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Data Fusion and IoT for Smart Ubiquitous Environments: A Survey

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ABSTRACT The Internet of Things (IoT) is set to become one of the key technological developments of our times provided we are able to realize its full potential. The number of objects connected to IoT is expected to reach 50 billion by 2020 due to the massive influx of diverse objects emerging progressively. IoT, hence, is expected to be a major producer of big data. Sharing and collaboration of data and other resources would be the key for enabling sustainable ubiquitous environments, such as smart cities and societies. A timely fusion and analysis of big data, acquired from IoT and other sources, to enable highly efficient, reliable, and accurate decision making and management of ubiquitous environments would be a grand future challenge. Computational intelligence would play a key role in this challenge. A number of surveys exist on data fusion. However, these are mainly focused on specific application areas or classifications. The aim of this paper is to review literature on data fusion for IoT with a particular focus on mathematical methods (including probabilistic methods, artificial intelligence, and theory of belief) and specific IoT environments (distributed, heterogeneous, nonlinear, and object tracking environments). The opportunities and challenges for each of the mathematical methods and environments are given. Future developments, including emerging areas that would intrinsically benefit from data fusion and IoT, autonomous vehicles, deep learning for data fusion, and smart cities, are discussed.

INDEX TERMS Internet of Things, big data, data fusion, computational and artificial intelligence, high performance computing, smart cities, smart societies, ubiquitous environments.

I. INTRODUCTION

The Internet of Things (IoT) [1] is set to become one of the key technological developments of our times provided we are able to realize its full potential [2]. IoT is ''a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies'' [3]. IoT was named by the US National Intelligence Council (NIC) in a 2008 report [4] among the six key civil technologies that could potentially affect US power. IoT is an enabler of ubiquitous computing envisioned by Mark Weiser. Fig. 1 depicts application areas of IoT: smart homes, warning systems, intelligent shopping, smart gadgets, smart cities, smart roads, healthcare, fire systems, threat identification systems, tracking and surveillance.

The number of objects connected to IoT is expected to reach 50 billion by 2020 due to the massive influx of diverse objects emerging progressively [5]. The main purpose of these increasing number and types of IoT objects is to produce useful data about our surroundings to make them smarter. This is realized by providing the environments access to the information it needs through the collection and analysis of past, present and future data. The data allows optimal decision to be made about us and our environments possibly in real-time.

IoT is expected to be a major producer of big data. This data would be produced by various vendors giving rise to data as a service. Sharing and collaboration of data and other resources would be the key for enabling sustainable ubiquitous environments such as smart cities and societies [6]. The fusion of various types and forms of data, i.e. data fusion, to enhance data quality and decision making therefore would be of prime importance in ubiquitous environments. Data fusion is defined as ''the theory, techniques and tools which are

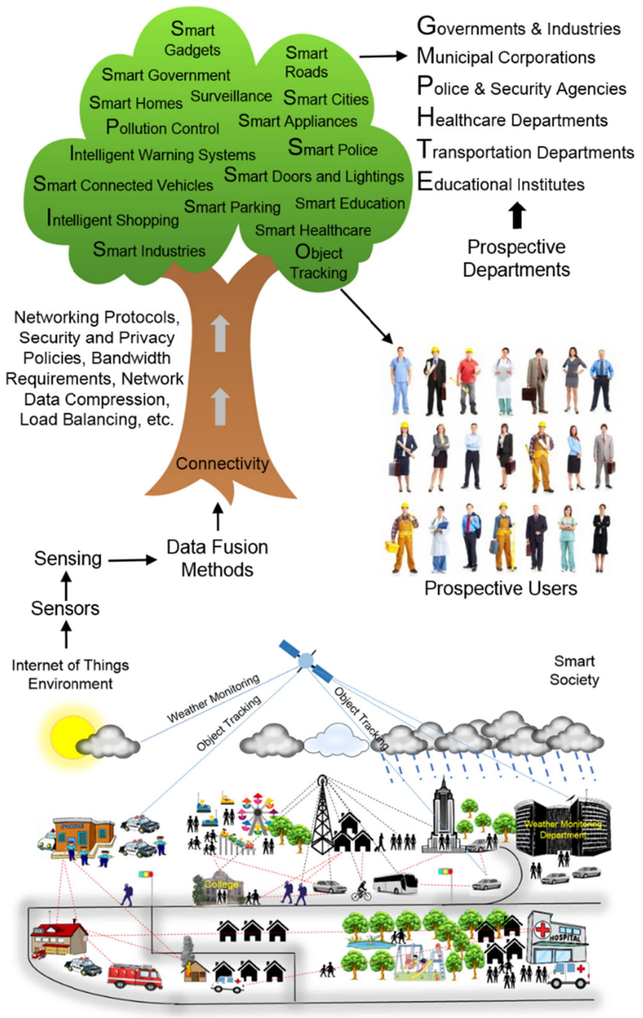

FIGURE 1. Info-graphic to show IoT landscape with respect to Data Fusion.

used for combining sensor data, or data derived from sensory data, into a common representational format'' [7]. A timely fusion and analysis of big data (volume, velocity, variety, and veracity), acquired from IoT and other sources, to enable highly efficient, reliable and accurate decision making and management of ubiquitous environments would be a grand future challenge. Computational intelligence would play a key role in this challenge.

A. CONTRIBUTION OF THIS WORK

The term ''Internet of Things'' was introduced firstly by Kevin Ashton in 1999 [8]. However, the key research and development works in IoT has started around 2010. One of the earliest and popular surveys were contributed by Atzori *et al.* [1], in 2010, where they described the fundamental building blocks of IoT and its applications. This survey was extended in [9]. Al-Fuqaha et al. in 2015 presented a survey of IoT enabling technologies, protocols and applications [10]. In [11], multi-sensor satellite image fusion methods are reviewed. The survey [12] has classified data fusion literature into three categories: data association, decision fusion and state estimation. In same year, 2013, another survey paper [13] classified the data fusion literature based on sensed data properties such as data imperfections, correlation and inconsistencies. In [14], progress and various challenges for data fusion in intelligent transportation systems are discussed. A recent survey [15] has presented a critical review of data fusion developments based on embedded sensors in mobile devices with particular focus on human activity recognition. Table 1 elaborates further the surveys relevant to our paper. A summary of the main focus of each relevant survey paper is given.

TABLE 1. Major data fusion surveys.

Surveys	Objectives and Topics
Dong et al., 2009 [17]	Focus on image data fusion methods in remote sensing, including object identification, classification, change detection and maneuvering targets tracking.
Faouzi et al., 2011 [15]	Developments and challenges of data fusion in intelligent transportation systems (ITS).
Qin et al, 2011 [18]	A brief and introductory data fusion survey for IoT.
Castanedo, 2013 [13]	Review based on a classification of the data fusion literature into three categories: data association, state estimation, and decision fusion.
Khaleghi et al, 2013 [14]	Classification of the data fusion literature based on data properties including imperfection, correlation, and insistencies
Gite et al, 2015 [19]	Focus on context awareness for multisensory data fusion IoT.
Wang et al, 2016 [20]	Classification of data fusion literature based on middleware, configuration, data processing, sensors, and portability.
Pires et al, 2016 [16]	Developments in data fusion for embedded sensors in mobile devices.

It is clear that, though a number of surveys exist on data fusion, these are mainly focused on specific applications (e.g., ITS, embedded sensors in mobile devices) areas or classifications (e.g., data properties, middleware). The aim of this paper is to:

- ✓ review literature on data fusion for IoT with a particular focus on
  - ✓ mathematical methods (including probabilistic methods, artificial intelligence, and theory of belief), and
  - ✓ specific IoT environments (distributed, heterogeneous, nonlinear and object tracking environments).
- ✓ to explore the opportunities and challenges for each of the reviewed mathematical methods and IoT environments
- ✓ to review the emerging areas that would intrinsically benefit from data fusion and IoT (including smart cities and autonomous vehicles).

B. PAPER STRUCTURE

The paper is divided into six sections. Section II discusses the opportunities and challenges of data fusion in general as well as specific to IoT. Section III reviews the data fusion literature based on the mathematical methods used for data fusion. These include probabilistic, artificial intelligence and theory of belief methods. Section IV discusses the literature based on the specific IoT environments including distributed, heterogeneous, and nonlinear and object tracking. Each mathematical method and environment of data fusion for IoT discussed in Sections III and IV have been elaborated with the relevant opportunities and challenges. Section V discusses the emerging areas that would intrinsically benefit from data fusion and IoT; these include autonomous vehicles, deep learning for data fusion and smart cities. Finally conclusions are drawn in Section VI.

II. DATA FUSION OPPORTUNITIES AND CHALLENGES

An enormous amount of data is produced in a quick span of time in the IoT environment. How to make this large volume of data precise and highly accurate is an open problem which needs to be solved because the quality of information plays an important role in decision making. Reliable and accurate information is critical. This can be achieved by data fusion or information fusion (terms which can be used interchangeably). Data fusion is an effective way for the optimum utilization of large volumes of data from multiple sources [11]. Multi-sensor data fusion seeks to combine information from multiple sensors and sources to achieve inferences that are not feasible from a single sensor or source [19]. The fusion of information from sensors with different physical characteristics enhances the understanding of our surroundings and provides the basis for planning, decision-making, and the control of autonomous and intelligent machines.

A. DATA FUSION OPPORTUNITIES

Data Fusion in the Internet of Things (IoT) paradigm can play a major role in its success due to the following reasons [7], [17]:

- Data Fusion makes information more intelligent, decisive, sensible and precise which is coming from multiple sensors and sources. The information from each sensor per se may not make much sense.
- A statistical benefit of fusion is obtained by computing the N independent observations; one can anticipate that the data are amalgamated in an optimal manner.
- In IoT, a big challenge is making very low power sensors which do not need battery replacements over their lifetimes; this popularizes the demand for energy efficient sensors. It has been an established fact that the sensors with high accuracy can result in the consumption of a high amount of power. To handle this issue, a set of very low power consumption sensors can be used with low accuracy. By using data fusion, highly accurate information will be created [20].
- Data Fusion can be helpful in handling the big data issues of IoT because we are fusing data from many sensors into more precise and accurate information.
- Another critical advantage of Data Fusion is that it helps to hide the critical information or the semantics which are responsible for the fused results. Examples of this are in military applications, some critical medical areas and in intelligence buildings.

