Multisensor Data Fusion Algorithm using Factor Analysis Method

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Abstract

Multisensor data fusion aims to overcome the limitations of individual sensors and produce accurate, robust and reliable estimates based on multisensory information. Data fusion algorithm plays significant role in achieving reasonable performance. In this paper, we present an algorithm that is employed to fuse data obtained from accelerometer and gyroscope in an inertial measurement unit (IMU). The proposed algorithm is developed based on decentralized data fusion notion that facilitates to study effect of noise parameter associated with individual sensors. Feature extraction and processing is accomplished using factor analysis model. Factor analysis is a statistical method used to study the effect and interdependence of various factors within a system. The performance of the algorithm is illustrated via computer simulations and compared with well-known Kalman filter algorithm.

Keywords: *Algorithm, Data fusion, Factor analysis, Inertial measurement unit*

1. Introduction

Sensor fusion is a process of integration and extraction of desired information from two or more sensors. In other words, it is a process of combining multiple sensors to provide more useful information than the sum of individual sensors. Fused sensor data from various sensors offers several advantages when compared to data from a single sensor [1].

Multisensor data fusion uses many techniques, such as the method of least squares, Bayesian method, Kalman filters, Dempster–Shafer's method, Fuzzy logic and neural networks [2]. Kalman filtering [3] is one of the most significant techniques used since past decade. The widespread use of Kalman-based solutions are a testament to their accuracy and effectiveness, however, they have few disadvantages, which are discussed by Madgwick [4].

In order to satisfy more and more demanding requirements of applications, new algorithms are continually being designed and developed. The choice of the most appropriate algorithm depends on the complexity of the target problem, obviously the more complex the problem is, the algorithm also becomes more complex. As discussed by the Hall [5] there is no perfect algorithm that is optimal under all conditions.

It is clear that different sensors provide different kinds of information and no sensor works perfectly in all real-world applications. How to effectively utilize the positive side of each sensor and avoid its negative side becomes critical issue in data fusion systems performance. To reach this goal, sensor technology and data fusion algorithms have been a hot research topic and playing a key role in the acquisition of more accurate and reliable information for the last two decades.

Data fusion algorithms are legionary, including mainly the physical models, feature-based inference techniques and cognitive-based models [6]. By the virtue of scalability and modularity, decentralized fusion algorithms have significant role in data fusion systems [7-9].

The paper presents fusion of estimates from gyroscope and accelerometer in an IMU employing factor analysis model. Exploiting factor analysis as a tool, a decentralized data fusion algorithm is proposed that extracts features (factors) from the raw data and fuse them to obtain global estimates. Decentralized data fusion approach is one in which features are extracted and processed individually and finally fused to obtain global estimates.

The paper is organized as follows, section 1 concisely outlines IMU, Section 2 briefly reviews application of factor analysis in various fields and different methods applied to fuse data in IMU, Section 3 describes factor analysis and the proposed algorithm, and finally we describe conclusion and future work.

2. Inertial Measurement Unit (IMU)

An inertial measurement unit (IMU) is an electronic device that measures and reports on a craft's velocity, orientation, and gravitational forces, using a combination of accelerometers and gyroscopes. IMUs are typically used to maneuver aircraft, including unmanned aerial vehicles (UAV), among many others, and spacecraft, including shuttles and satellites. An IMU works by detecting the current rate of acceleration using one or more accelerometers, and detects changes in rotational attributes like pitch, roll and yaw using one or more gyroscopes. A basic unit with assembly of components is shown in Figure 1. A detail description of principle, working and application of IMU could be studied in [10-11].

