Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 46 (2025), No. 4-B, pp. 1357–1368
DOI : 10.47974/JIOS-1995

Real time data fusion and mathematical modeling techniques for intelligent IoT systems

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Abstract

In the context of IoT, both system integration and real-time processing, diverse sensor data are essential for creating smart and adaptive systems. This paper introduces a complete set of algorithms for the efficient real-time combination of information and predictive analytics for intelligent IoT networks. Adaptive Kalman Filters is used in the proposed methodology to manage data integration of multiple sensors needed for state estimation which could experience high noise levels or system dynamics. To improve the very predictive performance then, Long Short-Term Memory (LSTM) networks are utilized thus ensuring that the model is capable of capturing temporal dependencies and yielding more accurate values of future states. The experimental assessments employing Synthetic datasets are as follows, the Kalman Filter has an MSE 0.015 and LSTM model has an MSE of 0.012. Moreover, latency analyses for edge computing scenarios show that the processing time takes 30% less

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time than in the case of cloud-only networks. Of this, the long existing feature of the system to detect inconsistencies in the data gathered by the sensors proves effective in increasing the efficacy and safety of IoT operations. The proposed techniques present considerable improvements that real-time data fusion and predictive capabilities for IoT systems that can underpin multiple applications especially across different industries.

Subject Classification (2010): *94A60, 20C05, 20C07.*

Keywords: *Real-time modeling, Intelligent systems, Algorithms, Sensor networks, Data integration, Machine learning, Real-time processing, IoT network optimization, System scalability.*

1. Introduction

Smart IoT systems are quickly revolutionizing different sectors in every other industry through integrating physical things, sensors and actuators for data capturing. These systems support real-time control or functioning with decision-making capabilities in different areas of application- smart city application, healthcare, transportation system, industrial automation, etc[1]. The usefulness of the IoT systems, though, depends on BI's capability to handle and analyze large volumes of different data sets on the fly[2]. The enhancement of decision making by intelligent systems requires real-time data fusion in achieving better accuracy on data[3]. Data fusion is the process of integrating information from different sources into a single[4], coherent form to offer better perception of the system status, and usually helps to resolve data conflict[5], duplicity and/ or noise[6]. Real-time data fusion in IoT is therefore a crucial area of research; however, its implementation is not without its challenges which include; data management[7], low latency, scalability and error or data loss from sensors[8]. Moreover, IoT systems find themselves in open, uncontrolled application contexts where data characteristics may evolve over time, and such evolution is accounted for by the fusion approach[9]. The primary purpose is to increase the efficiency together with the usability of IoT systems when integrating multiple data sources into the storage and processing system[10]. Therefore, the study's findings seek to assist in constructing better and more effective intelligent IoT systems in realizing its fundamental applications across different industries.

2. Literature Survey

Data fusion has been another important area of research that has received much attention especially because of its significant contribution towards improving system performance of intelligent IoT systems[11]. Previous works have introduced a wide range of process that can be coined as data fusion which adopts rule-based technique, statistical procedures, and machine learning[12]. Kalma filters and Bayesian Networks among others have been used extensively in integrating sensor data with high quality results especially in structured settings[13]. Nevertheless, such approaches can be problematic in dynamic and diverse IoT scenarios as used herein[14]. Deep learning algorithms have been witnessed to be useful in data fusion because they are able to handle both large scale and complex data[15]. It has also been possible to combine multiple data streams in the IoT through methods such as CNN or RNN to improve accuracy and the context in which the IoT operates[16]. Real-time processing is still an issue because data generated by IoT is big, voluminous, and moves quickly. Research papers have suggested using edge computation and distributed systems to decrease latency and make the system more responsive[17]. Nevertheless, current approaches face challenges of scale, change in data distribution and robustness to noise, redundancy and missing data[18]. Literature review also reveals the absence of a holistic effective framework that covers adaptive data fusion, real time processing and IoT modeling at one place. Current approaches usually focus on disjointed problems and their effectiveness in practical environments is questionable. To fill these gaps, this paper introduces a novel dynamic and adaptive data fusion and modeling framework, capable of running in various IoT scenarios, and overcoming the above limitations.