B. DATA FUSION CHALLENGES

Data Fusion has multiple challenges ahead, which are explored in various literature. Some of them are listed below:

- Data Imperfection: Sensor data is imprecise at times; it can be inaccurate and uncertain. This behavior is not infamous in wireless sensor networks. The imperfection must be dealt with effectively with the use of data fusion algorithms.
- Ambiguities and Inconsistencies: Impreciseness is not the only factor responsible for data inconsistencies; the environment in which a sensor is operating is largely responsible as well [21]. Outlier detection, replacement and data imputation are vital in IoT environment.
- Conflicting Nature: The conflicting nature of data can give rise to counter-intuitive results. The problem of conflicting data is visible more in evidential belief reasoning and Dempster's rule of combination. The data fusion algorithm must take critical care while treating conflicting data [22].
- Data Correlation and Alignment: This problem is more common in wireless sensor networks (WSNs) and can result in over or under confidence in a data fusion algorithm. An alignment problem which is also known as a sensor registration problem occurs when sensor data is transformed from every sensor's local frame to a common frame prior to fusion.
- Trivial Features: In IoT environment, applications may consist of several hundreds and thousands of sensors sensing different parameters. These sensed values in large setups such as smart cities and industrial plants consist of trivial and nontrivial data. Processing of trivial data may affect the data fusion accuracy. Thus most relevant features need to be selected before data fusion.
- Dynamically Iterative Process: Data fusion is not a static process in nature; however, dynamically iterative needs regular refinement of the estimates in a fusion environment. No Magical Algorithm: With time researches in data fusion area has advances and high performance algorithms are there now. However, it is still difficult to say that a perfect data fusion algorithm exists.

In IoT, environment information fusion can be used in various areas to enhance the IoT ubiquitous aspect. These areas are environmental monitoring, healthcare, crisis management, monitoring, controlling, tracking, intelligence gathering, and many more. Data fusion in IoT can take place at four stages: decision level, feature level, pixel level and signal level. With respect to Fig. 2, IoT data fusion can also be seen with two different perspectives. First, it can be viewed as a single hop where every sensor transmits data to the data fusion center directly. Second, it can occur by a multi-hop process, where data passes across adjacent sensors.

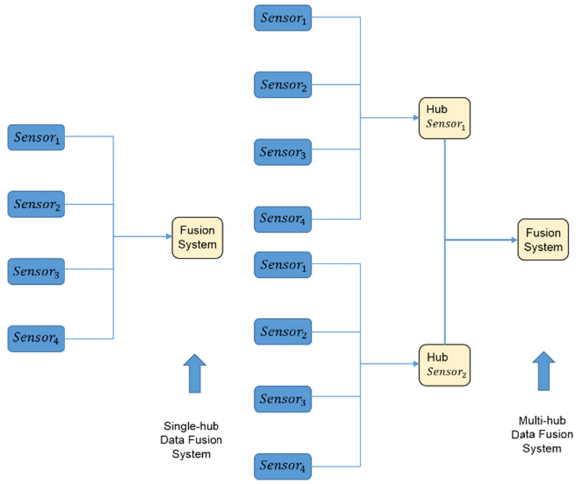

FIGURE 2. Diagram of Single hop and multi-hop sensor data fusion.

The multi-hop mechanism has several advantages which are discussed in Section IV.A of the paper.

III. MATHEMATICAL METHODS FOR DATA FUSION

Data fusion techniques can be classified based on the mathematical methods into three broader categories:

- Probability-based methods including Bayesian analysis, statistics, and recursive operators.
- Artificial Intelligence (AI) based techniques including classical machine learning, fuzzy Logic, Artificial neural networks (ANN) and genetic evaluation.
- Theory of Evidence based Data Fusion methods

In Data fusion systems, there are various architectural models; however, applications constantly use their own data fusion architectures. Some of the basic and fundamental models include the Joint Directors of Laboratories (JDL) Model, Modified Waterfall Fusion Model, Boyd Model and Dasarathy's functional model [23]–[25]. These models further divide into various layers, and then the layers into sub-layers. However, the core of data fusion does not lies in its architecture; it indisputably lies in the data fusion methods on which ultimate fusion processing takes place.

In this sections, we reviewed and classified the literatures based on different categories of data fusion approaches. This section is divided into three sub sections in which we reviewed literatures based on probabilistic data fusion methods, artificial intelligence-based data fusion methods and evidence theory-based data fusion methods.

A. PROBABILISTIC DATA FUSION ALGORITHMS

In this section, we reviewed some of the most recent works related to probabilistic data fusion techniques and algorithms. Probabilistic techniques are the most classical, are less complex and the most widely used for data fusion, though the accuracy might be low compared to integral techniques [19], [24]. Most of the conventional algorithms for data fusion have probability in their core. However, there are some challenges that occur for probabilistic data fusion, including: researches indicate that probabilistic data fusion systems can not represent complete information that is required for defining and depicting sensing and data fusion operations, a high level of complexities in handling non-monotonic logic through probability and it is difficult to handle graded membership if compared to fuzzy logic in a set [19]. Bayesian theory, Markov Chain and the Monte Carlo method are some of the most studied and widely used methods in data fusion in recent times.

Probability-based data fusion algorithms are widely used in target tracking problems. The most classical example of single target tracking is the Probabilistic Data Association (PDA) algorithm. Several improved versions of PDA have been given in literature, and are very efficient in single target tracking. We also observed that the situation and complexity changes in multi-target tracking (MTT). Track validation is difficult because tracks compete with each other, therefore a more efficient Joint Probabilistic Data Association (JPDA) algorithm is used for MTT. It uses a measurement-to-track association probabilities evaluation. JPDA algorithm is a suboptimal single-scan approximation to the optimal Bayesian filter where associations are made sequentially between the tracks which are known and the latest observations [19], [24], [26]. An optimize JPDA method is proposed in [27] which is computationally tractable than conventional JPDA algorithm in applications with higher clutter density. With optimized JPDA method and simple framework in [27], performed better than some well-known MTT algorithms. Both PDA and JPDA suffer from bias phenomenon. It is observed that PDA algorithm has more biases then JPDA algorithm. In cutter environment PDA algorithm has bias phenomenon and JPDA algorithm has rejection bias and coalescence [28].

Further, a more efficient algorithm than JPDA is known as the Multiple-Hypothesis Tracking (MHT) algorithm is developed. It is a recursive algorithm. In recent years, greater attention has been paid to MHT in practical applications. MHT is important in multiple dim target surveillances, as it allows for deferred decisions. Therefore, an easy and natural accumulation of target information has taken place. Easy implementation of new tracks is initiated with simple logic [29]. In MHT, multi-target tracking is carried out by doing a likelihood evaluation which enhances its performance over JPDA [19], [24]. However, memory requirements of MHT grow exponentially as frames increase for the purpose of resolving associations [30].

The eight steps of the classical MHT tracking algorithm [29] are illustrated in Fig. 3, where, at k_{th} cycle, MHT complexity can be expressed as:

$$C_{MHT}(k) = \sum_{i=1}^{8} C_i(k) \tag{1}$$

Where the computational complexity and each step complexity are denoted by C_{MHT} *and* C_i. In Fig. 4,

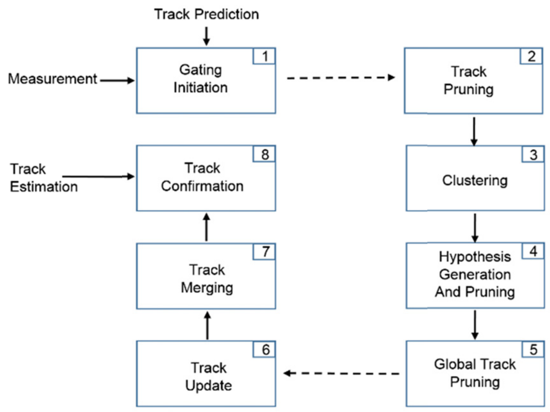

FIGURE 3. Eight steps of Multiple-Hypothesis Tracking (MHT) [29].

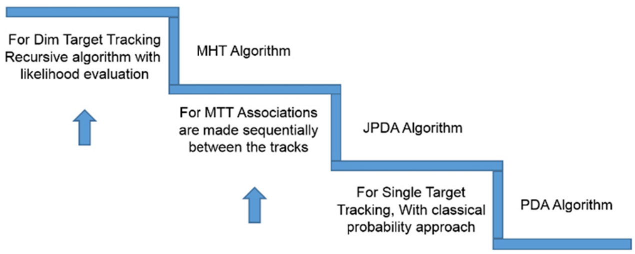

FIGURE 4. Comparative illustration for Probabilistic Data Association (PDA), Joint Probabilistic Data Association (JPDA) and Multiple-Hypothesis Tracking (MHT) Algorithm.

we visualize the comparison of PDA, JPDA and MHT algorithms based on their main objectives.

The Bayesian data fusion approach is the most classical fusion approach, as it is accepted and used widely for data fusion and it is the part of the core of various data fusion methods [31]. It combines multimodal information based on the probability theory [32]. The Bayesian approach constitutes of priors' definition, its specifications and posteriors computations. Several Bayesian approach-based data fusion methods are proposed in [33] and [34]. In [33], for distributed target detection, two methods have been proposed. The first one is the distributed Bayesian approach and the second method is the Generalized Likelihood Ratio Test (GLRT) for WSNs. Every sensor approximates the objects with a single bit prior to transmission to the fusion center due to energy and bandwidth constraints. The Bayesian approach proved to have better receiver operating characteristic (ROC) performance when compared to GLRT-based algorithms. The paper [33] also deals with the problem that at times the sensor number can be random and locations are unknown to the fusion center. For this problem, a fusion rule has been proposed based on the scheme that is utilized by the Scan Statistic. Whereas in [34], a method is proposed where the authors use two Bayesian trackers with various formulations. The solution handles challenges like shadows, occlusions, illumination changes, clutter, and motion changes. Thus, output is robust and with high accuracy due to the fact that the Bayesian approach is used here, incrementally calculating the probability based on new observations and uses likelihood's prior knowledge for inference.

