On Context Awareness for Multisensor Data Fusion in IoT

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Shilpa Gite
Symbiosis International University

Himanshu Agrawal
Curtin University

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Shilpa Gite and Himanshu Agrawal

Abstract With the advances in sensor technology, data mining techniques and the internet, information and communication technology further motivates the development of smart systems such as intelligent transportation systems, smart utilities and smart grid. With the availability of low cost sensors, there is a growing focus on multi-sensor data fusion (MSDF). Internet of Things (IoT) is currently connecting more than 9 billion devices. IoT includes the connectivity of smart things which focuses more on the interactions and interoperations between things and people. Key problem in IoT middleware is to develop efficient decision level intelligent mechanisms. Therefore, we focus on IoT middleware using context-aware mechanism. To get automated inferences of the surrounding environment, context -aware concept is adopted by computing world in combination with data fusion. We conduct a comprehensive review on context awareness for MSDF in IoT and discuss the future directions in the area of context-aware computing.

Keywords Context-aware system · Multisensor data fusion · Dempster–Shafer theory, IoT

1 Introduction

The concept of the internet of things (IoT) originated in the Auto-ID Center at the Massachusetts Institute of Technology in 1999 [1]. Kevin Ashton had imagined a world in which all electronic devices are networked and every object, whether physical or electronic, is electronically tagged with information applicable to that object. The underlying aim of this concept is the achievement of pervasive

S. Gite (✉) · H. Agrawal
CS/IT Department, SIT, Symbiosis International University, Pune, India
e-mail: shilpa.gite@sitpune.edu.in

H. Agrawal
e-mail: himanshu.agrawal@sitpune.edu.in

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connections between the internet and objects around us. It is perfect assimilation of real-world objects with logical things [2].

Multi-sensor data fusion system is analogous to human who can sense the environment with the help of their sensory organs like nose, ears, skin, etc. and make correct inferences about their surroundings [3]. Multisensor data fusion refers to the comprehensive fusing of sensory data from multiple sensors and related information in order to provide more reliable and accurate information that could be achieved using a single, independent sensor [4]. Sensor fusion technology was primarily developed for Military surveillance research and robotics by US DoD. Later, it has got commercially wider acceptance in the areas, such as intelligent transport system, geographic information, land and ocean surveillance, robotics, data and information security, medical surveillance, diagnosis, etc. [5, 6]. The only way to gain the required amount of information with the expected intelligence is viable with the help of multisensors data fusion approach [7].

Paper is organized as follows: In Sect. 2, MSDF and its various techniques are studied thoroughly. Section 3 deals with context-aware systems and its application scenario. In Sect. 4, we present Intelligent MSDF model, which takes decisions on user's behalf depending on current context. In Sect. 5, we conclude and provide future directions.

2 Overview of Multisensor Data Fusion Techniques

MSDF plays a key role in providing improved probability of detection, extended spatial and temporal coverage, reduced ambiguity, and improved system reliability and robustness [7]. Being multilevel process, it helps users to make decisions in complicated scenarios. It can have steps like automatic detection of objects, association and correlation with existing things, future estimation, and combination of data from single and multiple information sources [8].

Multisensor data fusion can be performed [9] by using four main ways:

(a) Using Kalman Filter–Kalman filter, which is named after Rudolf E. Kalman who proposed a linear data filtering algorithm in his famous paper in 1960 [10]. This is considered as one of the most well-known methods for data/sensor fusion algorithms. The results of data fusion process further can be improved with the help Advance Kalman Filter. Kalman equation is mostly used for location tracking, however, it has limitation in its capacity to identify the variety of contextual circumstances [11, 12].

(b) Using Neural Network Theory—The neural network deals with the mathematical modeling of nonlinear data (neurons). It can process data based on accumulated learning experience which is past analyzed data and it takes more processing time to produce results. Swift context inference and fast response to rapid changes can hardly be the area of the theory [13].

(c) Using Fuzzy Theory—Fuzzy logic deals with only two states: True/False. There are some problems in the multitarget tracking using multisensor data association with the conventional non-Bayesian or Bayesian method. In addition to some specific limitations of priori condition, such an association could not perform well under a high clutter tracking environment [14].

(d) Using Bayesian Theory probability theory- It has the advantage of when multisource information is available. Allocating belief to subsets of the universal set and a combination rule that is able to combine multisource evidence. This is an exceptional virtue for making decisions (Fig. 1).

