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Proposed Integrated Artificial Intelligence Techniques & Extended Kalman Filter in Marine Navigation of Unmanned Surface Vehicles

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Abstract: This paper proposed implementation of an Artificial Intelligence (AI) techniques and its potential business value in the context of enhancing Inertial Navigation System (INS). Albeit Global Positioning System (GPS) has wide used to enhance unmanned surface vehicle navigation systems, GPS can't offer continuous and dependable navigation systems among the sight of signal blurring and in addition blockage. At the beginning of presence of the Micro-Electro-Mechanical System (MEMS), a slight effort MEMS INS/GPS integration system enhanced route execution by combining the GPS exactness with the transient INS precision. This paper proposed smart information combination and handling procedures for such an easy mix framework by fusing the Artificial Intelligence (AI) with the Extended Kalman filter (EKF). It also introduces the action of applying a class of kernel-based technique called LS-SVM to support GPS/INS integration. In distinction to other methods, the SVM, which might be characterized by the convex optimization issues, has been improve in the field of statistical learning theory and systemic risk minimization. An experimental has been tested in the Mediterranean Sea, Alexandria. The implementation results show that the proposed technique enhanced the navigation system while the GPS outage by reducing the errors by 60%-75% during the 600m suggested trajectory. Generally, the paper results affirm the advantages and preferences of using the AI techniques with EKF to aid the minimal effort of GPS/MEMS-INS mix in Navigation System.

Key words: AI · GPS · MEMS-INS · EKF · SVM · USV

INTRODUCTION

Different applications of USV/UUV/AUV are used in marine navigation either on surface or underwater. GPS can be utilized for a route framework for most applications on the world's surface, however its signal isn't accessible for submerged and indoor regions. INS can be applied for route framework in such situations, yet it has error increment after some time [1]. This paper demonstrates technique used to update and enhance the navigation system of USV as soon as GPS becomes outage. It also proposed smart information combination and handling procedures for such an easy mix framework by fusing the AI with the EKF. Where EKF comprises of a low speed filter and a high-speed filter. The high-speed filter combines information from Real Time Kinematic (RTK) GPS and INS. This combination considered to insulate the noise and increase the accuracy and precision [2 - 3].

Some AI techniques has some disadvantages, such as the presence of several local minimum solutions and the struggle in selecting the number of hidden units such as; NN [3]. This paper presents the LS-SVM regression technique and the employment of a LS-SVM/EKF combined approach for GPS/INS fusion. The LS-SVM metric is used to precise the INS mistakes through GPS inaccessible, depend on the patterning accomplished from the proceed training once GPS is existing.

Navigation System Structure: Multi sensor frameworks can give more dependable and exact route arrangements by integrating repetitive or correlative data. The most ordinarily utilized route sensors in navigation framework applications incorporate GPS, INS and magnetic compass. GPS can give great long-haul route precision yet is restricted by the prerequisite of no less than three noticeable GPS satellites [4-5].

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The principle part of the navigation framework is GPS and MEMS-INS mobile to give the ceaseless navigation arrangement when GPS moves toward becoming blackout and limit mistakes of MEMS-INS framework when GPS is accessible. The navigation framework comprises of GPS, MEMS-INS subsystems and the KF. KF is used to evaluate the MEMS-INS position errors in light of GPS estimations. Global position framework (GPS) is a mainstream navigation framework. Coordinated GPS with MEMS-INS mobile sensors, topersistent navigation arrangement when GPS is out-age and limit mistakes of MEMS-INS framework when GPS is accessible. It can give worthy position data anyplace when there is an immediate viewable pathway to at least four satellites. In any case, it experiences the ill effects of the signal blackout in urban zone and underwater, where signals from the satellite can be blocked [6].

Inertial Navigation System (INS): INS is a strategy for navigating, that decides the status of stirring vehicle utilizing movement sensors without relying upon outside sources (satellite). Conditions of the vehicle allude to location, speed and direction of the vehicle. INS are utilized in aircrafts, ships, steered rockets and AUVs. INS is an autonomous framework that contains three-hub accelerometers and gyroscopes; put along the three commonly symmetrical bearings that fit for estimating vehicle liner speeding up angular velocity. Most smart mobiles contain numerous Micro-Electro Mechanical System (MEMS) sensors, for example, GPS, accelerometer, gyroscope, compass and altimeter, mugginess et cetera. Be that as it may, one of the disservices of these sensors is; their low precision [7]. These detriments of GPS and MEMS-INS can be reduced by joining strategies. GPS is integrated with INS to give the ceaseless navigation arrangement amid GPS blackout [2 - 25].