Most of the methods available to acquire the global estimates depend on data fusion. None of these methods are perfect. Tracking algorithms accuracy is affected by common process noise. Few adaptive techniques to handle common process noise in [35]–[37] literatures are used to subdue the filtering dilemma. This is achieved by using a set of two parallel groups of filters, namely, wide bandwidth and common process noises of narrow bandwidth. However, these methods are dependent on specific target scenarios and single maneuvering targets.

For handling the target dynamics variations in fast changing scenarios and diverse accuracy requirements, an adaptive data fusion estimation scheme is required, and a hybrid algorithmic solution is needed. In paper [38], a narrow bandwidth Information Matrix Filter (IMF) is selected at quiescent levels and for maneuvering phase target tracking, wide bandwidth IMF is chosen to overcome common process noise challenges. IMF prediction depends on the propagation coefficient, which is observation independent. It is also simpler to decouple and decentralize. The paper [39] also uses the IMF technique for a novel switching algorithm which is evolved from the Bayesian classification theory [38]. It initiates in a dual-band IMF for creating a Switching Adaptive Filter (SAF) for target dynamics unpredictability. The algorithm is designed by the fading memory formulation and sum of the normalized innovations squared. This is achieved by assumption of two classification classes on statistically independent data sets. The work gives better performance results than a single IMF for the tracking of maneuvering or non-maneuvering objects.

Markov Chain, Monte Carlo (MCMC) and some hybrid methods are also used in several literatures to track objects based on the probability theory. In one of these types of work [40], a technique is used for obtaining useful information for detecting and tracking humans with lasers and RGB-D in mobile robotics. An efficient tracking algorithm based on the MCMC method was proposed for the challenging environment which includes frequent occlusions and cluttered scenes. The proposed data fusion system is competent to discover and track several humans in classical service robot scenarios.

In another similar type of work [41], a hybrid tracking algorithm is proposed which uses the Bayesian filter and MCMC sampling to manage object interactions. In this work, long-term image information is used to handle missing and uncertain face identification. The algorithm exploits both static and dynamic observations for failure assessments. The performance of the algorithm is better than other state-of-art algorithms which are not using long term observations and the Hidden Markov Model, respectively [41]. The hybrid data fusion approaches exploit the benefits of every constituent's methods. Hybrid fusion algorithms are more computationally complex than non-hybrid approaches [42]. None of these algorithms have any clear advantage over the other. However, they are more efficient and can handle more challenges with respect to non-hybrid approaches [42].

IoT middleware is an interface that integrates and facilitates the interaction between the various elements called 'Things' and internet. A very critical part of IoT middleware is event processing. The predictive fusion analytics has been studied in [43], using Bayesian Model Averaging (BAM). For proactive complex event processing, prediction analytics can play a supporting role achieved by the fusion of data. The method is used for large scale IoT applications. The method uses the expectation-maximization (EM) inference and Gaussian mixture models for basic Bayesian predictions. MCMC approximation is used for Bayesian averaging and the developed model is based on event context clustering. Results showed that the method has a high accuracy when compared to other traditional approaches. However in [43], BAM and EM still needed to be parallelized in the developed technique. For event processing in IoT, there are various challenges, such as heterogeneousness of data and devices, high volume of data, unknown event occurrence time and distributed event processing.

One of the major difficulties in sensor data fusion is that sensors regularly provide false observations which are hard to predict. Due to this fact, the data fusion systems with these spurious values from sensors must be rectified by identification and elimination. Otherwise, they will result in a high rate of inaccuracy, which would affect the final estimation. To address the spurious data problem, paper [44] used a modified version of the Bayesian approach, which automatically determines the sensor measurement and inconsistencies. In the work, three Bayesian techniques are analyzed. The first is the simple Bayesian technique, the second is the centralized Bayesian technique, and the third is sequentially fusion with a modified Bayesian technique. In the third approach, the identification of spurious data and later eliminating this sort of data, giving the highest level of accurate results among the three. In addition, the second one performed better than the first, as it has a built-in mechanism for decreasing the weighting of spurious data.

1) OPPORTUNITIES AND CHALLENGES

After reviewing the various literatures in Section III.A, we concluded that the probability based approaches for data fusion are simple, less complex and widely accepted and considered as the most classical data fusion approaches [19], [24]. The Bayesian technique can exploit prior knowledge to a great extent, thus one of the biggest advantages of the Bayesian technique-based algorithms. There are few disadvantages of the probability approach:

- Limited to the subjectivity of prior and difficult to find prior values, particularly in case of BPT.
- It is hard to represent complete information for defining and depicting sensing.
- Can result in low accuracy.
- Probability based data fusion methods complexities increase with non-monotonic logic.
- Probability based data fusion methods are not a good choice for handling graded membership.
- Not able to handle uncertainly.
- Output in prone to common process noise.
- In PDA and JPDA, computational time rises exponentially as number of targets increase specially in tracking problems.

However, with time, several improved versions of JPDA [45]–[48], MHT [49]–[51], Bayesian [52], [53], MCMC and GLRT algorithms [54], [55] are proposed to overcome the above mentioned drawbacks. Still, there is a huge window for improvement in these algorithms to address these problems, which will open the gates for future researches.

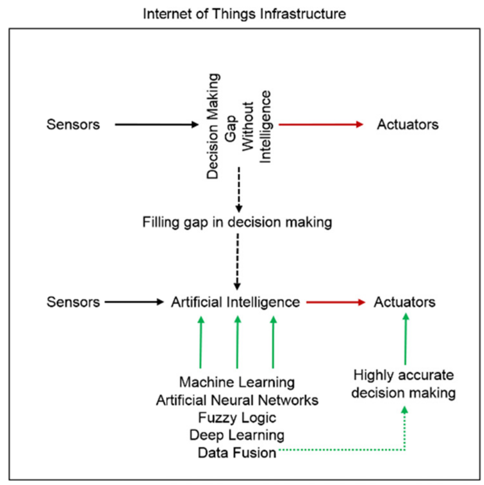

FIGURE 5. Illustration of how Artificial Intelligence enhances deci-sion making power of Internet of Things (IoT).

B. ARTIFICIAL INTELLIGENCE BASED DATA FUSION ALGORITHMS

We have to evolve IoT to be the Internet of Intelligent "Things" to make it truly ubiquitous. Sensor networks and actuators are becoming the backbone of IoT based applications such as healthcare, smart societies, military, seismic activities prediction and warning systems, intelligent transportation and tracking systems. Artificial Intelligence (AI) enables the actuators to take highly accurate and informed decisions based on the sensed data as mentioned in Fig. 5. This means AI can play a crucial role in the IoT paradigm, especially in the areas where decision making and prediction are of vital importance. Developing intelligence is a gradual process, acquired by machine learning, AI, Fuzzy Logic, Deep learning and data fusion as mentioned in Fig. 5. The process of developing intelligence for IoT-based smart societies are studied in various works [2], [6], [15],

The significance of AI in IoT can be seen in the latest happenings in the computing world. Former Apple's Siri director Luc Julia, currently the VP of Samsung Open Innovations, presented the Samsung Architecture for Multimodal Interactions (SAMI), which is part of Samsung's AI for its IoT based strategy [56]. Recently, Google acquired, DeepMind, an AI company, in its quest for IoT. Other recent big acquisitions consist of Boston Dynamics, a robotics company, and Nest Labs. All of this can be seen as the serious efforts of Google to boost their IoT development [57]. Similarly the Google of China, Baidu announces several IoT projects specifically focusing on AI [58]. AI in IoT is now widely used for sensor fusion, event processing and localization. In proceeding sections we will concentrate on AI based data fusion research and development endeavors.

1) SUPERVISED MACHINE LEARNING

Supervised machine learning (SML) is the approach where the algorithms learn from a set of rules known as training data. Number of independent variables represented by a response variable or dependent variable, which are often called as label. After training the SML algorithm which can also be called as classifier, prediction of response variables is carried out from given set of independent variables [59]. Various techniques of connecting intelligent things and acquiring key insights from sensed data from IoT are discussed in [60]–[63]. These studies also explains mechanisms to create intelligence environments to exploit the advantages of machine learning in IoT.

The practical application of data fusion based on Bayesian approach is pretty limited in the scenario where huge amount of data is involved. This is due to the fact that stored information is in form of quite sizable set of samples, so this data fusion approach is impractical for real-time usage where fusion centers have limited bandwidths. In [64], SVM based data fusion method is proposed to overcome the negative impact of huge datasets on Bayesian approach. Statistical learning theory used by SVM gives support for information compression with the help of representations based on optimal kernel.

Remote sensing will be one of the major application areas in near future which takes leverage from IoT infrastructure and its sensing capabilities. Better understanding of the site is achieved by fusing information from multiple sensors. In fusion research and development endeavors [65], SVM based data fusion algorithm is proposed for fusing multispectral and panchromatic data gather for the purpose of remote sensing of Shaoxing City, China. A generalize mathematical formulation of [65] is given below.

The training of SVM is given as:

$$(x_1, y_1), .., (x_\lambda, y_\lambda)\,, x\epsilon R^n, \quad \{y\epsilon +1, -1\} \tag{2}$$

Hyperplane is given as:

$$(w.x) - b = 0 \tag{3}$$

Classification can be represented as:

$$(w * x) - b \geq 1, \quad if \ y_i = +1 \tag{4}$$

$$(w * x) - b \leq -1, \quad if \ y_i = -1 \tag{5}$$

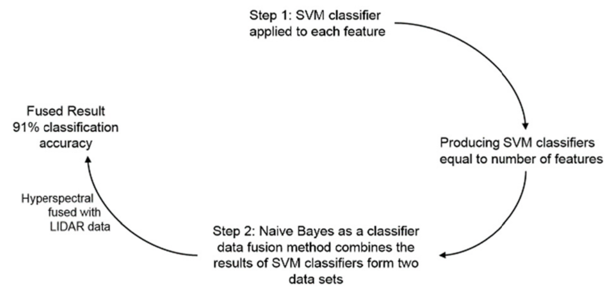

FIGURE 6. Illustration Hybrid data fusion method proposed in [66].

