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Improving the Reliability of GPS and GLONASS Navigation Solution in Urban Canyons Using a Tuned Kalman Filter

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Urban canyon is categorized as a hard environment for the positioning of a dynamic vehicle due to low number and also bad configuration of in-view satellites. In this paper, a tuning procedure is proposed to adjust the important factors in Kalman Filter (KF) using Genetic Algorithm (GA). The authors tested the algorithm on a dynamic vehicle in an urban canyon with a hard condition and compared the results with traditional KF and Weighted Least Square (WLS) methods. The outputs showed that this algorithm could be 114% and 61% more reliable than WLS and traditional KF.

Keywords*:*GPS, GLONASS, Urban canyon positioning, Kalman filter, Weighted least square

Introduction

Urban canyons are critical environments where many of the transmitted signals are blocked by buildings, trees and other tall objects. As a result, the Global Positioning System (GPS) as the most high-usage satellite-based navigation system has many challenges for accurate and reliable positioning. In such a situation, reducing the satellite visibility and weakening the geometric configuration above the receiver are the most important causes of unreliable GPS solutions [1-4].

GPS integration with other Global Navigation Satellite Systems (GNSS) such as the European Galileo and the renewed Russian Global Navigation Satellite System (GLONASS) is one of the possible approaches to increase the number of visible satellites and accordingly the accuracy of the receiver output. GLONASS augmentation to GPS is more popular, because it will be worldwide [5,6].

After extracting the ephemeris data from the received GPS and GLONASS signals, it is the time of position calculation by making relationship between the unknown parameters and the distance of the satellites from the receiver which is called the pseudo-range. Least Square (LS) method is the simplest approach to find the solution to this problem. In this method, solutions are time independent and calculations do not consider the last results which make the results vulnerable in urban canyons with a lot of noise and weak availability of the satellite [7-9].

In order to increase the reliability of the results, some receivers use Weighted Least Square (WLS) which weighs the satellite information according to the properties. How to weigh and model the satellite information is the subject of many papers. For example, Ref. [10] compared the results of different WLS models and showed that the proposed one which is based on sigma exponential weighting can improve the results by more than 50%.

On the other hand, in dynamic urban canyon scenarios, we need a navigation solution algorithm in which previous solutions can be effective on the

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present one. Kalman Filter (KF) is a recursive method which can estimate the system state using state space principle and system error modeling. In this method, the unknown state of a dynamic system is calculated by minimizing the mean-squared error at discrete real time intervals [11].

The traditional KF method is vulnerable to different error sources and unpredictable time to adapt the effective matrices which this vulnerability makes the convergence time longer than usual. In Ref. [12], a KF-based algorithm which is adapted with Genetic Algorithm (GA) is proposed to reduce errors in differential GPS receivers.

These days, shadow matching techniques [13] and integration with other navigation sensors such as Inertial Measurement Units (IMUs) [14-16] are the popular urban canyon navigation solution methods being discussed by different researchers. But the problems common among these methods are the hard calibration process and requirements of expensive tools.

The purpose of this paper is proposing a pre-adoption process to tune KF-based method and then comparing the output results with WLS and traditional KF for GPS and GLONASS integrated receiver mounted on a dynamic vehicle. Here, the focus is on “reliability” which refers to the consistency of the results provided by the system.

This paper is organized as follows; at first the basic principles will be reviewed in section 2 and then, the suggested algorithm is proposed in section 3. In sections 4 and 5, the data collection setup and the experimental results will be discussed, respectively. Finally, conclusion will be provided in section 6.

Basic Principles

Paper basic principles including GPS and GLONASS integration for positioning in urban canyons, WLS and KF methods for navigation calculation and GA for the purpose of optimizing the method parameters will be discussed in this section.

GPS and GLONASS Integration

GPS-only mode for positioning suffers from low reliability in urban canyons despite the GPS high accuracy in positioning and navigation in usual conditions. Signals from low-elevation-angle satellites are likely to be blocked by buildings. Besides, high-elevation-angle satellites are few and do not have good configuration. This is illustrated in Fig.1.