MEMS-INS System: MEMS-INS mobile sensors comprise of three gyroscopes and three accelerometers. The gyroscope sensors are utilized to decide angular rates (p, q and r) that utilization to decide attitude (□, θ, ψ). The accelerometer sensors are utilized to decide increasing speeds (a_x, a_y, a_z) that utilization to decide velocities (U, V, W) in the Vehicle Coordinating System (VCS) [5]. The attitude uses to discover the Direction Cosine Matrix (DCM) that is utilized to change over the vehicle speeds from VCS to Navigation Coordinating System (NCS) [8 - 9].

The Euler angles are utilized to express the connection between VCS and NCS [8]. The connection between the angular rates (p, q and r) and Euler angles is given by Eq. (1) beneath, [10]:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi/\cos\theta & \cos\phi/\cos\theta \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{1}$$

By integration of Eq. (1), we can arise that; the Euler angles uses primary situations of an identified attitude (□, θ, ψ). By a given time, the accelerations of the vehicle with the 3 frame axes are delivered by the MEMS-INS mobile accelerometers [24]. The initial velocities and angular rates are all obtainable as conditions. The acceleration because of gravity (*g*) is provided as a relation of position around the ground [11] and then *U*, *V* & *W* are given by:

$$\begin{aligned} \dot{U} &= a_x + rV - qW + g\sin\theta \\ \dot{V} &= ay - rU + pW - g\cos\theta\sin\phi \\ \dot{W} &= a_z + qU - pV - g\cos\theta\cos\phi \end{aligned} \tag{2}$$

By integration of Eq. (2), we can derive that thevelocities use primary situations of an identified attitude (U, V, W). At a specified time, The Direction Cosine Matrix [10] is given by DCM equal:

$$DCM = \begin{bmatrix} \cos\theta\cos\psi & \cos\theta\sin\psi & -\sin\theta \\ \sin\theta\sin\phi\cos\psi - \sin\psi\cos\phi & \sin\psi\sin\theta\sin\phi + \sin\psi\cos\phi & \sin\phi\cos\theta \\ \sin\theta\cos\phi\cos\psi + \sin\psi\sin\phi & \sin\phi\sin\theta\cos\phi - \sin\psi\cos\phi & \cos\phi\cos\theta \end{bmatrix} \tag{3}$$

DCM is used to convert Velocities (U, V, W) on VCS frame to North-East-Up (V_N, VE and V_U) that fame as follows Eq. (4):

$$\begin{bmatrix} V_N \\ V_E \\ V_U \end{bmatrix}_{INS} = DCM^T \begin{bmatrix} U \\ V \\ M \end{bmatrix}_{INS} \tag{4}$$

Since GPS is used as an updating and correcting the source of MEMS-INS System. It uses a geodetic frame (latitude, longitude and altitude). Letting ?, μ and □ represent the latitude, longitude and altitude of the vehicle at any instantaneous, respectively. Then the amount of variation of latitude, longitude and altitude (λ, μ) is given by Eq. (5) below:

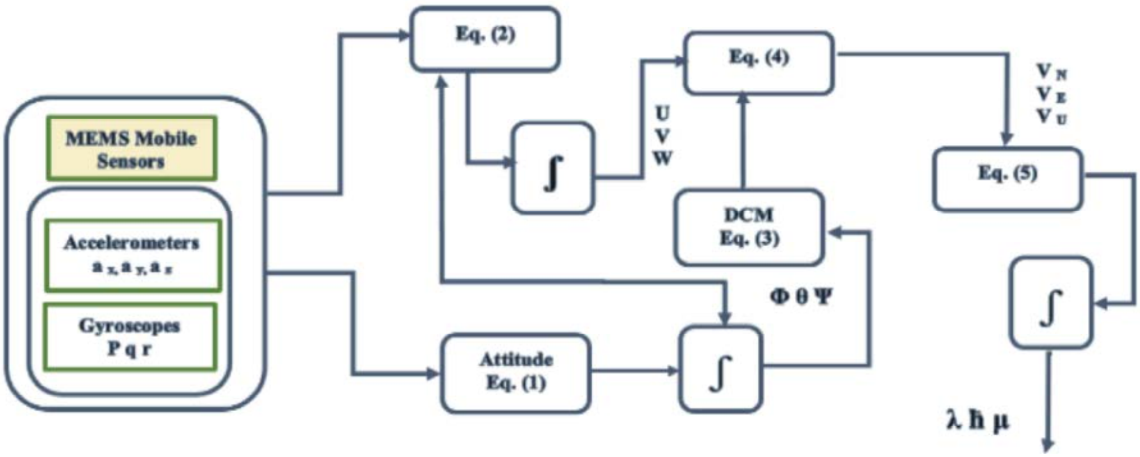

Fig. 1: Block diagram of MEMS-INS equations

$$\dot{\lambda} = \frac{V_N}{R_E}, \quad \mu^{\cdot} = V_E / (R_E cos \lambda), \quad {}' = V_U \tag{5}$$

By integration Eq. (5), giving the position (?, μ, □) in geodetic frame by using the initial condition of a known position at a given time. A block diagram representation of MEMS-INS equations is shown in Figure 1.

Kalman Filter: The Kalman filter is an assessment algorithm that works recursively depend on the preceding evaluations and previous information. It comprises of two phases, the prediction phase and the update phase [12]. In the prediction phase, the vector ($\hat{x}k$) and the error covariance matrix (Pk) at the beginning of the current interval (k) are expecteddepend on the information's got from the preceding epoch (k-1), it is given by Eq. (6) below [13]:

$$\hat{x}\overline{k} = f(k, \hat{x}_{k-1}^{+}) \tag{6}$$

where $f(k, x)$ is the integral of dynamics matrix.Error covariance matrix (Pk) is given by Eq. (7) below:

$$P_k^- = F_{k-1} P_{k-1} F_{k-1}^T + Q_k \tag{7}$$

where F_k denotes the system dynamics matrix and Qk is a spectral density matrix. In the update stage, Kalman gains (K_K) that is given by Eq. (8) below:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + R_k)^{-1} \tag{8}$$

where H_K is an observation matrix and R_k is the measurement matrix of noise. The state vector ($\hat{x}_k$) is then updated using the following Eq. (9):

$$\hat{x}_k^+ = \hat{x}_k^- + K_k z_k - h(k, \hat{x}_x^-) \tag{9}$$

where zk is the measurement vector and $h(k, x)$ is the integral of the matrix ofobservation (H_K). The error covariance matrix is then updated using the following Eq. (10):

$$P_k^+ = P_k^- - K_k H_k P_k^- \tag{10}$$

The previous information for example; the matrix of transition (□$_k$), shaping matrix (G_k), the matrix of observation (H_k), noise covariance matrix (Q_k)and measurement noise matrix (R_k) required to be measuredby the beginning of the experiment.

The matrix of transition (Φ_k) can be extended by means of the Taylor's series expansion. It is given by Eq. (11) below:

$$\Phi_k = \exp(F_{k-1} T_i) \approx I + F T_i \tag{11}$$

where $I$is the identity matrix and T_i is time varying. The noise matrix (Q_K) is given by Eq. (12) below:

$$Q_k diag(n_{rg}^1 I_3 n_{ra}^2 I_3 0_3 n_{bad}^2 I_3 n_{bdg}^2 I_3) T_i \tag{12}$$

where I_3 is a (3 x 3) the matrix of identity, n^2_{rg} is the power spectrum density (PSD) of angular rate error, n^2_{ra} is the PSD of the speed error, n^2_{bad} is the PSD of bias unbalance of accelerometer and n^2_{bgd} is the PSD of bias unbalance of gyroscope. The matrix of observation (H_k) is given by Eq. (13) below:

$$H_k = \begin{pmatrix} 0_3 0_3 - I_3 0_3 0_3 \\ 0_3 - I_3 0_3 0_3 0_3 \end{pmatrix}_k \quad (13)$$

where 0_3 is a (3 x 3) Zero matrix. The shaping matrix (G_k) is given by Eq. (14) below:

$$G_k = \begin{pmatrix} C_b^n & 0_3 \\ 0_3 & C_b^n \\ 0_{9x3} & 0_{9x3} \end{pmatrix} \quad (14)$$

where C_b^n is rotating matrix, to convert errors of the INS frame (b) to the navigation frame (n). The matrix of noise measurement (R_k) is the main square of measurement noise (v_k). It is given by Eq. (15) below:

$$R_k = E(v_k, v^T_k) \quad (15)$$

Extended Kalman Filter (EKF): The non-linear functions lead to non-Gaussian distributions, so the KF is not applicable anymore. This paper expanded the Kalman Filter to non-linear structure form to have approximate filter – the Extended Kalman Filter (EKF). This is done by discovering out an approximate error structure that is linear and employing the Kalman filter to this error system. As the EKF is got by a linear approximation of a nonlinear system. However, for many systems, the EKF has proven to be a useful method of obtaining good estimates of the system states [14].

This paper proposed smart information combination and handling procedures for such an easy mix framework by fusing the AI with the EKF. Where EKF comprises of a low speed filter and a high-speed filter. The high-speed filter combines information from Real Time Kinematic (RTK) GPS and INS. This combination considered to insulate the noise and increase the accuracy and precision [14].

In the state-space model, the error of the state vector and estimation vector are evaluated.The dynamic System ($\dot{x}k$) of EKF model is given by Eq. (16) below:

$$x_k = f(\hat{x}_k) + G_k w_k \quad (16)$$

where w_k is the procedure noise of INS and the estimation vector (z_k) of EKF model is given by Eq. (17) below:

$$z_k = h(\hat{x}_k) + v_k \quad (17)$$

Table 1: States of the integration EKF

State	Definition	Coordinate system
1 – 3	Position error	NED
4 – 6	Velocity error	NED
7 – 9	Attitude error	NED
10 – 12	Accelerometer error	b-frame
13 – 15	Gyro error	b-frame

As the essential of an integrated structure, the integration of EKF has to be sensibly designed. A 15-state EKF is used for the experiments reported in this paper, with the states listed in Table 1 [3]. The inertial measurement unit (IMU) sensor errors are the several measure reason errors, biases, non-orthogonally errorsand noise terms.

GPS/MEMS-INS Integrated System: Traditionally, MEMS-INS and GPS can be tied through various methods, namely; loosely and tightly coupled integration [15, 16,17]. Using the loosely coupled integration, data from the GPS is provided back to support and enhance the MEMS-INS system, but every one of them keeps its own specific data processing technique during the exchange procedure. While in the tightlycoupled integration, the integration is “deeper”; because raw measurements are directly combined system in a suitable filter. In this paper, the loosely coupled GPS/MEMS-INS integration strategy is used to provide a continuous navigation solution when GPS becomes outage and minimize errors of MEMS-INS system when GPS is available. It is shown in Figure 2.

The main advantage of the loosely coupled strategy; it has minor sizes of the state vectors in the filter, then it takes a short time and high-speed processing [18-19]. Additional benefit of this algorithm is the calculation simplicity of its implementation. The weakness of loosely coupled integration is that; the GPS receiver requires in any case three satellites to evaluate the navigation resolution in height-constrained method. In urban, indoor areas and underwater surface GPS signal maybe become weak or unavailable that effect on the accuracy of the loose integration method. Therefore, GPS signal must not be outage for a long time [7, 20, 21].