Where sample number is denoted by λ, input data dimensions are denoted by n, "." is the dot product and w is the normal direction of the hyperplane is the Euclidean function. Further the output shows the classification accuracy of 76.5 percent for [65]. Similarly a more recent work [66], which fuses hyperspectral and LIDAR data by using hybrid data fusion approach. Combination of SVM and Naive Bayes classifiers are used to perform data fusion in two steps as illustrated in Fig. 6. When hyperspectral and LIDAR data processed separately on the classifiers, produce 88% and 58% accuracy. However, data fusion results in 91% classification accuracy in [66]. Another feature oriented data fusion method for hyperspectral and LIDAR data is proposed in [67] which uses Random Forest machine learning algorithm.

As IoT shows promise to make our everyday life safer and prosperous by deploying safety critical applications such as smart healthcare systems, Tsunami and flood warning systems and intelligent vehicle management systems. These cyber-physical IoT systems make us aware of unwanted and dangerous situations that can arise due to the triggering of a particular event. For example brake fluid leakage in a car, this event can trigger a dangerous after-event of failure of breaks which can result in injuries to driver and co-passengers and even death. Fault detection plays a crucial role in this aspect which is critically analyzed in [68]. One of such work which addresses fault detection problem for motor using four step multi-sensor data fusion using SVM is introduced in [69] which is further explained in Fig. 7. Several machine learning based multi-sensor data fusion methods are evaluated in [70], such as K-nearest neighbor (KNN), Linear and Quadratic discriminant analysis. The data fusion is performed at feature level. Further these data fusion methods are tested on traffic management problem on multi-sensor data fusion architecture.

2) ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) have an extraordinary ability to derive meaning from complex and imprecise data. They can extract patterns and find new trends in highly complex data sets. They support adaptive learning with self-organization in a real time environment and can achieve a high degree of fault tolerance. In broader terms neural networks are basically for data fusion, as they are making data more accurate and precise by complex training and learning.

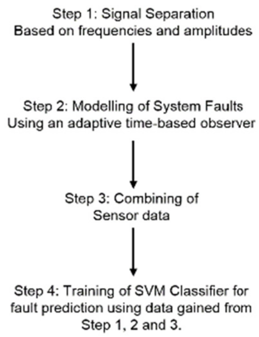

FIGURE 7. Four step of SVM based data fusion [69].

Fusing historical data by training and testing, ANNs are really helpful in predicting highly accurate values [71].

Recent travel time prediction algorithms generally require a large volume of data for the identification of algorithmic parameters. For this reason, these algorithms are less cost effective and too time consuming. To address this problem, ANNs based algorithm to compute travel time is proposed in [72]. It is a dynamic technique to predict speed, and it implements data fusion to combine speed sensors data in an expressway link. Another set of two algorithms are derived further which are Speed Integral Travel Time Calculation Method (SITCM) and Space Discretization Travel Time Calculation (SDTCM) algorithms. These two algorithms are more practical in prediction of travel time. The average prediction error is less than 10%; therefore, it can meet the requirements of on field use. Furthermore, these algorithms are simple and easy to implement. However, SITCM runs more smoothly than SDTCM, whereas SITCM is less accurate than SDTCM.

An important area where data fusion by ANNs is used effectively is wind speed forecasting. One of the such work uses ANNs to forecast wind speed by a prediction enabled by fusing the historical wind speeds together in [73]. Due to the highly complex nature of wind speed data, it is a hard task to predict future values. Accuracy in the estimation of wind power output is critical, as wind power generation is proportional to the cube of wind speed. This study provides a solution which predicts various trends of future wind speeds. It does this by proposing data fusion algorithm using several neural networks. ANNs are trained and tested by the wind data sets. The algorithm gives minimum mean absolute errors which are significant. For the prediction of monthly patterns of wind speed, two layers feed-forward back propagation (FFBP) networks with 6 in middle layer and 30 neurons in the output layers is used. For hourly prediction of wind speed, FFBP network with 30 and 12 neurons is used in [73]. Another such study [74], uses neural networks for wind speed prediction; however, the main difference between [73] and [74] is that in [74], two layered neural networks were used. However, in [73] multiple neural networks are used, which means increased complexity. Some short term wind power predictions methods are also proposed in [75] and [76].

Further ANNs learning through fusion of training data is also used in other areas like localization. The accuracy of indoor localization and navigation services based on radio signal strength indicators (RSSI) and radio frequency is on the lower side. This is due to the variable of the RSSI values. In paper [77], the multi-neural networks approach is used to solve the issue of RSSI. Bluetooth indoor localization with multiple neural networks is achieved by training and using neural networks based on user orientation. A highly accurate and cost efficient Bluetooth architecture for indoor navigation is possible.

3) FUZZY LOGIC

Lotfi Zahed in 1965 first introduced the term "Fuzzy" as he proposed fuzzy set theory and later he became famous for his fuzzy mathematics. Fuzzy logic has been used to manage concept of partial truth which range between completely true and false. It has numerous real life application as discussed in [78], such as AI, controlling, environment monitoring, gaming, electronic appliances automation, medical diagnosis and event detection etc. A technique of event detection using the fuzzy logic branch of AI in cluster Wireless Sensor Networks (WSN) for data fusion has been proposed in [79]. One of the most important applications of WSNs is environment monitoring which can be seen in larger perspective of IoT based smart societies. The system in [79] consists of multiple sensors for humidity, carbon dioxide and temperature sensing. A system based on fuzzy rules carried out the fusion of signals. Signals are collected at the cluster heads and then the fusion process takes place. The advantage of multi-sensor fusion is that it increases the accuracy and reliability. A important requirements of modern day societies are smart vehicle parking systems that can take leverage from IoT infrastructure to provided headache free parking management as in [80] and [81]. A fuzzy logic based data fusion algorithm is proposed in [82] for monitoring the parking space. For this purpose magnetic sensors are used and occupancy probability is computed of the corresponding parking space. The data fusion algorithm in [82] gathers information with high accuracy of the monitoring targets which results in correct decision making and has anti-interference ability. Focusing on making our societies more safer by using IoT infrastructure, in [83] an intelligent fire detection and controlling approach has been proposed which uses fuzzy based data fusion.

The use of fuzzy logic is increasing in popularity for tracking systems due to the numerous benefits mentioned above. Especially for tracking problems in the PDA and JPDA, as the number of objects increase in parallel and there is an exponential rise in the computational time. However, common sense is used in fuzzy logic to overcome this [84]. There are several fuzzy-based methods for fusion, such as the fuzzy inference correlation algorithm [85], the fuzzy double threshold track association algorithm and the fuzzy clustering means (FCMA) algorithm [86], [87].

In [87], a data fusion solution for track-to-track problems in multi-sensor and multi-target with multiple attributes is proposed. A fuzzy clustering mean algorithm (FCMA) is stated to minimize the number of tracks and by using the degree of membership of each target for determining associate duplicate tracks. For association and fusion purposes, sensor data with sensor resolution is used; the same is done to identify the most accurate sensors in the system. Monte Carlo simulation is used to show that the new scheme minimizes the computational complexity and increases the performance with respect to Euclidean clustering and Bayesian minimum mean square error method. The paper [88] concentrates on multi-sensor and multi-target distributed tracking systems, such as the ones discussed in [87].

The FCMA is robust to noise; however, selection of suitable parameters is difficult and is a challenge for providing optimal performance [87]. The work in [88] is based on track association. Association is very critical, as it is uncertain whether the particular tracks from distinct sensors represent the same target. Every sensor node performs noise measurements for distinct positions of the targets. After on board computation, data is carried to the data fusion center. This double-threshold fuzzy-based track association algorithm uses an adaptive threshold and provides less association errors, resulting in better performance.

A hybrid class of fuzzy and Kalman filter schemes are also used for data fusion purposes efficiently. One such study [89] proposes fuzzy logic-based adaptive Kalman filter (FLAKF) for multi-sensor data fusion. The measurement for the noise covariance matrix is adaptively adjusted for every local FLAKF to fit noise profile statistics for in-coming data. A fuzzy inference system is used for adaptation. The use of fuzzy logic helps to handle imprecise data. Whereas the Kalman filters tune the covariance matrix to obtain more accurate estimations. Thus, the obtained hybrid technique is more accurate. Similarly, the integration of fuzzy logic and Kalman filter is developed for data fusion in [90] for autonomous vehicles guidance.

With respect to all the literatures surveyed in Section III.B, it can be said that AI-based data fusion approaches are gaining popularity in practical use. These techniques are more accurate than other methods of data fusion and can be applied for a wide range of fusion problems. Fuzzy logic can handle sensor data uncertainty efficiently. ANNs are ideal for nonlinear systems and complex pattern discoveries are achievable. However, neural networks failed to explain how they learn to fuse from the input sensor values and AI approaches are computationally complex. In addition, some challenges remain, as a 100% correct prediction is still not achievable through fusion.

4) OPPORTUNITIES AND CHALLENGES

In recent times, the use of AI based data fusion methods is increasing. Supervised learning methods such as SVM can handles high dimensional data. ANNs and Fuzzy logic allow imprecise and contradictory inputs and handle arbitrary complexities efficiently. Fuzzy logic data fusion systems are better for handling imprecise sensor inputs and uncertainty as compared to probabilistic approaches. The ANNs data fusion approach is one of the best for nonlinear data fusion systems, and complex pattern discoveries are possible. AI fusion systems are highly accurate compared to probabilistic systems. However, they are complex and computationally expensive.

C. THEORY OF EVIDENCE BASED DATA FUSION ALGORITHMS

Dempster's, first proposed the theory of belief in understanding. Later, Shafer mathematically formalized it based on evidence-based reasoning [91]. To handle imprecision and uncertainty, the belief functions theory is a popular choice to consider. The Dempster–Shafer theory (DST) is viewed as a generalization of the subjective Bayesian probability theory (BPT). There are few differences in the DST and BPT. Firstly, BPT does not have an unknown state, whereas in DST, the unknown state could be the state of knowledge for us. Secondly, BPT assigns priors, however DST uses masses for the meaningful assignments for all the states. Thirdly, less computation is required in BPT than in DST [24].