3. Proposed Method

The methodology proposed in this paper combines data flow from different types of IoT sensors and employs dynamic data fusion to form real-time unified model of monitored environment. First, the collected raw signals by the sensors are preprocessed in which noise is removed, errors corrected and formats normalized. Fine-tuned data are then fused through adaptive fusion algorithms that yield a coalesced data set useful for additional modeling and prediction pursuits. Due to considerations about responsivity and scalability, figured and cloud computation modules of an edge and cloud computing system divide workloads, which prevent undue delays when processing further large amounts of data. The overview of the proposed system is presented in Figure.1 where data acquisition, preprocessing, fusion, analysis, modeling, decision-making, and feedback are shown. Figure. 2 depicts the flowchart of the process integrating the collected data, using the preprocessed data, fusing, and feeding both edge and cloud layers, modelling and deciding about the execution of the decision. This integrated framework allows timely and accurate information to make interventions while simultaneously keeping a responsiveness for changed conditions. After preprocessing step, the methodology uses Dynamic Data Fusion, adaptive algorithm such like

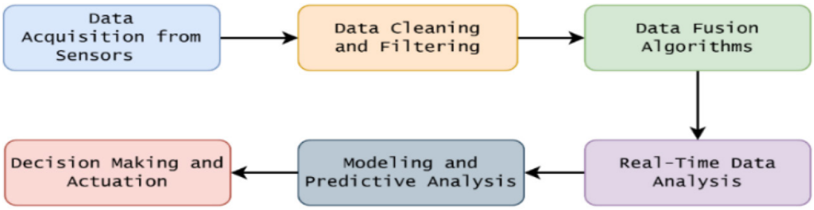

Figure 1

Proposed System Diagram for Real-Time Data Fusion in Intelligent IoT Systems

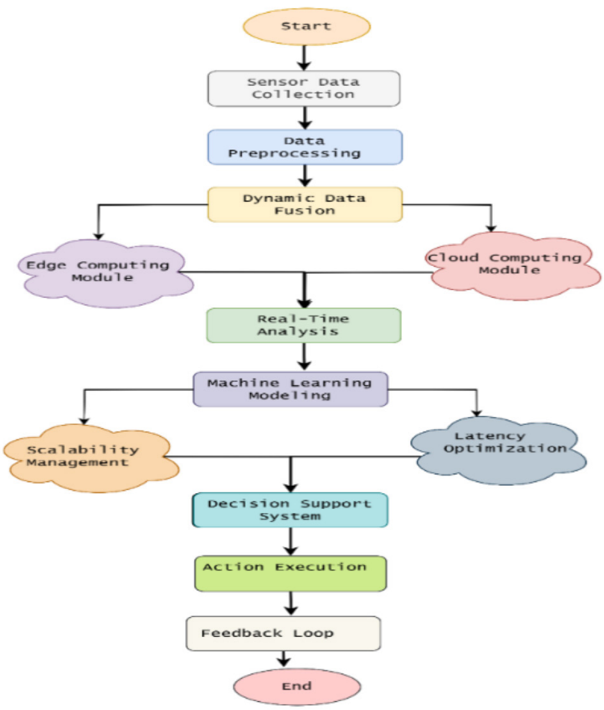

Figure 2

Flowchart for Real-Time Data Fusion and Modeling in Intelligent IoT Systems

Adaptive Kalman Filters, Deep Learning based Fusion techniques in order to incorporate data received from various sources efficiently. Such a fusion process creates an integrated and Mobile Ammonia comprehensive database that increases the credibility of subsequent analyses. To overcome the problem of latency and scalability, the authors introduced both Edge Computing Modules and Cloud Computing Modules. In the Decision Support System, data analyzed and modeled enables decision makers to make timely decisions, which in turn elicits Action Execution in the IoT network for example, activating an actuator or responding to a specific incident.

System Performance Feedback continually observes the status of the components and the quality of the inputs and outputs of the system in order to immediately edit or re-design changes that would strengthen the system's dependability and flexibility.