The Least Squares Support Vector Machine (LS-SVM): LS-SVM is a new class of kernel-based techniques support GPS/INS integration. In contradiction of some AI methods, the SVM, which can be characterized by the convex optimization complications, has been improved in

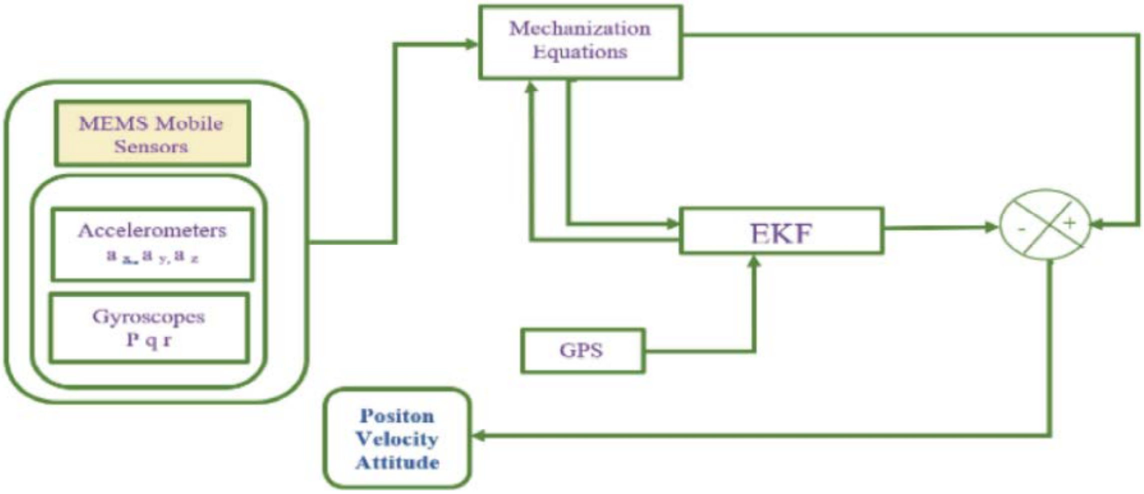

Fig. 2: MEMS/EKF/GPS navigation system outages

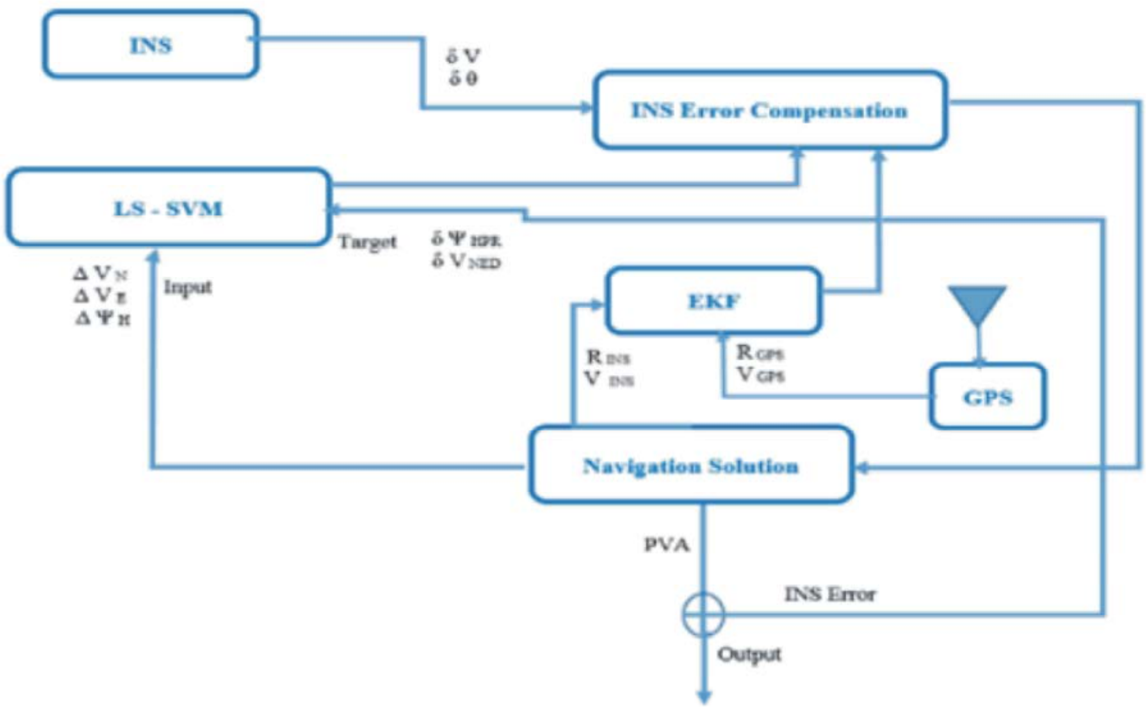

Fig. 3: Structure of the LS-SVM/ EKF fusion metric

the area of statistical learning system and organizational risk minimization. LS-SVM metrics scale so fit to great dimensional input spaces. Additionally, with weighted least squares and special pruning methods, it might be working for strong nonlinear assessment. LS-SVM is widely used for nonlinear estimation [22].