Nowadays, the DST based [92] fusion approach is widely in use. DST is a very efficient method for feature extraction in a multi-sensor environment [92]. The ability of DST to handle uncertain and incomplete data makes it viable in multi-sensor systems [93]. DST based fusion systems are globally applicable and are independent of satellite image due to the empirical and reasoning parameters determination [94]. DST field is widely studied and extensive research has been done. Light Detection and Ranging (LIDAR) is a remote sensing technique that helps to determine the distance by illuminating a target with a laser and examining the reflected light. LIDAR is an important area where DST fusion can be used significantly. However minimum attention is given to the following areas: derivation of slope from LIDAR data, quantitative assessment of the classes and the interpretation of plausibility, maximum probability, support, conflict maps and uncertainty. To address the above mentioned issues, paper [95] proposed a data-driven DST application for fusing multi-sensor data to achieve feature extraction of land cover. The technique is both cost and time efficient.

A data fusion technique based on DST for fusion of digital map road signs and video detected road signs is proposed in [96]. Another similar type of work [97] which uses a fusion system for detecting traffic sign existence by merging map data and video image, whereas [98] uses DST and situation context for assigning priority for using digital maps or camera-based system. However, none of these works address false positive detection of respective camera systems. Moreover, bad weather and light conditions, and road speed limits can reduce data fusion system performance, and are rarely taken into account. Also, no quantitative data is given with respect to the computational speed of these methods. To manage these issues related to reliabilities, in paper [99], five fusion algorithms are proposed to deal with the unaddressed fusion issues of [96]–[98]. Four of them are based on information priority and the fifth algorithm is based on

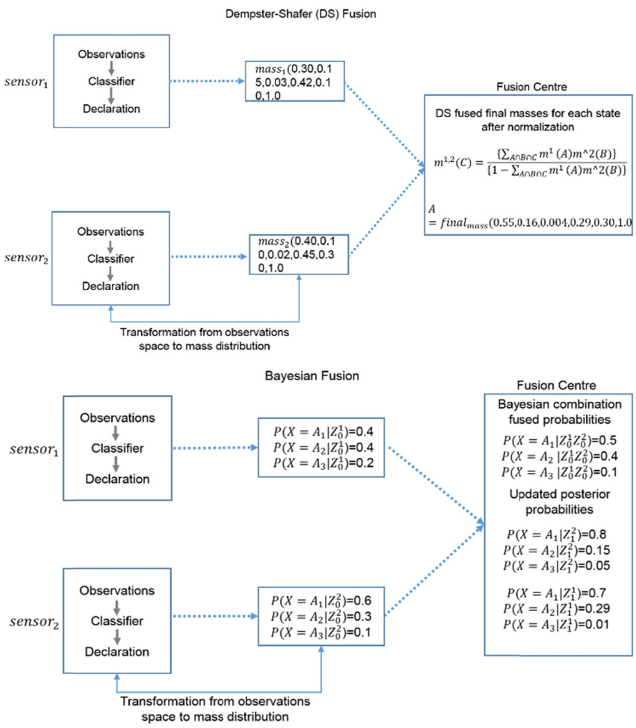

FIGURE 8. Bayesian Fusion and Dempster-Shafer (DS) Fusion.

classical DST. All five algorithms were more efficient and produced more accurate outputs.

1) OPPORTUNITIES AND CHALLENGES

We concluded the above analysis of the DST literatures on two main grounds: benefits and open challenges for DST. DST obviates arduous problems in specifications of priors and with respect to uncertainty; it can be ignored on a case-by-case basis. DST is a simple approach which describes evidence patches with diverse abstraction levels and further unites the evidence. Complexity in computation is a problem in DST. Further, it cannot be considered as a proven decision theory like the universal acceptance of BPT. Primarily, BPT consists of two states which are either an event or nonevent; however, an unknown state is missing. The DST incorporates the third state called the unknown state. The DST mass functions definition is the most critical and difficult task in its implementation. The DST has been extensively studied in computer science and AI, but has never been accepted completely by statisticians [100]. In Fig. 8, we couple [42] and [101] to form a visualization of BPT and DST, which gives a succinct explanation of fusion.

IV. DATA FUSION METHODS FOR IoT-SPECIFIC ENVIRONMENTS

There are several challenges associated with data sensing. A few of the universal challenges are:

- Distributed environment of WSNs which are the subset of IoT.
- The highly heterogeneous nature of IoT due to various heterogeneous devices and data.
- Nonlinearity and tracking issues like: multi-target tracking (MTT), cost effectiveness, error mitigation, asynchronous and track-to-track (T2T) problems.

In this section, we review and classify literature based on the above mentioned challenges faced by data fusion methods. This section is divided into four parts: distributed environment challenges, heterogeneous environment challenges, nonlinear environment challenges and tracking environment challenges.

A. DISTRIBUTED ENVIRONMENT

Theoretically, distributed data fusion is a fairly developed concept in the last few decades, and has been studied in depth [102]. However, the practical implementation of these techniques is still a challenging task in the IoT environment. The distributed algorithms do not have any centralized control. They can also be referred to as sub branches of parallel algorithms. The fundamental elements of a distributed information fusion system in IoT are the sensors and processors. Sensors are responsible for data generation by observing the operating environment. Processors are responsible for fusing the data. In this section, we review and classify the distributed data fusion algorithms in WSNs which can be seen as subsets of IoT. In the distributed environment, the fundamental estimation algorithm is the distributed Kalman Filter (KF) algorithm and is highly scalable. In various practical problems, KF based algorithms play significant roles. KF can be considered a prediction corrector filtering algorithm which is achieved by evolution or state propagation and data updating. We can consider KF as a Bayesian fusion algorithm, as proved in [101]. The various areas where distributed KF have been implemented include weather and environmental monitoring, surveillance, tracking and medical areas.

Most of the algorithms in this class are static in nature; however, the real environment network topology is dynamic. This change in network topology may be caused by the failure of the node, which is a result of reduced energy. The study [103] deals with such types of networks. The work based on simulation of 200 sensors is distributed randomly in a dynamic environment. The Central Kalman filter (CKF) is used for evaluation of Distributed (KF) in the work. The proposed algorithm behaved very close to CKF. The Distributed (KF) algorithm-based sensor can run up to six neighboring sensors. KF implementation in a distributed manner holds the advantage of gaining matrices computational cost when compared to CKF. The other advantage for Distributed (KF) is that the scalability is easier, which is required in a dynamic environment like IoT.

In IoT, energy efficiency plays a critical role, since we have hundreds of sensors operating together. The system must be energy efficient. Otherwise, a lot of cost is incurred on energy consumption by the sensors. A Cuckoo Based Particle Approach (CBPA) is used by the random deployment of nodes based on static clusters with the Cuckoo Search in a distributed WSN. After the cluster heads are selected, the data is collected, aggregated and forwarded. A generalized particle approach algorithm is used and the data is forwarded to the base station. The network energy consumption problem transforms into dynamics and kinematics, completed by the Generalized Particle Model Algorithm (GPMA). The outcome of this hybrid approach results in a reduced low cost energy efficient technique. A high degree of consistency with a low level of complexity due to the sub-optimal algorithm is also achieved [104]. With the same goal, work [105] aims to reduce energy cost related to the distributed data fusion process. It is achieved by providing an approximate solution known as P2lace. This is done in two phases; in first phase, a task graph partition takes place, and in the second, task graph placement occurs.

Another way to reduce energy consumption in the distributed WSNs fusion systems is to put some sensor nodes in a sleep mode for some time, while the remaining sensor nodes are active. A distributed data fusion algorithm for sensor nodes has been proposed in [106]. The algorithm is time driven, which performs network data aggregation and is accomplished by nodes scheduling and batch estimation. The scheduling of the least sensor nodes is done in the clusters. This is done because of two reasons: firstly, to meet the conditions of the acquisition cycle, and secondly, to reduce the time that the sensor nodes are in a working state. In parallel, data fusion is introduced based on batch estimation. Output produced by the algorithm shows reduced network energy usage and improved reliability. This fusion system can be efficiently used in health monitoring applications.

A similar study to [106] is proposed in [107] which is based on cluster formation and reduces the energy cost of data fusion. However, the major difference in the contribution of these two works is that the data fusion technique of [107] is based on a multiple path selection with a packet delivery ratio on the higher side. A few more ways of achieving energy efficiency are proposed in [108]. Two energy planning algorithms for progressive estimation are proposed. The authors also computed energy cost for consensus estimation; it is a technique for the distributed fusion in the multi-hop sensors model based on peer-to-peer networks. The set of algorithms evolved from the following principles to achieve energy efficiency [108]:

- Multi-hop are highly energy efficient because they refrain from long distance data transmission.
- By progressive data fusion which hops through sensors resulting is low energy consumption.
- Reducing energy by the predetermination of transmission energy. It is done with the help of the prior knowledge of all channel state information and a routing tree.

Scalability is a challenging task in a distributed environment such as IoT, which is also heterogeneous and dynamic. In an environment like IoT, a significant issue is that suddenly a number of sensors can awake, adding several nodes in WSNs. The data fusion algorithm must be efficient to deal with these kinds of situations. To address this issue, [109] discusses and analyzes several sub-optimal algorithms. These algorithms include the following:

1) CHANNEL FILTER

It is a simple data fusion approach. Only the first ordered redundant data is taken into account. Every channel has a pair of agents, a transmitting agent and a receiving agent. Redundant information is removed by the transmitting agent. However, ad-hoc WSNs transmitting data sometimes does not reach the other end. Therefore, the receiving agent can do the task of transmitting agent in the dynamic ad hoc WSNs. Channel Filter fusion equation is given as:

$$p(x) = \frac{p_1(x)\, p_2(x)/\bar{p}(x)}{\int p_1(x)\, p_2(x)/\bar{p}(x)\, dx} \tag{6}$$

In Equation (6), $p_1(x)$ and $p_2(x)$ are the density function fusion probabilities and $\bar{p}(x)$ is the previous density function received. The advantage of this algorithm is that there is no need to maintain a high volume of history of past activities. Though one disadvantage is that during the filter, dependent information is removed. However, this effect can be minimized if the time between current processing and when redundancy occurred is too long.