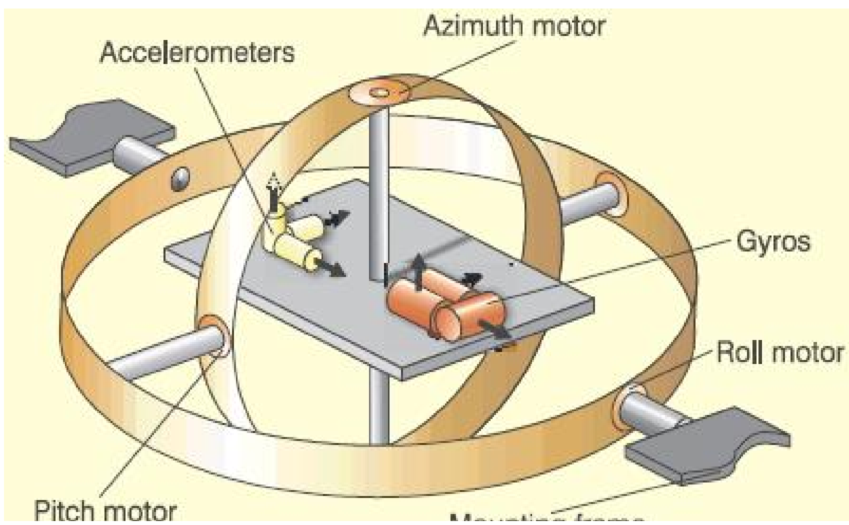

Figure 1. Inertial Measurement Unit [11]

An ideal MEMS gyroscope produces a predictable output when it is subjected to a known rate of rotation. It has no noise, perfect linearity, and no offset, however, that is not possible to achieve practically. Mark Looney [10] discussed many factors on which the performance of gyroscope depends such as bias effect, noise, scale factor error and displacement-measurement errors. King [11] discussed many errors encountered during practical use of gyroscope such as Initial tilt error, gyro drift error and azimuth gyro drifts.

Although gyroscope and accelerometer are associated with many errors as stated above, in this the paper the authors have focused on development of data fusion algorithm using factor analysis model. An effort is made to explore the effect of noise variance and estimation error using the proposed algorithm.

3. Related Work

Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved, uncorrelated variables called factors. It was originated in psychometrics, and is used in behavioral sciences, social sciences, marketing, product management, operations research, and other applied sciences that deal with large quantities of data [12].

We will first discuss in brief the role of factor analysis in various applications and then will proceed with the developments of fusion methods in IMU.

Jing [13] applied factor analysis model for stochastic signal estimation. An algorithm for estimating transfer functions (factor loading) was presented. For estimating a common stochastic signa1, pseudo least squares estimates (PLSE) and pseudo maximum likelihood estimates (PMLE) were generated. Depending on the latent roots of the covariance matrix, the time delays were estimated.

Over recent years, Joint Factor Analysis (JFA) has demonstrated state-of-the-art performance for text independent speaker detection tasks in the NIST speaker recognition evaluations (SRE) [14-17]. JFA proposes powerful tools to model the inter-speaker variability and to compensate for channel/session variability in the context of Gaussian Mixture Models (GMM) [18].

Kenny and Dumouchel [19] reported the results of some speaker verification experiments on the NIST 1999 and NIST 2000 test sets using factor analysis likelihood ratio statistics. The factor analysis model treated the channel space as a continuum and combined the priors underlying classical maximum a posteriori (MAP), eigenvoice MAP and eigenchannel MAP. The results were comparable to (but not better than) the best results that have been attained with standard methods (GMM likelihood ratios and handset detection).

Kenny *et al.*, [15] presented joint factor analysis model that was capable of far better performance than eigenchannel modeling. It was shown that the joint factor analysis model can perform very well in speaker verification using a computationally inexpensive decision rule that steers a middle course between the ‘exact’ and ‘simplified’ scoring rules in [20].

Kenny *et al.*, [21] proposed an approach to the problem of estimating speaker factor loading matrices that enhances the effectiveness of the classical MAP component of factor analysis. The work was concerned with the speaker variability component of factor analysis. The role of this component was to provide a prior distribution for maximum a priori (MAP) estimation of speaker-dependent GMM’s at enrollment time.

Kristjansson *et al.*, [22] developed framework called ALGONQUIN employing EM strategy for speech processing system. The performance of speech cleaning and noise adaptation algorithms is heavily dependent on the quality of the noise and channel models Estimation of the noise and channel model parameters is complicated by the fact that the observations contain a combination of speech, noise and channel distortion. The performance of a feature cleaning method is greatly dependent on how well the noise and channel distortion are estimated and modeled. The learning algorithm could successfully disentangle the non-linear effects of noise and linear effects of the channel and achieve a relative reduction in word error rate (WER).