LS-SVM is accustomed to modifying the INS errors through GPS stoppages, depend on the patterning accomplished from the proceed training when GPS is accessible. Experimental test data is accustomed to evaluating the efficiency of the proposedsystem and the outcome is contrasted with the more common supported GPS/INS methods.

LS-SVM/EKF Fusion Technique: The LS-SVM regression technique is employed here to develop the precision of the INS-only navigation resolution through GPS stoppages. This paper proposed the LS-SVM regression technique and the design and implement of the LS-SVM/EKF hybrid technique for GPS/INS combination.

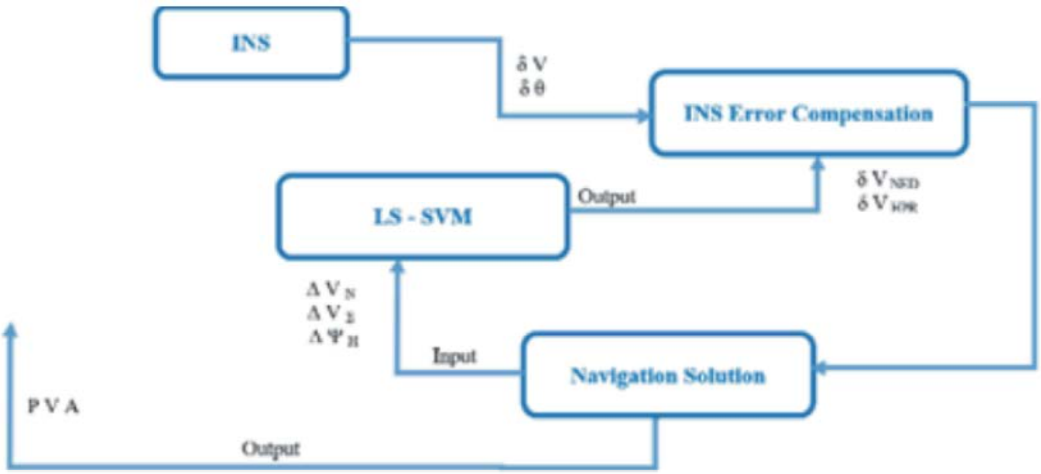

Fig. 4: Structure of the LS-SVM-based expectation through GPS unobtainable

Fig. 5: Reference trajectory (Mediterranean Sea, Alexandria)

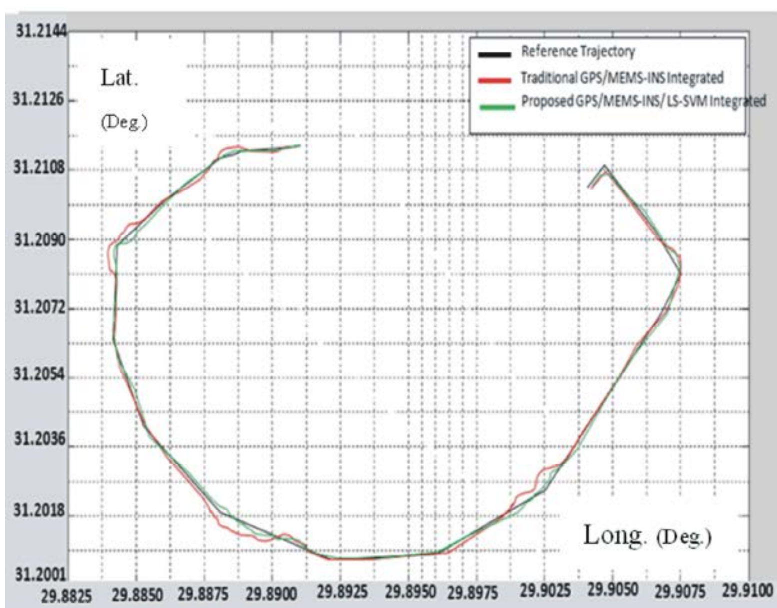

Fig. 6: Three estimated trajectories (reference[1]- traditional GPS/MEMS–INS [2]integrated & GPS/MEMS-INS/LS-SVM/EKF[3] integrated)