2) Naïve FUSION

It is one of the simplest data fusion techniques. It is anticipated that the dependency between the density functions is minimal; however, the technique is unreliable. Due to the lack of past information, over-confidence can occur. The naïve fusion equation can be written as:

$$p(x) = \frac{p_1(x)\, p_2(x)}{\int p_1(x)\, p_2(x) dx} \tag{7}$$

3) Chernoff FUSION

In unknown dependency distribution, the Chernoff technique can be used. Theoretically, two arbitrary density functions can be combined using Chernoff fusion in a log linear fashion. However, fused density may be distracted. Another disadvantage is that extensive computation is required. Chernoff equation is given as:

$$p(x) = \frac{p_1^{w}(x)\, p_2^{1-w}(x)}{\int p_1(x)\, p_2(x)/\bar{p}(x)\, dx} \tag{8}$$

Where w ϵ [1, 0]

Though there are several studies based on data fusion algorithms in a distributed environment, there are still several challenges that remain. As stated in [109], the data fusion process is described mathematically by the set theory in the given equation:

$$\Phi(.|I_i) = \Phi\left(.|\bigcup_{i=1}^{n} I_i\right) \frac{1}{C} \prod_{i=1}^{n} S_i^{(-1)^{i-1}} \tag{9}$$

Where S_i is the i event probability combinations, the alternating division and multiplication of the joint probabilities from (6), get rid of conditional dependencies form of shared information in the datasets.

4) OPPORTUNITIES AND CHALLENGES

In the theoretical distributed data fusion, removal of duplicate information is simple. Duplicate information identification for distributed fusion systems is arduous when this theory is put into practical use. In distributed fusion, it is difficult to recognize correlated information originating from past fusion events and to get the values of previous data sets. IoT is highly heterogeneous, both with respect to devices and data, which makes distributed fusion challenging. Due to its dynamic nature, distributed WSNs change their shape and size frequently, therefore network scalability is an issue of concern in distributed fusion systems. Heterogeneity is also a challenge for IoT. In the next section, we analyze and review the literatures of heterogeneous data fusion algorithms.

B. HETEROGENEOUS ENVIRONMENT

IoT environment is not always homogeneous; therefore, heterogeneity is not rare in this diverse environment in terms of both devices and data. One of the major difficulties which heterogeneous fusion systems face is due to the different feature spaces of data sets. In heterogeneous systems, data sets are generally represented in several feature spaces. This makes it difficult to analyze relationships among different data, even when the data sets are related to each other semantically.

As the solution of the above problem, a graph embedding framework in [110] is used to deal with space alignment issues in heterogeneous fusion systems. The proposed framework converts every data set into a graph and zero distance assignments between corresponding pairs, which eventually results in a single graph. A non-metric multi-dimensional scale is proposed which uses rank order. The advantage of using rank order is that this type of fusion system can manage alignment as well as deformation. This technique proved efficient and better than the existing constrained Laplacian eigen-maps, tensor decomposition and Procrustes analysis methods.

A Bayesian filtering-based method for heterogeneous systems is addressed in [111]; the state space model is used for locating the estimation of radio measurement and speed sensors. The tracking problem is divided into several local constraints with mutual interactions with factor graphs by message passing. During every iteration, the messages are passed efficiently with reliable information. This takes place between the prediction and the correction phase. To obviate the effects of error propagation due to speed sensor variances, the algorithm used a fixed-lag smoothing technique which relied on the past and future data of a particular point. The algorithm is less complex and shows high accuracy, thus tends to minimize the computational load. Several additional schemes are suggested in [112] and [113] to manage heterogeneous bio-medical data using the Bayesian technique. Various fuzzy logic-based algorithms and hybrid algorithms-based on the combination of fuzzy logic and the Kalman filter are better and more effective for heterogeneous sensors systems, which measure the same parameters with diverse dynamics and noise statistics [84].

Fusing data from heterogeneous observations promises to find complex multivariate relationships among the data sets. In the analysis of multivariate data from the two sets of variables for the extraction of correlated features, there are two fundamental methods: canonical correlation analysis (CCA) [114], [115] and Partial Least Squares regression (PLS) [116], [117]. PLS is feasible when two sets of variables are dependent on each other or one set of variables holds the explanation of the other [114]. On the other hand, CCA is more viable when two sets of variables are symmetrically related to each other. CCA is widely studied for explanatory multidimensional statistical analysis. The main goal of CCA is to determine the linear combinations of every variable in the given data sets; this is accomplished when the correlation is at its maximum among the linear combinations.

The major disadvantage of CCA is that the data fusion output degrades dramatically with noisy datasets [114]. In paper [118], a novel method is proposed called Noise-Outliers Removal Algorithm (NORA). NORA handles noisy data sets in heterogeneous data fusion systems in which [114] (Gonzalez, 2009) lacks. NORA is used to filter features and non-informative data points before the execution of CCA. Specifically in [118], NORA is used for preprocessing neuropsychology and Magnetic Resonance Imaging (MRI) prior to CCA execution for identifying the association between them. Several other methods were proposed to handle heterogeneous data using Bayesian analysis [119], DST [120], multiple-metric learning method [121] and hybrid data fusion method based on probability and DST in [122].

1) OPPORTUNITIES AND CHALLENGES

Heterogeneity in IoT environment is a challenging issue to handle during system integration due to disparate sources of data. These data sources cannot be combined as it is, methods are required to transform heterogeneous data to homogenous space. Further heterogeneous datasets add uncertainty. Complex multivariate relationships among the datasets. However, fusing data from heterogeneous observations promises to find complex multivariate relationships among the data sets.

C. NONLINEAR ENVIRONMENT

Nonlinear time-varying sensing also brings formidable challenges to multi-sensor data fusion. Nonlinearity can result in less accurate estimations. In [123], it is shown that an improved estimation can be produced in acute nonlinear systems at the fusion center with the assistance of optimal data fusion in a multi-sensor setup. An optimized algorithm according to each sensor's channel conditions for power allocation of respective sensor nodes is proposed. It performs dynamically for the power assignment of all sensor nodes subsets. The technique is based on a semi-definite program (SOP) [124]. Therefore, it guarantees the best available state estimation by intending to reduce mean square error values.

The Extended Kalman Filter (EKF) has been one of the most comprehensive algorithms in nonlinear tracking environments [125], [126]. However, more accurate values have been obtained from unscented Kalman Filter (KF) than EKF with the help of approximation statistics [127]. In practice, EKF has three disadvantages [128]:

- Unstable filters can be produced due to EKF linearization.
- Using EKF, linearization can only be performed if the Jacobean matrix exists.
- Linearization using EKF is highly difficult to implement due to the fact that Jacobean matrices derivation is non-trivial in most of the cases.

An unscented linear fractional transformation (LFT), which is more efficient than unscented KF, is proposed in [129]. The LFT transforms the nonlinear system to a tantamount linear model and an unscented transformation handled nonlinear structure. Further [123] broaden the LFT technique to a multi-sensor environment using the Bayesian approach.

1) OPPORTUNITIES AND CHALLENGES

KF based data fusion methods are a popular choice for non-linear environment. It is simple, less complex and easy to implement and widely accepted. However not viable with spurious observations. Exposure to outliers can result is KF breakdowns especially in sensor dense environment like IoT. It Accuracy can be questionable with respect to AI and hybrid methods and extensive computation is needed in KF if too many sensors are involved. KF are better for linear systems and conditional independence is involved. Fuzzy logic-based data fusion methods are really useful in non-linear and multi-variable systems. They are also easy to modify. A fuzzy system-based on rules fuses raw data acquired from sensors. Along with this fuzzy predictor to make data fusion highly accurate for too sensitive applications, this fusion system can work with high bandwidth and efficiency [130]. In nonlinear systems, the update problem is also critical. Regardless of several works, nonlinearity is still a complex task to manage in multi-sensor data fusion systems.

D. OBJECT TRACKING

The tracking of objects is one of the oldest areas where the use of data fusion comes into the effect. Data fusion in tracking domain plays an important role in military applications, robotics, wireless systems, and transportation. In [131], various positioning principles and the interaction between IoT and objects in tracking and positioning systems are described. Some of the possible benefits of tracking and surveillance fusion systems include correct target selection, locating the threat, identification of unidentified and unauthorized moving objects in high-level security zones and timely decision making. In this section, we review and classify various challenges in tracking data fusion algorithms, including multi-target tracking (MTT), cost effectiveness, error mitigation, asynchronous and track-to-track (T2T) problems.

A multi target tracking algorithm uses a scene adaptive hierarchical data association. This scheme adaptively determines the features with high reliability in the respective scenes for the given targets. With the help of reliable features, hierarchical feature spaces have been created, and different layers data associations take place. The algorithm works efficiently and effectively in both indoor and outdoor systems [132], whereas in [133] a MTT algorithm based on the sensor allocation problem and a set of sensors are dynamically identified. Later, track data fusion objects are tracked and collaboration is performed. As target objects move from time to time via sensor assignments, the formulation of the problem in regards to constrain optimization for maximizing tracking performance for respective targets has been done. The algorithm then performs an iterative sub gradient search which is near optimal for the integer programming problem. The stated solution is cost effective and scalable. The paper [134] also discusses the coverage guarantee and energy efficiency. Another multi-object tracking fusion technique uses ego vehicle odometry, image and radar where data fusion takes place at a high level which gives highly reliable results. This scheme also locates stationary objects and can perform width estimation. These algorithms are implemented using the application SASPENCE. This approach proves to be highly robust in difficult environmental conditions [135].

Data fusion in tracking and positioning applications is also popular in the automobile industry. Global Positioning System (GPS) data fusion along with data from Inertial Navigation System (INS) is popular in positioning systems. Although INS applications are highly accurate, the installation of INS is costly and time consuming. Vehicle positioning systems estimation must be highly accurate, reliable and with the information continuity provision. Low cost GPS receivers are commonly used in traditional automobile applications. These systems are not highly accurate or reliable, and do not provide a guarantee of information continuity provision during GPS error.