Fabrizi *et al.*, [23] described two possible structures for a localization system to exploit ultrasonic sensor measures as well as inertial and odometric data to maintain a correct estimate of the location of a mobile robot. The objective was to reduce the position and orientation error in the presence of slippage, and, at the same time, to identify the bias of the gyroscope. The proposed two fusion algorithms had the classical predictor-corrector structure of the Extended Kalman Filter, but they differed in the use of the angular velocity measure coming from the gyroscope.

Gomes and Oliveira [24] exploited signal-processing technique for the interpolation and regularization of multidimensional sampled signals with missing data, based on PCA. The non-iterative methodology proposed corresponds to the optimal solution to a regulated weighted least mean square minimization problem, based on estimates for the mean and covariance of signals corrupted by zero-mean noise. An estimate was deduced for the mean square interpolation error, with upper and lower bounds. The proposed method was applied to bathymetric data acquired during tests at sea. Bathymetric was acquired from Sonar, global positioning system (GPS) receiver and an IMU. The results obtained paved the way to the use of the proposed framework in a number of sensor fusion problems, in the presence of missing data.

Brodie *et al.*, [25] developed fusion integration algorithms for fusion motion capture (FMC) system. FMC is a composite system that fuses data from inertial motion unit, video, GPS and a speed-resolution scan (RS-Scan) insole system to determine segmental and whole-body kinematics and kinetics. The proposed method improved the accuracy of the independent Kalman filter solutions provided by the vendors of both the GPS and IMU.

Shi *et al.*, [26] presented fall recognition algorithm based on MEMS motion sensing data. Human motion information was obtained using MEMS accelerometers and gyroscopes. The method proposed PCA for feature generation and independent component analysis (ICA) for feature extraction. Support vector machine (SVM) was used for training process.

Qasem *et al.*, [27] developed inertial navigation multi sensor node to improve the accuracy of the measurement acquired from a set of inertial sensors and magnetic encoders. The proposed technique tried to achieve minimum error of position and direction over a given travelled distance by thorough characterization of the errors that affect the navigation accuracy.

Koo *et al.*, [28] presented a real-time heading estimation algorithm using IMU and strap down magnetometer without any other external heading reference system. Particle filter and extended Kalman filter was introduced for the performance comparison, which was carried out through flight trace simulation. Simulation result demonstrated that accurate heading estimation error is less than 1 degree for both algorithms when there exist small initial heading error and hard iron effect, yet particle filter provides more robust and precise result than the extended Kalman filter in case the initial heading error and biases are large.

Zimmermann, R [29] presented a framework to fuse inertial measurement data with a visual sensor data in an IMU. The visual measurements were fused with the IMU-data by using an extended Kalman filter (EKF). The major advantage of fusing these complementary sensors exploited the high bandwidth of the IMU while bounding the growing dead reckoning error (resulting from double integration) using vision based absolute pose measurements

Ghasemzadeh *et al.*, [30] presented a golf swing training system that incorporates wearable motion sensors to obtain inertial information and provide feedback on the quality of movements. The inertial sensors are placed on a golf club and athlete's body at positions that capture the unique movements of a golf swing. The quantitative model used signal processing techniques including PCA and LDA (Local Discriminant Analysis) to extract features for data fusion.

Ghasemzadeh [31] presented an effective data fusion technique for understanding the inertial information obtained from distributed sensor nodes. Proposed data fusion model was based on the concept of PCA. PCA-based feature selection technique, called principal feature analysis (PFA) takes a set of start times as input and produces the times that are best representative of the movements. Motion transcripts were generated by grouping sample points with consistent physical behavior together. Each group is called a primitive and its timing information is fed into PCA for feature selection. Prominent primitives reported by PCA are then used to generate a unique transcript that is the best representative of all sensor nodes.

Many researchers have done error analysis in IMU [32]. Saini *et al.*, [33] presented an online approach to estimate MEMS sensor stochastic state space noise model for MEMS IMU. The proposed method to analyze sensor noise make use of simple Kalman filter and EM algorithm that works on sensor data with some a-priori estimates which converges to the true parameter estimate.

Madgwick [4] presented a novel orientation filter applicable to IMUs consisting of tri-axis gyroscopes and accelerometers, and MARG (Magnetic, Angular Rate, and Gravity) sensor arrays that included tri-axis magnetometers. The task of the proposed orientation filter was to compute a single estimate of orientation through the optimal fusion of gyroscope, accelerometer and magnetometer measurements. The MARG implementation incorporated magnetic distortion and gyroscope bias drift compensation. The filter used a quaternion representation, allowing accelerometer and magnetometer data to be used in an analytically derived and optimized gradient-descent algorithm to compute the direction of the gyroscope measurement error as a quaternion derivative.