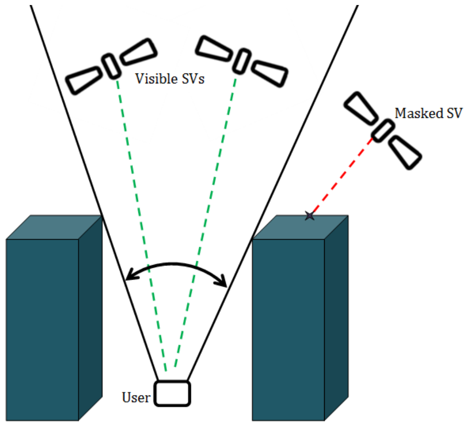


Figure.1. Satellite blocking in urban canyons.

In this condition, augmentation with GLONASS will help the situation by increasing the number of satellites and improving the configuration. This will lead to more satellite availability and accessibility and as a result, more accuracy and reliability of the solutions. Fig. 2 shows that in GPS-only mode, there are just 5 satellites in view and this has been increased to 9 after augmentation with GLONASS.

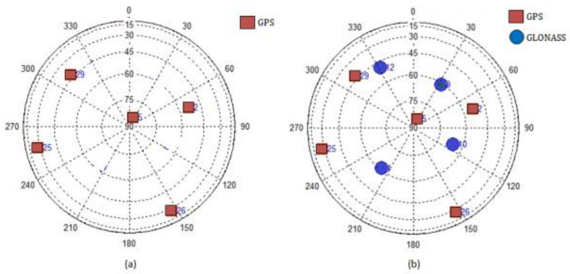


Figure2. Sky plot of (a) a GPS-only receiver and (b) a GPS and GLONASS integrated receiver.

GPS and GLONASS are similar with some differences in constellations and signals. The nominal number of GLONASS satellites is 24 but GPS constellation is configured with 32 active satellites. The Frequency Division Multiple Access (FDMA) structure of GLONASS signals makes its receiver different from GPS ones with Code Division Multiple Access (CDMA) algorithm [17-20].

WLS for GNSS Navigation Solution using Pseudo-Range Measurement

In GPS and GLONASS integration, five unknown parameters should be calculated in navigation solutions process. So, the state vector is as follows:

$$\vec{X} = \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta z \\ \Delta t_{GPS} \\ \Delta t_{GLO} \end{bmatrix} \quad (1)$$

Where $\Delta x, \Delta y, \Delta z$ are the updating values of the position. Δt_{GPS} and Δt_{GLO} also represent the receiver clock offsets with respect to GPS and GLONASS times, respectively.

In WLS method, the solution can be obtained as:

$$\vec{X} = \left(A^T\ W\ A\right)^{-1} A^T\ W\ \vec{L} \quad (2)$$

Where A is the design matrix and W is the weighting matrix with n×n dimensions. W is diagonal and its elements are signal variances which can be calculated as bellow:

$$w_i = \frac{\sigma_0^2}{\sigma_i^2(n)} \quad (3)$$

In which σ_i and σ_0 are the i[th] observation and reference variances, respectively. L is also the observation vector with n rows and each row is the difference of measured pseudo-range and the actual range between the satellite and the receiver position [21].

Kalman Filter

KF algorithm uses the measurement vector, measurement model and system model to maintain optimal estimations of the state vector.System propagation and measurement update are the main steps of a KF. The forward state vector and error covariance are predicted in the system propagation phase and they are corrected using new measurement in the measurement-update phase. These steps are summarized as following:

Step 1: Initialize the state vector and state covariance matrices X_0^- and P_0^- .

Step 2: Compute Kalman gain matrix:

$$K = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1} \quad (4)$$

Where P_k^- is the priori state covariance matrix, H_k is the observation model matrix and R_k is the observation noise covariance matrix.