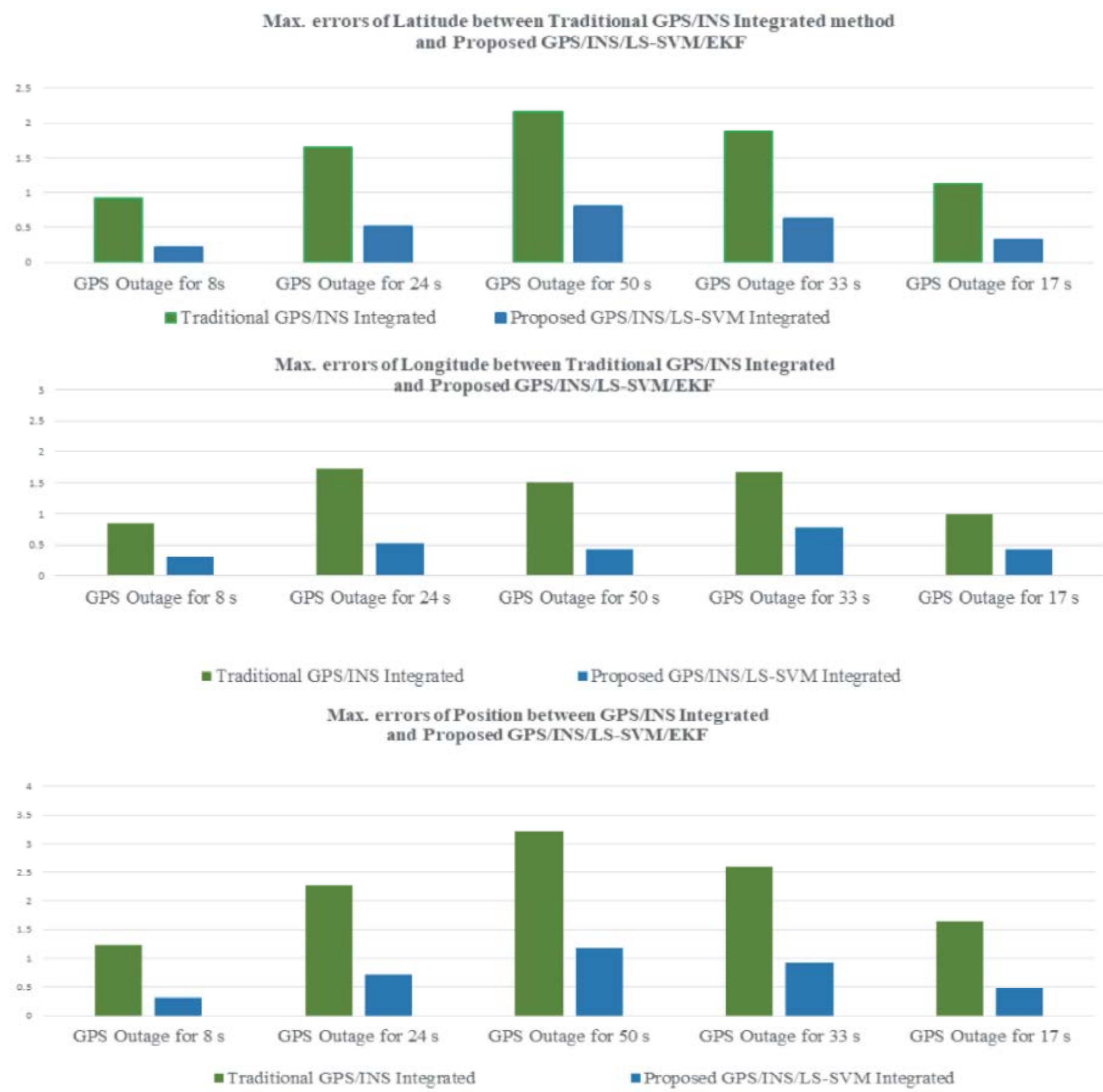

Fig. 7: Maximum. estimated errors of latitude, longitude and position between two testes