To mitigate the errors in GPS, several Bayesian filter-based data fusion algorithms have been discussed in past literatures; the performance of Bayesian filter estimations largely depends on the selection of a process model. The dynamic driving conditions must be taken into account by the Bayesian filters. An Interacting Multiple Model (IMM) based data fusion positioning algorithm is proposed in [136]. The IMM filter uses GPS and embedded sensors to adjust with respect to different dynamic driving conditions. The kinematic vehicle model and a dynamic vehicle model are integral parts of the IMM filter in the study. The algorithm is cost effective, accurate and reliable in dynamic driving scenarios. This is due to the fact that the IMM filter uses N parallel KF and is an approximation algorithm. From the group of various multiple model filters, the IMM filter algorithm accomplished

$$Cov\,[X,Y] = \begin{pmatrix} E\,[(X_1 - E\,[X_1])\,(Y_2 - E\,[Y_2])] & E\,[(X_1 - E\,[X_1])\,(Y_2 - E\,[Y_2])] \\ E\,[(X_2 - E\,[X_2])\,(Y_1 - E\,[Y_1])] & E\,[(X_2 - E\,[X_2])\,(Y_2 - E\,[Y_2])] \\ E\,[(X_3 - E\,[X_3])\,(Y_1 - E\,[Y_1])] & E\,[(X_3 - E\,[X_3])\,(Y_2 - E\,[Y_2])] \end{pmatrix} \quad (10)$$

first-order generalized pseudo-Bayesian (GPB1) estimator computational capabilities. Specially, GPB1 is a very powerful technique for behavior evaluation.

Locating critical targets is one of the most important applications of data fusion for the military and other highly sensitive security areas. High rates of detection probabilities and low error rates must be present for stringent performance. Data fusion is an effective approach for ameliorating detection performance by enabling collaboration via sensors with limited reliability. Military sensor network deployment is costly; therefore, it is preferable that optimal location placement of sensors are used to reach utmost performance. This is computationally complex, non-convex and a non-linear optimization problem. Based on the probabilistic data fusion model, a fast and efficient sensor placement algorithm is proposed [137]. It performed better compared to other algorithms in the literature.

Tracking data fusion systems use association and estimation. The IoT system consists of multi-sensors and is also designed for multi-targeting. The two broad types of association used in these systems are measurement to track (MT) and track-to-track (T2T) associations. The major difference between the two is that sensor level implementation is carried out in MT, and implementation is done at data fusion center level in TT. The association in T2T fusion is crucial. Due to false and missed tracks, random errors and sensor bias make it more perplexed. A Bayes joint decision and estimation (JDE) is optimally implemented in parallel with sensor bias to obtain a simplified JDE. With the checking of association error sensor bias, this scheme results in improved accuracy [138].

A complex asynchronous problem arises in T2T fusion during tracking of fast moving objects; however, it is insignificant for slow moving objects. To solve this problem, authors in [133] proposed a solution; the solution is executed in three different phases. In the first phase, estimation takes place at the fusion center. Recording the actual time corresponding to the fusion center time reference after acquiring the sensor data is done in first phase. In second phase, predictions are used by the fusion center to shift the received data, which will then start the next fusion cycle. This step synchronizes the data required for real time un-correlated track-to-track fusion. In the third and last phase, pseudo-synchronized data with a linear minimum variance un-biased estimator algorithm is used to fuse all the sensors' data.

An asynchronous KF is often used in T2T fusion without regard to its known drawbacks as mentioned in [138]. A comparative analysis has been done in [139] of three well-established T2T algorithms: Cross covariance [140], Covariance intersection [19] and Covariance union [141] with asynchronous KF to access the performance for the T2T fusion problem.

The Cross covariance T2T fusion outperforms the other two with respect to root mean squared errors (RMSE) and also the run time of Cross covariance is minimum. The Covariance intersection gives the second minimum runtime, where RMSE is just over asynchronous KF. In the Covariance union, RMSE is approximately equal to Cross covariance but with a high computational cost. The reason why asynchronous KF for T2T fusion gives minimal performance is due to the following facts:

- The unified KF object list is asynchronously updated at every instance when new sensor object list arrives. This is principally incorrect for KF as sensor objects of every sensors are correlated on a temporally basis which is the outcome of previous filtering and the same correlation phenomenon is observed for tracked objects.
- Implementing KF to already KF filtered data will produce additional phase delays due to low-pass property of KF.

The mathematical formulations of these methods are given below:

a: CROSS-COVARIANCE EQUATION

The cross-covariance matrix [140], [142], between X and Y is a M X N matrix denoted by Cov [X, Y], where X and Y are the random vectors, E is expectation operator and $X = [X_1X_2X_3]^T$ and $Y = [Y_1Y_2]^T$ [see (10), as shown at the top of this page].

b: COVARIANCE INTERSECTION EQUATION

Covariance intersection algorithm [19] is used for fusing two or more state variable estimates in a KF with unknown correlation. a and b are two known information items which are to be fused into information item c. Item a and b have mean/covariance $\hat{a}$,A and $\hat{b}$,B, however the cross correlation is unknown. The mean and covariance for item c has been given by covariance intersection update as:

$$\mathrm{C}^{-1} = \omega A^{-1} + (1+\omega)\,B^{-1} \quad (11)$$

$$\hat{c} = C(\omega A^{-1}\hat{a} + (1+\omega)\,B^{-1}\hat{b} \quad (12)$$

Here ω must be computed for reducing the norm.

c: COVARIANCE UNION EQUATION

The covariance union method proposed in [141], allows to fuse two tracks, even if the difference of the state estimates exceeds the covariance presented by at least one track. A new state vector $\hat{\varepsilon}_C$, is used to obtained u fused estimate. Fused covariance matrix is denoted by P_c which exceeds both P_a and P_b. The fused estimate $C = \{\hat{\varepsilon}_C, P_c\}$ is

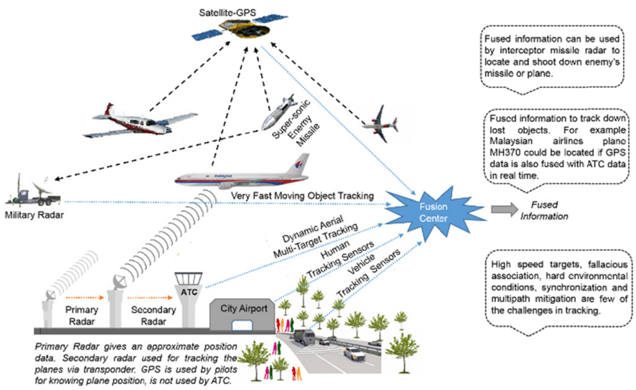

FIGURE 9. Heterogeneous multi-object tracking scenario in real time.

determined by: $U_a = P_a + \left(\hat{\varepsilon}_c - \hat{\varepsilon}_a\right).\left(\hat{\varepsilon}_c - \hat{\varepsilon}_a\right)^T$ and $U_b = P_b + \left(\hat{\varepsilon}_c - \hat{\varepsilon}_b\right).\left(\hat{\varepsilon}_c - \hat{\varepsilon}_c\right)^T$ where $P_{ab} = \max(U_a, U_b)$ and $\hat{\varepsilon}_c = \arg\min(\det(P_{ab}))$

T2T fusion faces some challenges: (1) in T2T, asynchronous data fusion in real-time tracking is a hard task to achieve, (2) the problem of dependency between the estimation of tracks and states of various sensors in data fusion center, and (3) the problem of data redundancy and common process noise which may be due to sensor biases and correlation [133], [143].

Also, tracking data fusion algorithms face challenges, such as fast moving objects, high density clutters and asynchronous systems. There are several other challenges for tracking data fusion algorithms with respect to IoT: (1) multipath mitigation in radio frequency, (2) short term and precise synchronization and pre-synchronization is required, and (3) IoT cannot render the use of localization cells for a single node exclusively because it is not feasible.

In Fig. 9, we illustrated an info-graphic to show several tracking scenarios. In [144], the deficiencies are explained of current commercial airplane tracking systems. Recently, the Malaysian airlines flight MH370 crash site could have been located if it was tracked by multiple trackers like ATC and satellites; then fused data could be used to identify the plane's location. This is just one real life example showing how useful data fusion can be.

1) OPPORTUNITIES AND CHALLENGES

With time, multiple target tracking is getting popular in terms of applications areas which are human-computer interaction, motion-based identification, automated surveillance, traffic monitoring and vehicle navigation [137]. Past works in multiple target tracking combine the set of features for uniquely identifying the objects. However, it is inclined to give high computational costs with error accumulation, especially in the IoT environment. Today's network camera setups are complex with fast changing scenarios. Therefore, fixed techniques for feature selection are not feasible. There are some major challenges for multi-object tracking data fusion algorithms in the IoT domain [132], [133], [134], [145]:

- The complexity of data association in IoT based systems is high, as critical association decisions are performed locally. This can be optimal for local domains but not globally.
- Fallacious association decisions are impossible or difficult to undo once they occur.
- The asynchronous fusion problem is inevitable in high speed target tracking, especially in T2T fusion.
- Object occlusions and complex shapes of objects.
- Information loss during 3D to 2D projection.

V. EMERGING DATA FUSION TRENDS

Recent research and development endeavors on data fusion show its evolution from conventional domains to more futuristic application domains such as infotainment systems, human activity recognition, connected and autonomous vehicles. In this section, we will focus first on recent application trends where data fusion can be applied and how deep learning can enhance data fusion.

A. AUTONOMOUS AND CONNECTED VEHICLES

An autonomous vehicle is self-driven, which has its own intelligence to understand the environment around it to drive steadily and safely. Various machine learning algorithms are used to perceive the driving environment by processing data from one type of sensor (source) such as: RGB camera, LIDAR, GPS etc. Another way to achieve driving environment perception is to combine data from multiple sensors for accomplishing a single objective. For example: combining GPS and camera images to predict safe driving distance to another vehicle on the road. Use of data fusion is quite old in autonomous vehicles. However, not much work has been done in this field prior to the year 2010. In recent years self-driving cars research and development works gained popularity and enormous interest are shown by Information technology and automobile industry titans for developing ''intelligence to drive''. This paved the way for developing state-of-art data fusion technologies for autonomous driving.