Step 3: Update the state vector:

$$X^+{}_k = X_k^- + K(Z - HX_k^-) \quad (5)$$

In which Z is the measurements vector. X_k^- and X_k^+ are named as priori state estimate vector and posteriori state estimate vector, respectively.

Step 4: Update the error covariance:

$$P^+{}_k = [I - K_k H_k] P_k^- \quad (6)$$

Where P_k^+ is the posteriori state covariance matrix.

Step 5: Predict new state vector and state covariance matrix:

$$X^-{}_{k+1} = \phi_k X^+{}_k \quad (7)$$

$$P^-{}_{k+1} = \phi_k P^+{}_k \phi^T{}_k + Q_k \quad (8)$$

That ϕ_k is the state transition model matrix and Q_k is the process noise covariance matrix [22,23].

Genetic Algorithm

GA is an approach based on the principles of genetics and natural selection. Although GA cannot always provide an optimal solution, it has its own advantages. GA starts with an initial population of random members with N_{pop} chromosomes and continues based on specified rules to minimize the cost function. The main operators of GA are as following:

- Selection: The task of this operator is selecting a set of chromosomes with the highest fitness to survive to the next generation.
- Crossover: It creates offspring from the selected chromosomes.
- Mutation: This operator randomly mutates some members.

The described process is iterated until an acceptable solution is found [24,25].

Proposed method

In order to design a KF, it is important to select appropriate values for process noise covariance matrix 'Q_k' and observation noise covariance matrix 'R_k'; because these matrices have significant roles in the performance of KF. As it is clear, Kalman gain is affected by R. So, if R is too large, Kalman gain will be too small and state estimation will be slow to converge to the true value or it will respond slowly to the changes in the system. Conversely, if R is too small, Kalman gain will be too large. So, the recent measurements have more influence on the estimation state in the update phase which may result in unstable estimation.

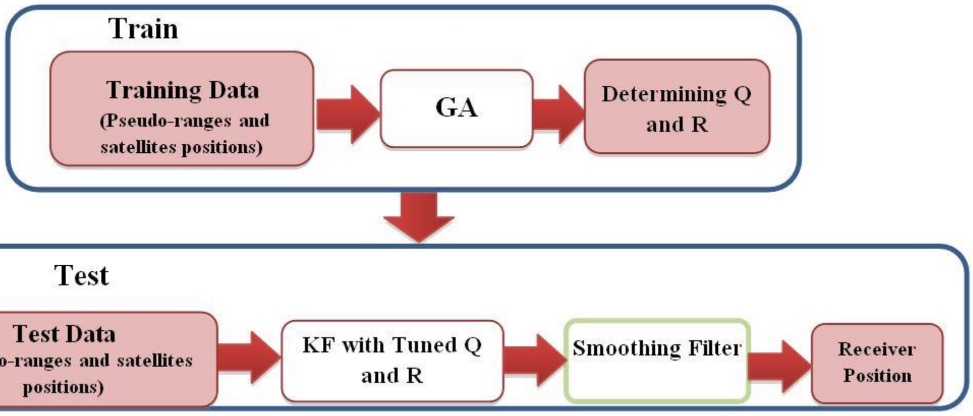
In this paper, GA is used for pre-setting the optimal parameters of KF. It means that the performance of KF will be better if we obtain the best values of ‘Q’ and ‘R’ using GA before vehicle movement starting. The first step to achieve this goal is defining a proper fitness function. The aim of this paper is to optimize the whole KF parameters. We defined a fitness function containing all the specifications of KF performance as Eq. (9).

$$Fitness \quad Function = RMS * STD * MAX \tag{9}$$

That RMS is Root Mean Square of positioning error, STD is Standard Deviation and MAX is the Maximum error of positioning. Minimizing the defined fitness function improves the KF performance.