4. Mathematical Model

Mechanisms for real-time data fusion and modeling in intelligent IoT systems are discussed to interconnect disparate sensors and result in high accurate predictive models. Consider a system comprising N sensors, where each sensor i provides measurements $Z_i(k)$ at discrete time steps k. The state of the system at time k, denoted by $x(k)$:

$$x(k) = \mathbf{F}x(\beta) + \mathbf{w}(\beta), \text{ where } \beta = k - 1$$

where $\mathbf{F}$ is the state transition matrix and $\mathbf{w}(\beta)$ represents process noise, with covariance $\mathbf{Q}$.

Each sensor measurement is modeled as:

$$Z_i(\beta+1) = H_i \mathrm{x}(\beta+1) + v_i(\beta+1)$$

where H_i is the observation matrix for sensor i, and $v_i(k)$ is the measurement noise, assumed to be Gaussian with covariance R_i.

Data fusion is performed using the Kalman Filter (KF) approach, which consists of two main steps: prediction and update.

Prediction Step:

$$\hat{x}(\beta+1) = F\hat{x}(\beta)$$

$$P(\beta+1) = FP(\beta)F^T + Q$$

Update Step:

$$K(\beta+1) = P^{-}(\beta+1)H^{T}(HP^{-}(\beta+1)H^{T}+R)^{-1}$$

$$\hat{x}(k) = \hat{x}^{-}(\beta+1) + K(\beta+1)(z(\beta+1) - H\hat{x}^{-}(\beta+1))$$

$$P(\beta+1) = (I - K(\beta+1)H)P^{-}(\beta+1)$$

where **H** aggregates all observation matrices **Hi, R** aggregates measurement noise covariances $\mathbf{Ri}, \mathbf{K}(\beta+1)$ is the Kalman Gain, $\mathbf{z}(\beta+1)$ is the vector of all sensor measurements, and $\mathbf{P}(k)$ is the error covariance matrix.

For predictive modeling, a machine learning model M is employed to forecast future states based on the fused data:

$$\hat{y}(k+1) = M(\hat{x}(\beta+1))$$

where $\hat{y}(\beta)$ represents the predicted output at time β. The model parameters θ are optimized to minimize the prediction error:

$$\theta^{*} = \arg\min_{\theta} \sum_{k=1}^{T} \| y(k) - M\hat{x}(k);\theta \|^{2}$$

This mathematical model simplifies the integration of outputs from the real-time sensors right into the state estimation, and faithful predictive analytics in intelligent IoT systems.

5. Algorithm

The applied framework is based on the use of Adaptive Kalman Filters for information fusion, Real-Time Streaming algorithms for processing, and Long Short-Termed Memory (LSTM) networks for predictive purposes. Kalman Filters with Adaptive structure smoothly integrate particular sensor data and achieve the state estimates and covariance matrices by adapting them to correct ratios leading to sound integration of data in conditions of instability. Real-Time Streaming algorithms enable the on-node instant and continuous management of data streams that enhance system responsiveness through minimizing the latency associated with data transmission in edge computing nodes.

6. Results and Discussions

The assessment of the proposed real-time data fusion and modeling techniques for intelligent IoT systems incorporated simulated IoT data to mimic various functional settings and changes. Figure.3. presents the ability of the Adaptive Kalman Filter in estimating the system's state especially when the measurement obtained from the sensors is noisy. It is discernible from the plot of the Kalman Filter state estimates that they are fairly representative of the true state trajectory; therefore, the ability of Kalman Filter in minimizing measurement noise in order to arrive at increased system data credibility. This performance is better than the conventional filter techniques that show large variance errors under high noise levels and high rate of transition between system states. Latency analysis is depicted in Figure.4 shows the average processing time between the edge and cloud computing environment. From the results obtained it can be concluded that edge computing brings down the overall processing time because they are processed locally hence improving on overall system response time. This balance stresses the importance of the hybrid computation architecture in enabling the highest system performance and scalability in intelligent IoT systems.