There exists many methods of data fusion in IMU, however the authors expect the attempt of utilizing factor analysis model in IMU data fusion is innovative. The algorithm presented obtains raw data from gyroscope and accelerometer. Two set of estimates are obtained, one incorporating noise variance and in other noise variance kept zero. The estimates of gyroscope and accelerometer incorporated with noise variance are fused, simultaneously estimates of the same with zero noise variance are also fused in order to obtain two set of global estimates. Further, analysis and comparison is carried out for the obtained results.

4. Factor Analysis

Factor analysis is a collection of methods used to examine how underlying constructs influence the responses on a number of measured variables also used to assess the reliability and validity of measurement scales. Factor analysis is related to principal component analysis (PCA), but the two are not identical. The factors produced by principal component analysis are conceptualized as being linear combinations of the variables whereas the factors produced by common factor analysis are conceptualized as being latent variables. Computationally, the only difference is that the diagonal of the relationships matrix is replaced with communalities (the variance accounted for by more than one variable) in common factor analysis. A detail discussion could be found in [34].

The developed algorithm exploited guidelines and basics from various sources [13, 35-38].

The first step is collection of data from sensors. Data is obtained from the SparkFun IMU that has noise variance of 0.07701688 for accelerometer and 0.00025556 for gyroscope [39].

Considering each object or record has p features, so Xij is the value of feature j for object i.

We will center all the observations (subtract off their mean). We now postulate that there are q factor variables, and each observation is a linear combination of factor scores Fir plus noise:

$$X_{ij} = \varepsilon_{ij} + \sum_{r=1}^{k} F_{ir} w_{rj} \tag{1}$$

The weights w_{rj} are called the factor loadings of the observable features; how much feature j changes, on average, in response to a one-unit change in factor score r. Notice that we are allowing each feature to go along with more than one factor (for a given j, w_{rj} can be non-zero for multiple r). This would correspond to our measurements running together what are distinct variables.

Here ε_{ij} is as usual the noise term for feature j on object i. We will assume this has mean zero and variance ψ_j that is, different features has differently sized noise terms. The ψ_j are known as the specific variances, because they are specific to individual features. We will further assume that $E[\varepsilon_{ij}\, \varepsilon_{lm}] = 0$, unless i = l, j = m, that is, each object and each feature has uncorrelated noise.

We can also re-write the model in vector form [35],

$$\vec{X}_i = \vec{\epsilon}_i + \vec{F}_i \mathbf{w} \qquad (2)$$

With w being a q x p matrix. If we stack the vectors into a matrix, we get

$$X = \varepsilon + Fw \qquad (3)$$

This is the factor analysis model.

Factor analysis is carried using the Matlab Statistics Toolbox™. Factor analysis is a way to fit a model to multivariate data to estimate just this sort of interdependence. In a factor analysis model, the measured variables depend on a smaller number of unobserved (latent) factors. Because each factor might affect several variables in common, they are known as common factors. Each variable is assumed dependent on a linear combination of the common factors, and the coefficients are known as loadings. Each measured variable also includes a component due to independent random variability, known as specific variance because it is specific to one variable.

Specifically, factor analysis assumes that the covariance matrix of data is of the form

$$\sum\nolimits_x = \Lambda\Lambda^T + \Psi \qquad (4)$$

Where Λ is the matrix of loadings and the elements of the diagonal matrix Ψ are the specific variances. The function factoran fits the factor analysis model using maximum likelihood.

Factor analysis assumes that the covariance matrix of data is of the form [38].

$$\text{SigmaX} = \text{Lambda*Lambda'} + \text{Psi} \qquad (5)$$

Where Lambda is the matrix of loadings and the elements of the diagonal matrix Psi are the specific variances.

The flow of data and various steps of the algorithm are shown in flowchart in Figure 2.

Two set of maximum likelihood estimates are obtained, case1) with noise variance (arrow marks in flowchart shown in red color); Case 2) without noise variance (arrow marks in flowchart shown in green color)

In the final step of algorithm, ML estimates incorporating noise in gyroscope & accelerometer (case1) and ML estimates without noise (case2) are fused and subsequently global estimates are obtained as shown in Figure 3.