For the training purpose, the vehicle stops or moves in a known position point or trajectory for a short period of time and GA will adopt the optimization parameters simultaneously. After this pre-adopting process, the vehicle equipped with the optimized receiver can start the movement in the unknown path.

In all these epochs, the navigation results are smoothed using a Wavelet Transform (WT) filter. The simple block diagram of the stages discussed is presented in Fig. 3.



Figuer 3. Proposed algorithm

Hardware and Software Setup

A designed front-end board consists of MAX2769 with an ALTERA FPGA core for controlling was used for data collection. The received signals were sampled and digitalized by the front-end and transported to a data recording laptop. All other processes were performed in MATLAB-based software which was designed as GNSS software receiver. Fig. 4 is a simplified block diagram of this setup and Fig. 5 shows how the hardware setup was mounted on the test vehicle.

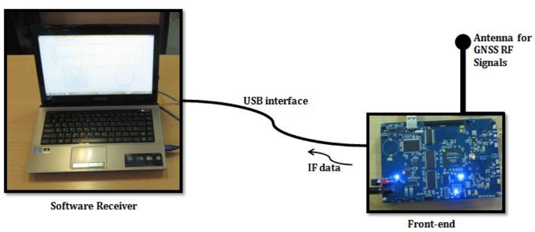


Figure4. Hardware and software setup.

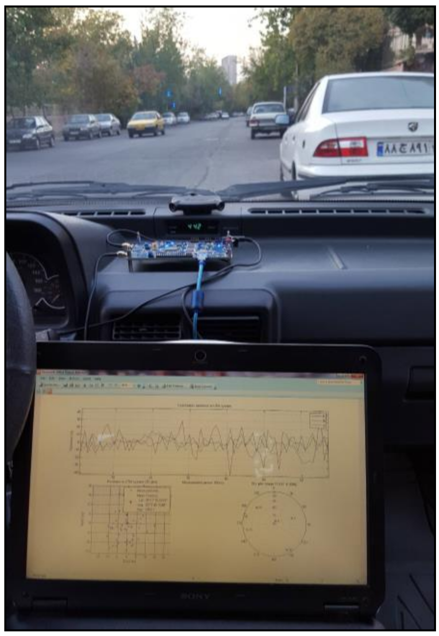


Figure 5. Mounting the hardware on the test vehicle.

(Continuation) Figure5. Mounting the hardware on the test vehicle.

Experimental Results and Discussions

The GPS and GLONASS antennas were mounted on the roof of a test vehicle and data collection was performed in IUST campus where the view to the sky was blocked by buildings and trees. The car velocity was about 20 km/h. Fig. 6 shows the test trajectory.

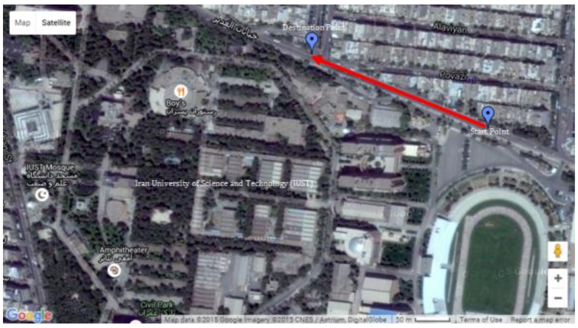


Figure6. Data collection position

The configuration and the number of satellites above the receiver were not as good as predicted because of the tall buildings and trees beside the test trajectory. This is obvious in the sky plot of the receiver shown in Fig. 7. In this condition, the receiver could lock only on 3 GPS and 2 GLONASS satellites which were less than 4 and it was not a sufficient number for 3D position calculation in GPS-only and GLONASS-only systems. Additionally, the total number of visible satellites exceeded the least condition and therefore the integrated receiver could find the position.