The fusionmetric consists of two phases. The first is the LS-SVM/ EKF combined system. The second is the LS-SVM-based prediction through GPS blockage. The LS-SVM metric for nonlinear function assessment has the succeeding illustration in the feature space in Eq. (18) below:

$$y(x) = \omega^{T}\varphi(x) + b \tag{18}$$

where the entered data is $x \in R^n$ and the equivalent output is $y \in R$. The nonlinear function φ transfers the input space to a greater dimensional feature space. The term b is the bias term. Figure 3 shows the structure of the LS-SVM/ EKF fusionmetric [14, 22, 23].

The Input/output Design of LS-SVM: Figure 4 presents the structure of the LS-SVM-based expectationthrough a GPS inaccessible. The LS-SVM functions in the prediction case, in which the productivity of the LS-SVM is utilized for error compensation. The vehicle dynamics obtained from the navigation solution are always input into the LS-SVM, as was completed through the training stage [3].

Test Efficiency of Proposed Marine Navigation System: An experimental has been tested in the Mediterranean Sea, Alexandria as shown in figure 5. The objective of this research is to provide a reliable and continuous solution of the USV navigation system during GPS outages. It is based on integrated traditional GPS/MEMS-INS with

Table 2: Estimated RMS errors of latitude, longitude and position during GPS outages

	Estimated RMS errors by Traditional GPS/MEMS-INS Integrated			Estimated RMS errors by Proposed GPS/MEMS-INS/LS-SVM/EKF Integrated		
GPS Outages	Latitude (m)	Longitude (m)	Position (m)	Latitude (m)	Longitude (m)	Position (m)
8s From (34s to 42s)	0.83	0.79	1.14	0.19	0.21	0.28
24s From (152s to 166s)	1.33	1.41	1.93	0.49	0.45	0.66
50s From (273s to 323s)	1.98	1.89	2.73	0.77	0.79	1.10
33s From (481s to 524s)	1.56	1.48	2.15	0.56	0.53	0.77
17s From (560s to 577s)	0.92	0.96	1.32	0.27	0.25	0.36

proposed LS-SVM/EKFfusion algorithmic. To verify the efficiency of navigation system based on the proposed GPS/MEMS-INS/LS-SVM/EKF integrated method through GPS outages, the navigation system is tested on 600 m reference trajectory. The reference trajectory(in black color) is shown in figure 6. Also, there are two trajectories that represented the integrated methods, are used to test the efficiency of navigation solution of USV. They are listed below:

- First (in red color); Traditional GPS/MEMS-INS Integrated method.
- Second (in green color); Proposed GPS/MEMS-INS/LS-SVM/EKF Integrated method.

In order to compare between the two integrated methods during GPS outages. The GPS signal is switched off several times in the same period for 8, 24, 50, 33 and 17 seconds respectively, on parts of reference trajectory. Figure 7 shows the Maximum Estimated errors of latitude, longitude and position between two tests during GPS outages.Table (2) also shows the RMS estimated errorsduring GPS outages for 8s, 24S, 50 s, 33s and 17s.

CONCLUSION

This Paper proposed design and implement of LS-SVM/EKF combination method for GPS/INS integration. The results show that during GPS outages for 50 second, the RMS errors of position by traditional GPS/MEMS-INS integrated method is about 2.73 meters. On the other hand, the RMS errors of position using the proposed method based on integrated GPS/MEMS-INS/LS-SVM/EKF integrated method is about 1.10 m. It is observed that the proposed technique enhanced the navigation system by reducing the errors in the position by 60%-75% during the 600m suggested trajectory at different time during GPS outages. The proposed integrated algorithm can provide a reliable and continuous solution during GPS outages for length of time. The proposed navigation solution can reduce cost and provide a suitable size for most Unmanned Vehicles (UVs) and it can be implemented in several applications such as exploration, tracking targets and so on.

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