In order to find the estimation error, the difference between the ML estimates and the mean value estimates is calculated. The mean value estimates are obtained following tutorial guidelines [40].

Estimation error is calculated by finding the difference between mean values of obtained measurements and the final fused factors obtained from maximum likelihood estimation extraction.

The authors in an earlier paper have carried out Kalman filter analyses using the same data [41]. Estimation error obtained using proposed algorithm is compared with the estimation error using Kalman filter, as shown in Figure 4 the estimation error encountered in the proposed method is severe thus rendering poor performance.

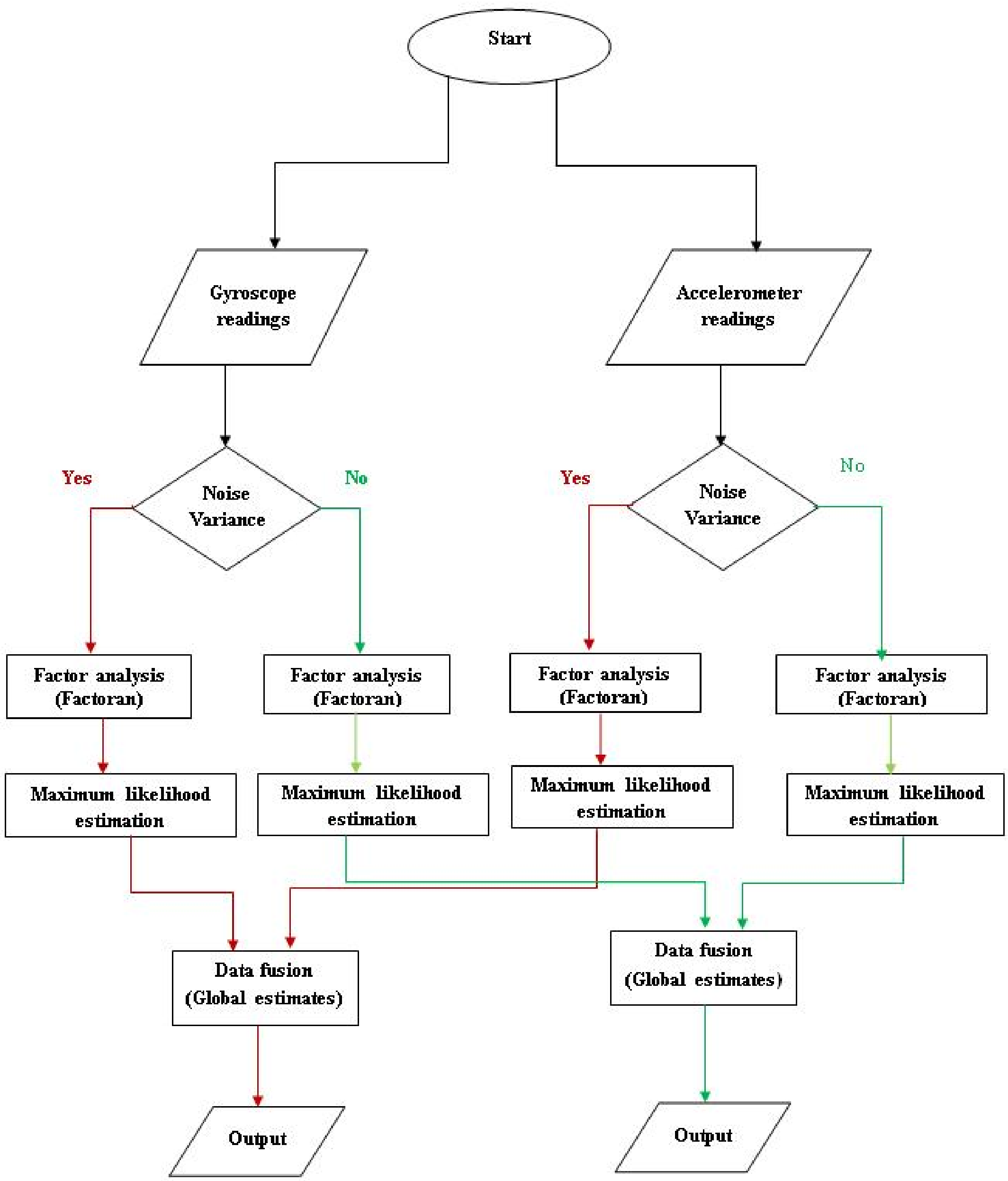

Figure 2. Flowchart Representation of Decentralized Data Fusion Algorithm

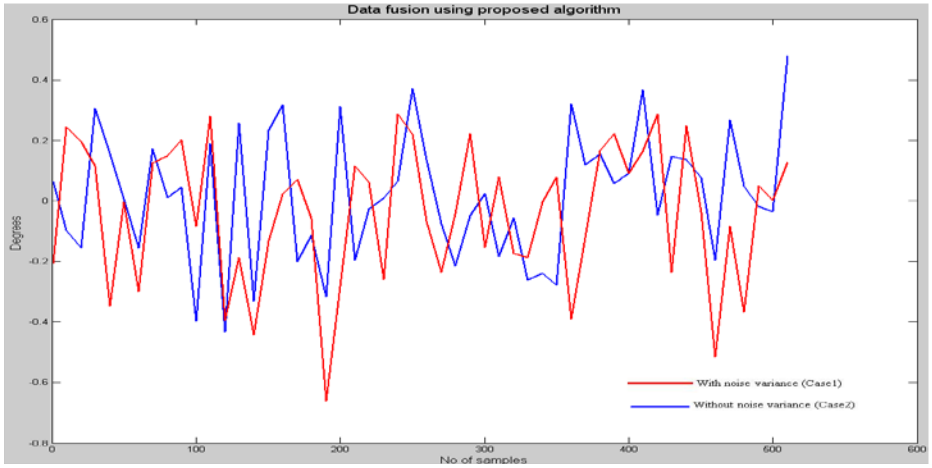

Figure 3. Data Fusion using Proposed Algorithm

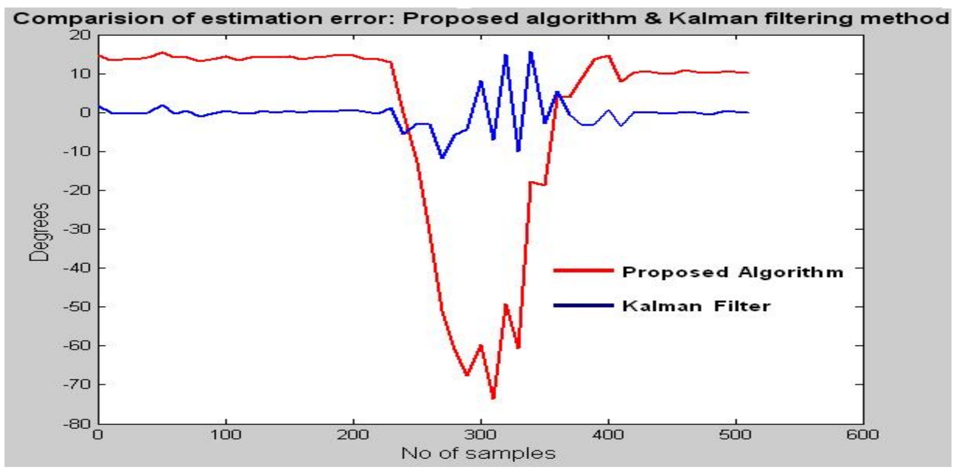

Figure 4. Estimation Error in Proposed Method and Kalman Filtering

5. Conclusion and Future Work

Development of algorithm plays significant role in the performance of data fusion system. The paper presents development of decentralized data fusion algorithm to fuse data in an IMU, utilizing factor analysis model. One of the main concerns in data fusion technique is the risk of producing fused estimates that are worse and lead to discontentment. Poor estimation could be responsible for poor performance of data fusion system. The same has been encountered in the proposed algorithm. Regrettably, poor estimates, the noise factor, and other inaccuracies contribute to estimation error in fusion process that is severe using the proposed method when compared with Kalman filter technique.

Obviously, there is need for lot of refinement and improvement in the proposed method to improve the performance and reduce the estimation error. Proper filtering is required at feature generation stage to avoid introduction of noise. The future work also includes the impact of missing data on the data fusion performance.

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