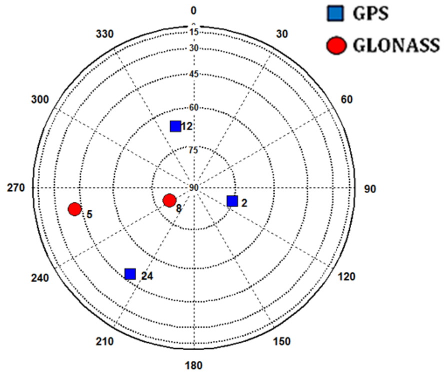


Figure7. Sky plot of the receiver in the test time

High Geometric Dilution of precision (GDOP) factor is another proof for demonstrating the abnormal satellite configuration which will lead to high error in the output results. The average GDOP value for the period of data collection is 12.08. The status of Carrier to Noise Ratio (C/N_0) is also unsuitable because of tall trees and buildings beside the path. Table 1 shows the C/N_0 value for the test case.

Table 1. C/N_0 values.

Constellation	GPS			GLONASS	
# Satellite	1	2	3	4	5
C/N_0	30.10	30.04	28.45	30.34	26.98

So, the receiver had to be supported by a powerful navigation solution algorithm which could cope with this hard condition. The first 20 epochs of received data were used for GA training and then the algorithm was tested using 100-epoch dynamic scenario. The initial population in GA process was 50 members and selection rate was 50%. Heuristic crossover method was also used and random numbers substituted the members in mutation process. All these rates and populations were selected through trial and error. In order to smooth the results, the daubechies 4 (db4) mother wavelet in 5 levels were also utilized [26].

After the test stage, the positioning results for the three discussed methods were plotted on Google map as shown in Figs. 8 and 9. As it is obvious, the divergence of KF in the start period of movement led to high error results. Furthermore, tuned KF could converge to the correct positions rapidly due to the pre-adoption using GA. WLS method could also find the position in a short time, but with a lower accuracy.

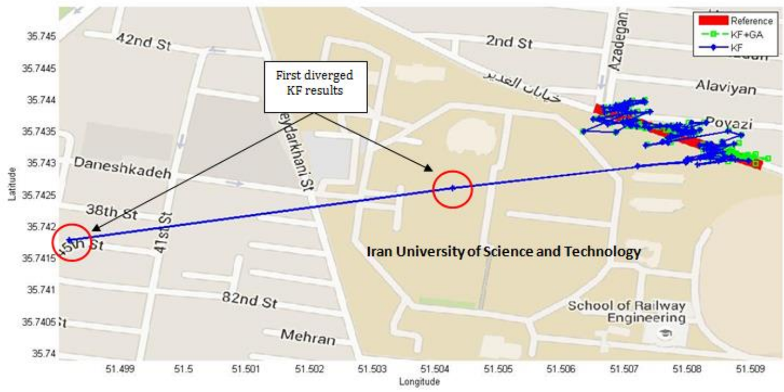


Figure 8. Position estimation by KF and KF tuned by GA on Google map

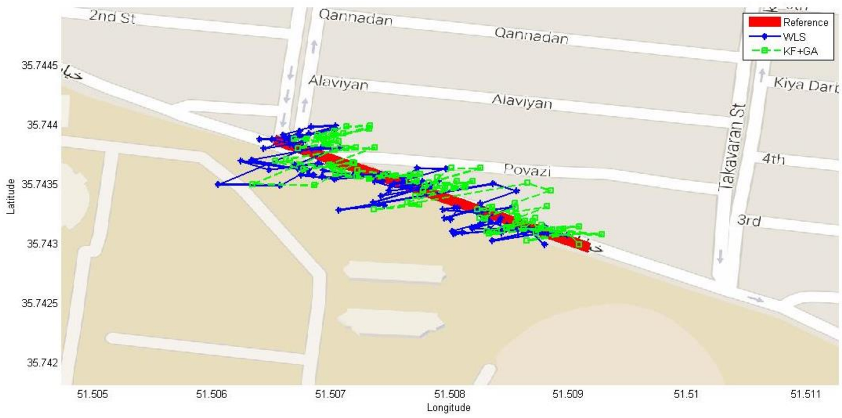


Figure 9. Position estimation by WLS and KF tuned by GA on Google map.