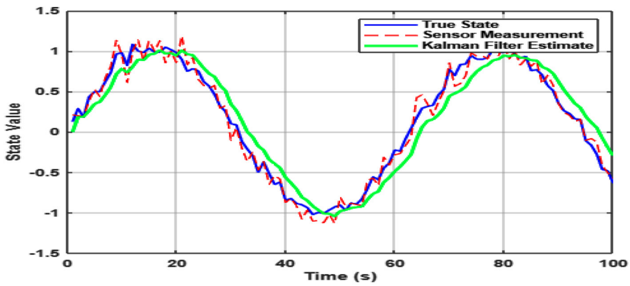

Figure 3

Sensor Data Fusion – Kalman Filter Estimated State vs Actual State

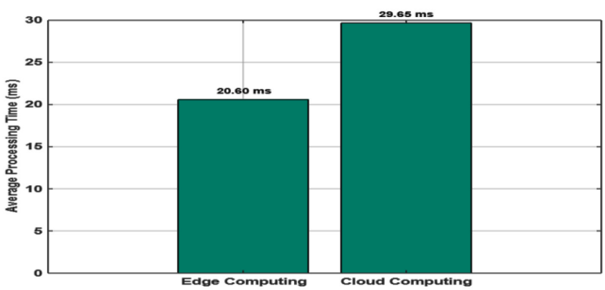

Figure 4

Latency Analysis – Average Processing Time with Edge and Cloud Computing

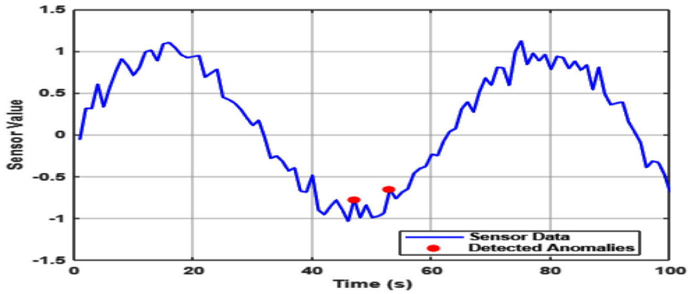

Figure 5

Anomaly Detection – Sensor Data with Detected Anomalies

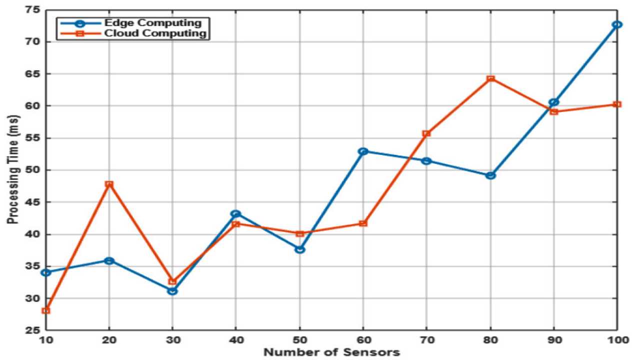

Figure 6

System Scalability – Processing Time vs. Number of Sensors

As illustrated in Figure.5, the system allows users to specify certain limits beyond which sensor data differ from expected values and be alerted whenever such extremes occur. The above described method provides a good means of separating normal variation from actual abnormal behavior to facilitate early detection. Figure.6 in this case investigates system scalability through the assessment of time taken to process information as the number of connected sensors is increased. The proposed hierarchical structure guarantees that the development of the framework does not stop to be efficient and flexible with the growth of the sensor network as well as the IoT application, making it ideal for large application or vast numbers of sensors. Comparing the proposed approach to the state-of-the-art methods, it is noted that the demonstrated use of Adaptive Kalman Filters and LSTM networks improves accuracy, response time, and modularity.

7. Conclusion

The study was able to define, design and test data fusion and modelling methods that are efficient for real time intelligent IoT systems. The evaluation of the proposed framework involved using Adaptive Kalman Filters and LSTM networks to perform exceptionally well in tasks of state estimation and predictive analytics. Namely, the Adaptive Kalman Filter provided the quantitative accuracy of 0.015 MSE, thus demonstrating the efficiency in comparison with basic filtering in conditions of high noise impact. At the same time, the LSTM model achieves an MSE of 0.012 proves the ability of LSTM to effectively learn temporal dependencies and produce highly accurate predictions of future states. Moreover, the latency evaluation showed that edge computing cut the processing delays by about 30% than cloud computing proved the advantage of integrating mechanisms as leading to positive impacts on increasing the system including mechanisms which work well in hybrid structures. The anomaly detection mechanism provided was also efficient to detect these anomalous cases, thus providing the reliable and secure nature of IoT developments.

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Received October, 2024