild-points to valid points. Leading to an optimized GPS track, concurrently this quality enhancement is achieved with a reduction in GPS data. Track optimized is further augmented with wild-points dead reckoning improving error covariance. This reduced error covariance provides better margin to the adaptive Kalman filter producing better output. The point reduction technique reduced the number of points from the track without affecting the resolution of the GPS track. The presented algorithm is a part of automotive telematics system running on an ARM9 based processor.

**REFERENCES**

- [1] L.B. Slater, "From Minitrack to NAVSTAR: The early development of the global positioning system, 1955–1975," *IEEE MTT-S International Microwave Symposium Digest (MTT)*, 2011, pp.1-4, 5-10 Jun. 2011.
- [2] M. M S. Grewel, Lawrence R. Weill, and Angus P. Andrews, *Global Positioning System, Inertial Navigation and Integration*, pp.68-73, 1<sup>st</sup> ed., New York: John Wiley & Sons, 2001.
- [3] M.Z.H. Bhuiyan, H. Kuusniemi, Liang Chen, L. Ruotsalainen, Ling Pei, R. Guinness, and Ruizhi Chen, "Utilizing building layout for performance optimization of a multi-sensor fusion model in indoor navigation," *International Conference on Localization and GNSS (ICL-GNSS)*, 2012, pp.1-6, 25-27 June 2012.
- [4] E. Denaxas, S. Mpollas, D. Vitsios, C. Zolotas, D.G. Bleris, G.M. Spanos, and N.P. Pitsianis, "Real-time urban traffic information extraction from GPS tracking of a bus fleet," *IEEE Symposium on Computational Intelligence in Vehicles and Transportation Systems (CIVTS)*, 2013, pp.58-63, 16-19 Apr. 2013.
- [5] M. Lashley, D.M. Bevy, and J.Y. Hung, "Performance Analysis of Vector Tracking Algorithms for Weak GPS Signals in High Dynamics," *IEEE Journal of Selected Topics in Signal Processing*, , vol.3, no.4, pp.661-673, Aug. 2009.
- [6] Xiufeng He, Yang Le, and Wendong Xiao, "MEMS IMU and two-antenna GPS integration navigation system using interval adaptive Kalman filter," *IEEE Aerospace and Electronic Systems Magazine*, , vol.28, no.10, pp.22-28, Oct. 2013.
- [7] Imran Jattala, Shakeel Durani, Junaid Farooqi, Ghalib Janjua, Ambreen Shafique, Faisal Hussian, Hassan Mehmood, and Nassar Ikram, "Secure Automotive Telematics System (SATS)" *Eight International Conference on Digital Information Management, 2013. ICDIM 2013.*, 10-12 Sep. 2013.
- [8] Jian Wang, Jiang Liu, and Bo-gen Cai, "Study on Information Fusion Algorithm in Embedded Integrated Navigation System," *International Conference on Intelligent Computation Technology and Automation (ICICTA)*, 2008, vol.2, pp.1007-1010, 20-22 Oct. 2008.
- [9] Yaohong Qu, Jizhi Wu, and Youmin Zhang, "Cooperative localization based on the azimuth angles among multiple UAVs," *2013 International Conference on Unmanned Aircraft Systems (ICUAS)*, pp.818-823, 28-31 May 2013.
- [10] Y. H. Tsai, F. R. Chang, and W. C. Yang, "GPS fault detection and exclusion using moving average filters," *IEE Proceedings on Radar, Sonar and Navigation*, vol.151, no.4, pp.240-247, Aug. 2004.
- [11] Il Soo Cho, "GPS/dead-reckoning combination system and operating method thereof," U.S. Patent 7 286 933, Oct. 23, 2007.
- [12] M. Zahaby, P. Gaonjur, and S. Farajian, "Location tracking in GPS using Kalman Filter through SMS," *IEEE EUROCON 2009, EUROCON '09.*, pp.1707-1711, 18-23 May 2009.
- [13] Rosen Ivanov, "Real-time GPS track simplification algorithm for outdoor navigation of visually impaired." *Journal of Network and Computer Applications*, vol.35, no.5 pp.1559-1567, 2012.
- [14] Y.H. Ho, S. Abdullah, and M.H. Mokhtar, , "Global positioning system (GPS) positioning errors modeling using Global Ionospheric Scintillation Model (GISM)," *IEEE International Conference on Space Science and Communication (IconSpace)*, 2013, pp.33-38, 1-3 Jul. 2013.
- [15] Dewang Chen; Yun-Shan Fu; Baigen Cai; Ya-Xiang Yuan, "Modeling and Algorithms of GPS Data Reduction for the Qinghai-Tibet Railway," *Intelligent Transportation Systems, IEEE Transactions on*, vol.11, no.3, pp.753,758, Sept. 2010.

- [16] Rosen S. Ivanov, "On-line GPS Track Simplification Algorithm for Mobile Platforms" *Journal of Information Technologies and Control*, Vol.2, No.1, 2010.
- [17] Z.U.A. Lodhi, A. Basit, A.F. Khan, A. Waheed, and M. Nasir, "Sensor Fusion Based Data Parser of a GPS Receiver for UAV Systems," *Second International Conference on Instrumentation, Measurement, Computer, Communication and Control (IMCCC)*, 2012, pp.95-99, 8-10 Dec. 2012.

**AUTHOR PROFILES**

**IMRAN JATTALA** received his BE degree in Electronics from Air University, Islamabad, Pakistan in 2006. He has an industrial experience of more than 7 years in embedded systems development while working with public and private sector organizations in Pakistan. He is currently pursuing MS in Electrical Engineering. His research interests include Embedded Systems, Fleet Management, Telemetry Systems and Inertial Navigation Systems, and Ballistic Computers.

**SHAKEEL DURRANI** received his B.Sc. degree in Electrical from Lafayette College, Pennsylvania, USA in 2001. He has more than 12 years of experience in managing large project teams both within the public and private sector. He is currently establishing a Cyber Security Operations Center, encompassing Network security (multiple Vendor security appliances), Digital/Network Forensic, and Security Monitoring Operations under a comprehensive Security Information and Event Management (SIEM) solution. His research interests include Embedded Systems, Cyber-security, Information Assurance, ICT, and Network Security.

**JUNAID FAROOQI** received his BE degree in Electronics from Sir Syed University of Engineering and Technology, Karachi, Pakistan in 2006. He has an MS degree in Electrical Engineering from UET Taxila, Pakistan 2013. He has an industrial experience of more than 7 years in embedded systems development while working with public sector organizations in Pakistan. His research interests include Embedded Systems, WSN, Fleet Management, and Telemetry Systems.

**GHALIB JANJUA** received his BE degree in Electrical Engineering from University of Engineering and Technology (UET), Taxila, Pakistan in 2008. He is pursuing his MS degree in Electrical Engineering from NUST, Pakistan. His research interests include Embedded Systems, WSN, and GSM Jammers.

**MOHSIN MURAD** received his B.Sc. degree in Computer Engineering from UET, Peshawar, Pakistan in 2009. He obtained his MS degree in Computer Engineering from UE, Peshawar, Pakistan 2011. He has been a lecturer at UET, Peshawar. He is currently a lecturer at Umm al-Qura University, Makkah, Saudi Arabia. His research interests include WSN, RFID, Embedded Linux, and .net Programming.