The convergence time comparison of the algorithms is much more distinct in Fig. 10. As it is shown, KF output got to an acceptable boundary after about 20 epochs, whereas tuned KF was in this range from the beginning of the test movement. It should be noted that the convergence time is not defined in WLS method because every epoch is calculated independently. However, its output results are in the acceptable range, but with a higher error than that of tuned KF.

Fig. 11 also depicts the histogram of the result errors for the test scenario. In these histograms, every bin shows the number of 10-period of meter error. For example, the first bins are the number of epoch with errors between 0 to 10 meters which are 0, 19 and 10 for WLS, KF and tuned KF methods, respectively. As it is shown, the traditional KF has bins in high error parts, whereas the bins of WLS and tuned KF have gathered in the low error parts of histogram. This is because of slow convergence speed in traditional KF.

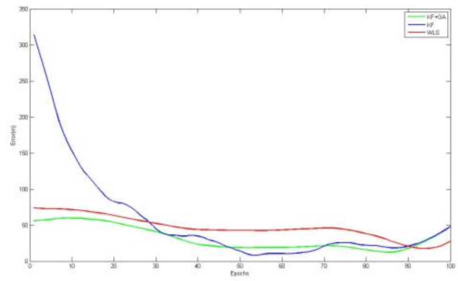


Figure 10. Error comparison

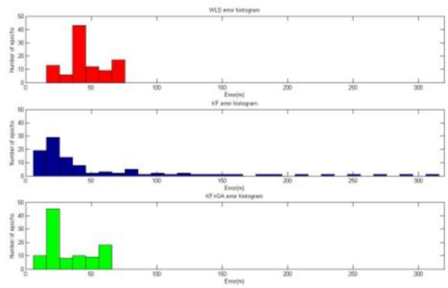


Figure11. Histogram of errors for the three discussed methods

For the purpose of comparison, three discussed methods were examined and RMS, STD and MAX errors were recorded. It should be noted that, 2D RMS error was calculated as in Eq. (10).

$$RMS = \sqrt{\frac{1}{M}\sum_{1}^{M}[(x_{predicted} - x_{real})^2 + (y_{predicted} - y_{real})^2} \quad (10)$$

Where M is the number of data-base epoch.

The other comparison factor is Availability which is the percentage of epochs when the position error is less than an acceptable threshold. In this paper, a 20-meter error is selected as the threshold. The output results of the discussed methods are reported in Table 2 in which availability is the availability of the system.

We define the reliable system as the system with lower STD, MAX and RMS error and with a higher availability. As it is obvious in Table 3, the proposed algorithm could improve the traditional KF results more than 61.9% and its results were more than 114.9% better than those of WLS method. So, it can be concluded that it is more reliable than two other methods.

Table 2. Result comparison for discussed methods

Method / Parameter	WLS	KF	KF+GA
STD	11.08	43.67	12.76
MAX	73.91	313.80	59.71
RMS	49.20	86.97	35.77
Availability	7%	27%	37%

Table 3.KF+GA improvements over traditional KF and WLS

Parameter	Improvement rather than WLS (%)	Improvement rather than traditional KF (%)
STD	-15.16	70.78
Max	19.21	80.97
RMS	27.30	58.87
Availability	428.57	37.04
Average	114.98	61.92

Conclusion

Position estimation in urban canyons with low visible angle to the sky is a challenging problem which can become softer by GPS and GLONASS integration. In this condition, selecting a suitable navigation solution algorithm for a dynamic vehicle with an acceptable reliability is the other question that the authors tried to answer in this paper. Two popular methods, WLS and KF, for positioning were compared with an improved KF with a proposed pre-tuning. The reported experimental results for a dynamic car in a distinct trajectory showed that the proposed methods could calculate the output results with 114% and 61% higher reliability than WLS and traditional KF, respectively.

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