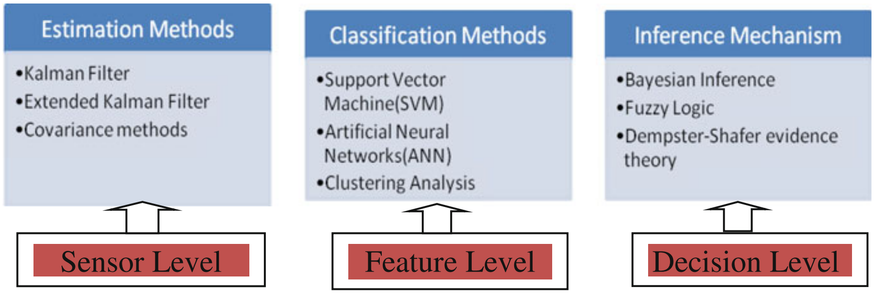

Fig. 1 Overview of MSDF techniques

Table 1 Comparative analysis of MSDF techniques

MSDF technique	Advantages	Limitations
Kalman Filter [10–12]	• Easy implementation • Efficient in terms of computation • Most useful • Sequential method	• Accuracy issues • Too many state vector components result in a significant computational overhead
Extended Kalman filter [9]	• More efficient than Kalman Filter • Works well in nonlinear and non-Gaussian uncertainty problems	• High computational complexity • Unstable results in small time durations
Covariance methods [18, 19]	• Easy to use and implement • Result accuracy • Effective for decentralized data fusion	• Conflicting behavior in some cases
Support vector machine [16, 20]	• Effective for heterogeneous sensor data • Better results for inconsistent sensor data	• Sensitive to noise • Text categorization problems are linearly separable
Artificial neural network [13]	• Handles non-linear data • Efficient for heterogeneous sensor data • Good for high-level inference	• High complexity • Unreliable results in some cases • Slow context inference

(continued)

Table 1 (continued)

MSDF technique	Advantages	Limitations
Clustering analysis [21]	• Can perform well under a high clutter tracking environment. • Generates result of multitarget tracking using multisensor data association	• Computational overhead • Cluster head formation is a difficult process
Bayesian network [15, 22]	• Works well when multi-source information is available • Can combine multi-source evidence • Appropriate methods for high-level inference	• High memory requirements • Consumes longer time before producing a result
Fuzzy theory [14]	• Decision based methods • Fast response to rapid changes • Useful for contextual representation	• Results may be doubtful. • More computational efforts
Dempster–Shafer theory [20, 23]	• Decision based method • Deals with statistical problems or to model uncertainties • Can draw good inference with less available sensor data • Adds a new flavor to safety and reliability modeling compared to probabilistic approaches • Powerful tool to assign uncertainty or ignorance to propositions • More flexible than probabilistic approaches	• Computational complexity increases as no. of sensors increase • Belief and probability may differ sometimes

Table 1 shows a comparative analysis of various MSDF techniques which are most frequently used and efficiently utilized in all kind of applications nowadays. Each technique has some pros and cons, so depending on the application area, particular technique is used.

3 Context-Aware Systems

The term Context was defined first in 1994 by Schilit and Theimer [16]. Context-aware systems are basically self-aware systems, which have the capability of judgement of the surroundings, inference mechanism and accordingly take decisions without human intervention. Depending on the current context, an automated response is generated. Figure 2 shows a big picture of context which covers all perspectives of a context. Context covers location of the objects or person, identify of a person, time information, activity, environment information or constitution information, etc. in order to get all kind of details about users' surroundings [17].