Fusing the multiple inputs into a single output is a complex problem but the outcome tends to be more accurate than single sensor data analytics as achieved by proceeding literature. For example in [146] authors use combination cameras and LIDAR for driving scene understanding by labeling image segments where as in [147] camera and laser are used to create object grid maps. In [148] and [149], single source data is used to identify pedestrians. Addressing the same problem, however using multiple data sources, a smoothing-based depth up-sampling technique for pedestrian detection is proposed in [150] which fuses camera and LIDAR data. Similarly in [151] authors uses knowledge of object classes to detect pedestrian, car obstacles and bicyclists. A multi-layer perceptron (MLP) classifier is used in [152] to Identifying, explaining and tracking independent moving objects. Combination of stereovision, speedometer and LIDAR data is used and feeded to MLP in [152]. Hane et, al use cameras image and wheel odometry for extracting static obstacles [153] whereas in [154] DST is implemented to fuse sensors data and identify the obstacles using camera, laser radar, GPS, perception sensor. As roadway condition knowledge is vital for safe and smooth driving, in [155] camera and LIDAR data combined together for performing lane estimation. None of these literature mentioned above have any clear advantages and disadvantages over the other due to the fact that, driving environment conditions, learning models and data used for testing are distinct.

Looking at the pace of technological advancement in autonomous driving and successful deployment of IoT infrastructure for creating future smart societies in developed economies around the world, increase the thrust to enhance ''Intelligence to drive'' to newer level in near future. This can be achieved by connecting autonomous vehicles together by using IoT infrastructure and let them talk and share their data and intelligence. The recent deadly crashes of Google [156] and Tesla [157] self-driving cars put a question mark on maturity of ''AI to drive'' developed by these technology titans. Data fusion methods as discussed in Section V.A are fusion of data from within the sensor board of the autonomous vehicle, no external data is used other than GPS data. To the best of our knowledge, there is hardly any focus on developing data fusion methods for an autonomous vehicle so that it can fuse information which it is acquiring from other autonomous vehicles which are connect to it using IoT infrastructure.

However, to develop data fusion methods in future for autonomous connected vehicles can bring a completely different set of challenges. We believe that this will further improve the driving environment understanding for autonomous driving.

B. DEEP LEARNING FOR DATA FUSION

Deep learning (DL) branch of machine learning is getting significant attention. Gartner classified deep learning as one of the top 10 technology trends which have significant impact on the strategic planning of most organizations for the year 2016 [158]. Deep learning is a representation learning model that mimics the neural system of humans. It takes raw data as input and automatically discovers representations required to do predictions. Deep learning tries to model higher level data abstractions. Deep learning model can have several layers between input and output which helps it to think. An intriguing fact about deep Learning is that, layers of features are learned from data automatically. LeCun the director of AI research at Facebook in his famous Nature review publication on deep learning [159], stated that deep learning will see many near future successes because of two important factors: (1) it needs very little engineering by hand and (2) it inherently benefits from the increases in the amount of available computational resources and data. In another review, Wang and Raj examine deep learning evolution from its initial stage to present [160]. Deep learning reviews in [159] and [160] addressing the same topic but with different objectives. Paper [159] critically explains the present state-of-art developments in deep learning with its application area. Further giving future possibilities in deep learning whereas in [160] authors discuss the past and Present of deep learning and how it transformed from classical ANNs to deep learning. Deep architectures and mathematical formulation of deep learning models are comprehensively discussed in [161] and [162] which can be referred for further information.

Classical machine learning methods such as SVM, Random Forest etc. are widely used for fusing information from multiple sources. However, with a very slow pace deep learning branch of machine learning is making inroads into data fusion domain. DL models are successfully applied for multimodal learning in [163]–[165] which involves complex learning procedures. In [163], audio and video features are correlated to extract relating information, whereas in [164] authors proposed deep learning model for deep multimodal fusion of discrete events. Further in [165], deep fully convolutional neural networks are used to for multimodal fusion of Earth observation data. A deep belief networks (DBNs) based data fusion method is proposed in [166] for fault monitoring of ball screws which identify critical ball screw health related patterns. Another work [167], uses DBNs for data fusion. It uses 128x128 Dynamic Vision Sensor and 64-channel AER-EAR silicon cochlea data as inputs. The proposed data fusion method able identify digits even in the presence of distractions [167]. There are handfull of few more deep learning based data fusion methods proposed for different application domains in the following literatures such as data fusion for activity recognisation in [168], data fusion for network traffic [169], audio and visual data fusion in [170] and pedestrian detection in [171].

DL branch of machine learning has several issues. Firstly, they are resource consuming,. This means they need significant processing power and memory. But in recent days hardware cost is decreased and tends to decrease in future, so the resource consuming aspect of deep learning can be overlooked. However, Incase of data fusion system resides within a mobile device rather than a power system, in this scenarios applicability of deep learning is arguable. Secondly, deep learning methods are vulnerable to adversarial samples at training phase. Thirdly, deep learning methods need tons of data to get trained but a human can perceive environment just from one sample or few samples. Despite these issues deep learning is proving its worth in several application areas such speech recognisation, image analysis, autonomous driving and pattern recognisation.

C. MOBILE DEVICES, SMART CITIES AND SOCIETIES

With the daily increasing number, people are actively migrating from rural areas to urban areas in search of better life. This is eventually putting an extraordinary burden on urban infrastructure and services. This means that most essential resources are getting scared such as water, power, medical facilities and transportation etc. Even the basic services in big cities around the world are in turmoil. There is an urgent need to manage available resources very efficiently and to predict highly accurate future requirements for growing urban population. How to achieve this goal? The answer lies in the premise of Smart City which looks intriguing [172], [173]. The ''notion of smart cities can be extended to smart society;

i.e. a digitally-enabled, knowledge-based society, aware of and working towards social, environmental and economic sustainability'' [6]. Smart City uses IoT infrastructure, where several thousands of sensors are sensing our environment. Further, the sensed data which is huge in size and in various formats aid the actuators to take the conducive actions. As already discussed in previous sections by fusing data from multiple sensors, improved accuracies and inferences can be achieved than single data source. For Smart Cities, data fusion is vital due to its property to make inferences based on heterogeneous data sources with high accuracies and further, it creates an urban knowledge base.

Data Fusion has been studied for various applications of Smart Cities such as traffic management, warning systems, event detection, healthcare, power supply management and pollution control. Data from European Project SmartSantander is fused to correlate traffic patterns in Santander City with respect to the temperature [174]. Whereas in [175], intelligent road traffic application is proposed by combining data from roadside sensors at fusion center in an energy efficient and cost effective manner. In Smart City, different sensors can record different attributes of a particular event. For example, static (fixed) sensors can record attributes like ''where what and how'' but failed to describe ''who''. Whereas wearable sensors can record the attribute ''who''. A data fusion algorithm is introduced in [176], for combining such data streams which sense the same event but distinct attributes of it. Several other works which are aimed at different applications of Smart Cities by implementing data fusion such as water management [177]–[179], social big data [180], smart power supply and management [181]–[183], intelligent traffic management [184]–[186], and smart healthcare [187]–[189] are introduced to take leverage from IoT infrastructure. Other works relevant to various services in smart cities or societies include emergency management systems [190], [191], [208], IoT-based proposals for improving cultural virtual reality based traffic event simulations [192], autonomic mobility systems [193], [194], urban logistics [195]–[198], location based services [199], multimedia performance analysis over networks for smart cities [200], [201], [203], crime-sourcing [204], community resilience [198], vehicular ad hoc networks that could be used for mobility and data forwarding (such as fog) purposes [191], [205], green computing for mobiles [206], cloudlets [207], artificial intelligence [208], intelligent mobility with social conscience [209], and location based services with data privacy [199], internet of cultural things and similar proposal [210]–[212], and city planning [8].

The increasing use of mobile devices like smartphone, smart watches, and tablets etc. is on a rise, the various applications on these devices need to access a lot of information and of a different type for a better understanding of our contexts. This, in turn, increases the demand for platforms that facilities sensor data fusion. This power the next generation of smart mobile devices for future smart societies. A smartphone consists of an accelerometer, gyroscope, digital compass, ambient light sensor, and a proximity sensor which holds the ability to provide better context-awareness. Pires et al, in their work comprehensively reviewed data fusion methods applied to embedded sensors in mobile devices for human activity recognition [15]. Further in [213] and [214], they proposed several fusion methods based on mobile devices to recognize various daily living activities. Very little work has been done on data fusion methods which are particularly focused on the daily use of mobile devices. We believe in future there will be far greater use of mobile devices, hence better context-aware application will be needed, where data fusion can play a major role.

Today, the total and large scale implementation of smart cities around the world are in their infancy period due to financial and technological limitations. Real challenges are ahead when in near future the above-discussed applications of smart cities are sum-up together for transforming our present day social and technological environment to vibrant smart societies.

VI. CONCLUSION

The Internet of Things (IoT) is set to become one of the key technological developments of our times provided we are able to realize its full potential. The number of objects connected to IoT is expected to reach 50 billion by 2020 due to the massive influx of diverse objects emerging progressively. IoT hence is expected to be a major producer of big data. Sharing and collaboration of data and other resources would be the key for enabling sustainable ubiquitous environments such as smart cities and societies. A timely fusion and analysis of big data, acquired from IoT and other sources, to enable highly efficient, reliable and accurate decision making and management of ubiquitous environments would be a grand future challenge. Computational intelligence would play a key role in this challenge. A number of surveys exist on data fusion. However, these are mainly focused on specific application areas or classifications.

In this paper, we aimed to review literature on data fusion for IoT with a particular focus on mathematical methods and specific IoT environments. The mathematical methods discussed included probabilistic methods, artificial intelligence, and theory of belief. The environments discussed included distributed, heterogeneous, nonlinear and object tracking environments. The opportunities and challenges for each of the mathematical methods and environments were discussed. Emerging areas that would intrinsically benefit from data fusion and IoT, autonomous vehicles, deep learning for data fusion and smart cities, were also discussed. The opportunities and challenges of data fusion in general as well as specific to IoT were provided. To the best of our knowledge, currently, no such survey exists.

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