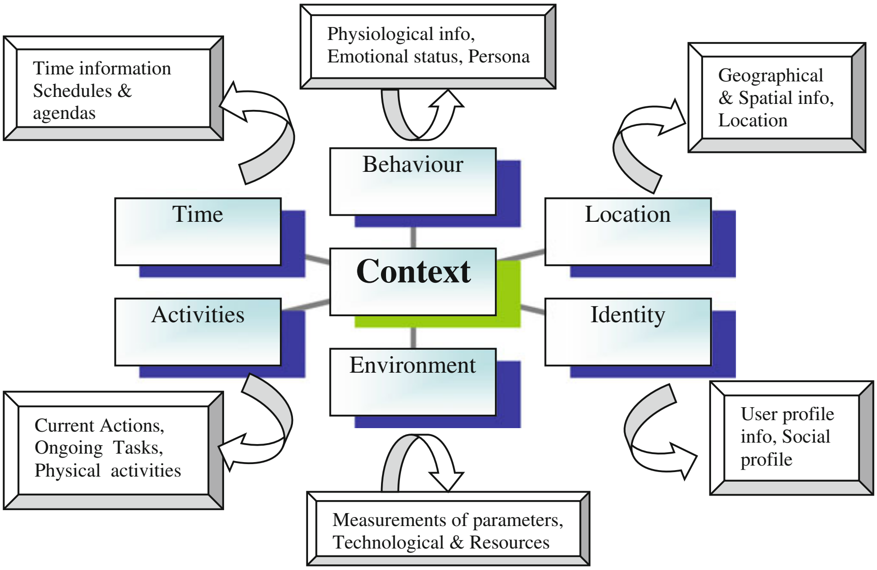

Fig. 2 Big picture of context

Context-aware process follows a series of subprocesses like context acquisition, context processing, and context usage. In *context acquisition*, with the help of sensors, data like pressure, temperature, etc. would be captured and further sent to improvement. In the next stage of *context processing*, four activities are involved, such as *Noise removal, data calibration, context interpretation,* and *context prediction*. In *noise removal* process, unnecessary sensor data and noise would be removed out with the help of filters like Kalman or Extended Kalman filter so that only required and useful data would be efficiently passed further. *Data calibration* deals with the updating or correction of a device. It is basically comparison with standard values which are previously established. *Context interpretation* deals with understanding and analysis of contextual data which is self-aware kind of process. And *context prediction* is basically prediction process which is based on prior estimates. Thus with these four activities, effective context processing takes place [16].

Figure 3 shows real-time (actual) working diagram of context-aware process. In real-time scenario, how data is captured by various sensors and then further processes like data processing, data fusion, and context inference take place. After getting a model ready for context-aware system, it is applied to various application areas like intelligent transportation system (ITS), road-traffic monitoring, biomedical applications, robotics, surveillance etc.

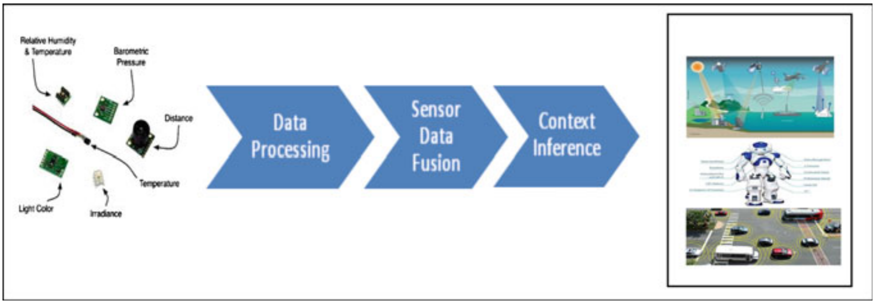

Fig. 3 Real-time diagram of context-aware process

4 Proposed Intelligent MSDF System

Hereby, we are proposing a novel MSDF approach for context-aware systems. The concept of applying intelligence to fused sensor data in order to produce context-aware inference has the novelty in computing field. Lower level data processing involves with data filtering whereas at the higher level intelligence on gathered and processed data takes place. It is basically a five-step process, which includes data collection, filtering process, situation analysis, decision making and inference mechanism process. Figure 4 shows the stepwise process details.

In this paper, we propose an additional intelligent inference based on Dempster–Shafer theory (DST) step to the MSDF approach. As per our understanding, no

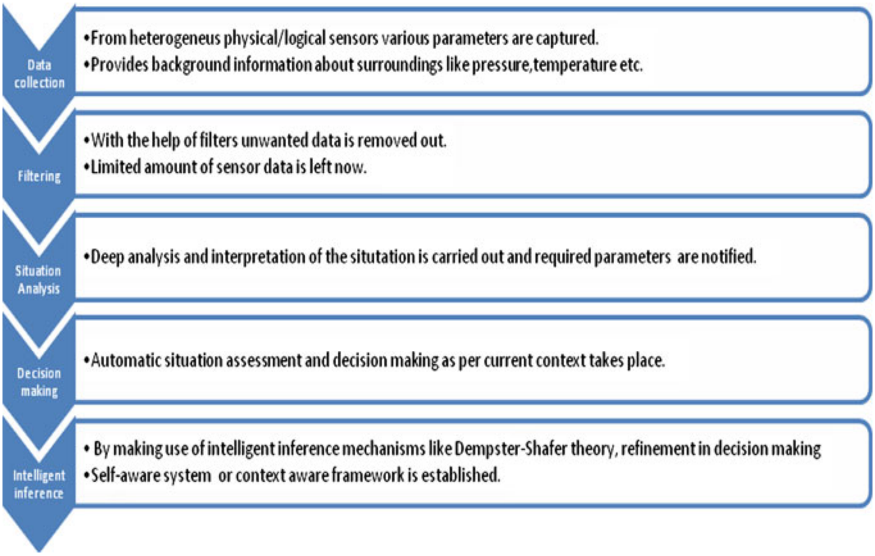

Fig. 4 Novel context-aware approach for MSDF

previous attempt has been made in this direction. DST helps to find out uncertainty factor along with 0/1 or T/F state. DST is very accurate in generating results so it is mostly used in context-aware systems. So we are making sensor data intelligent with context-aware systems that in addition to DST.

Being more analogous to our human perception-reasoning processes, the DST adds a new zest to safety and reliability modeling as compared with other techniques. DST can be successfully combined with other techniques like ANN or fuzzy logic for more realistic results.

4.1 DST in Context-Aware Systems

Dempster–Shafer theory as a theory of evidence has to account for the combination of different sources of Evidence. Rule of Combination is an essential step in providing such a theory. In this scenario belief functions are constructed by means of multivalued mappings [18].

Bel and its dual, Pl (plausibility), are special kind of lower/upper probability functions.

We can see it by defining PBel = $\{\mu\colon \mu(U) \geq \mathrm{Bel}(U)$ for all $U \subseteq W\}$ and showing that Bel = (PBel)* and Pl = (PBel)*.

- The lower bound of the confidence interval is the belief confidence, which accounts all evidences E_k that support the given proposition "A":

$$\text{Belief }_i(A) = \sum_{E_k \subseteq A} m_i(E_k)$$

- The upper bound of the confidence interval is the plausibility confidence, which accounts all the observations that does not rule out the given proposition:

$$\text{Plausibility }_i(A) = 1 - \sum_{E_k \cap A = \varphi} m_i(E_k)$$

Combination of belief and plausibility leads to a mass function which handles uncertainty effectively to produce more correct inferences. Thus, context-aware systems can draw inferences on its own and take decisions on the user's behalf.

4.2 DST Versus Bayesian Networks

Being most popular inference mechanisms, we tried to compare Bayesian networks with DST in Table 2. Both use probabilistic approach for data fusion. DST is basically advancement in Bayesian networks which handles the third aspect as uncertainty rather than just True/False or 0/1.

Table 2 Comparison between inference mechanisms

Parameters	Bayesian networks	Dempster–Shafer theory
High-level fusion	Yes	Yes
Decision making	Possible	More correct
Uncertainty management	Limited extent	Effectively done
Tolerant of imprecision	Limited extent	Possible
Availability of probabilistic information	Works best when Availability of full probabilistic information	Works better than any other probabilistic methods when lack of full prepositional information
Combination with other algorithms	Not much useful	Produces more accurate and robust results
Effective use in	Medical diagnosis	Robotics
Limitations	Difficulty to deal with temporal variations	Nonintuitive results when dependent belief functions

Depending on the availability of probabilistic information, particular technique is chosen in context-aware systems. Here, we found that DST turns out to be superior over Bayesian networks when full probabilistic information is not available.

5 Conclusion

In this paper, we have proposed context-aware framework and have reviewed MultiSensor Data Fusion and internet of things (IoT). In the next 5 years, i.e., by 2020, IoT is expected to connect more than 25 Billion devices. Therefore, there will be lot of research rigor in IoT middleware, which will require further attention in terms of the development of novel solutions. Context-aware computing is going to be the prime focus of many researchers to address various challenges in IoT middleware.

In our paper, we have stated role of DST in context-aware systems to get correct inferences from the environment. Also we have compared DST with Bayesian networks which are an alternative option for probabilistic data handling. As ongoing work, we are focusing on the robustness aspect using DST which would generate more comprehensive view about the environment. To decrease the computational overhead of DST can also be considered as a research challenge. Another possible extension will be in the direction of the Hidden Markov Model. We will be investing on HMM-based model as our future work to address the uncertainty aspect.

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