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ORIGINAL RESEARCH

A context-aware data fusion approach for health-IoT

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Abstract The technological advances in low-cost sensor devices and communication technologies bring rapid increase in development of smart homes and smart environments. The developments in wireless sensor networks (WSN), body area networks (BAN), cloud computing and big data technologies trigger the use of Internet of Things (IoT) in healthcare industry. This poses many challenges such as heterogeneous data fusion, context-awareness, complex query processing, reliability and accuracy etc. Data fusion techniques are used to extract meaningful information from heterogeneous IoT data. It combines individual data from sensor sources to collectively obtain a result, which is more reliable, accurate and complete. Apart from wearable sensors, additional context sensors need to be added to build a context. Health IoT applications has potential benefits of using context-aware data fusion. By using context information, the behavior of the application can be customized according to the specific situation. This paper provides a brief concept of context-aware data fusion and includes data management approach for context-aware systems for healthcare applications. Finally, a context-aware data fusion approach for health IoT is proposed. It includes context acquisition, situation building and reasoning and inference.

Keywords Data fusion · Context-awareness · Healthcare · Internet of Things

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1 Introduction

Internet of Things (IoT) is trending technology that attracts many researchers around the world. It helps to make our daily life more intelligent and smart by interconnecting physical objects. The main concept of IoT is the pervasive presence of a variety of things (objects) around us, which can interact with each other and collaborate with their neighboring objects to achieve common target [1].

IoT is a multidisciplinary field, which may include but not limited to embedded systems, electronics, wireless sensor networks, communication networks, and computing paradigms. IoT serves as an umbrella above these technologies, which diversifies its applications area. Its applications include smart cities, smart homes/smart buildings, environment monitoring, smart business and product management, emergency response systems, intelligent transportation, security and surveillance, energy and industrial automation, and healthcare etc. [2].

The continuous growth of IoT projects towards its adaptation by diverse industries, even low cost organizations are also feeling the effects. For the reason, IoT needs its own dedicated wide area network. Typically, wide area networks require larger batteries or continuous power supply, which is not feasible in all the situations. The development of low power wide area (LPWA) networks is solution to this challenge, which provides benefits including reduced total cost of ownership, increased battery life, and long coverage range. Keith et al. [3] discussed basics of low power wide area (LPWA) networks for IoT and provides a survey of two LPWA technologies, namely LoRa technology by Semtech and ultra-narrow band solutions by SigFox, in terms of physical layer and medium access control layer. Konstantin et al. [4] analyzed the capacity and scalability of LoRa wide area networks. On the basis of their analysis, they supposed that LoRa can be efficiently utilized in moderately dense network of devices with low traffic, and low latency and reliability requirements such as environment monitoring and non-critical infrastructure applications.

As in IoT, every 'thing' is connected over internet and information is shared among them, this imposes severe security challenges. Mostly, IoT is applied to critical applications so their security requirements are quite high. Hui et al. [5] reviewed security challenges in IoT and discussed its security characteristics and requirements. They analyzed four layered security architecture for IoT which includes perceptual layer, network layer, support layer, and application layer. Quandeng et al. [6] also highlights security issues of IoT in perception, network and application layers. They also proposed secure construction of IoT by describing security policies in each layer. Research in IoT security is still in its initial phase and more research is needed in this field.

With the advent of IoT in healthcare, many low-cost devices are used to monitor patient's health status remotely. IoT has been widely adopted for both in-home and in-hospital care. In medical systems, the use of wearable sensors and wireless sensor networks is increasing rapidly. Body sensor networks (BSN) or wireless body area networks (WBAN) is a type of wireless sensor network that deploys to the patient's body to collect physiological measurements [7]. It facilitates developments in pervasive monitoring systems by providing an integrated hardware and software platform [8].

A generic BSN consists of a variety of sensor nodes which records patient's physiological data. The different wearable body sensors capture the patient's data such as blood pressure, electrocardiogram (ECG), blood sugar level, galvanic skin response, and electromyography etc. [9]. In case if any of these values crosses the threshold value, the system alerts the medical emergency response center. Such systems are helpful when a patient is not in a condition to visit hospital for routine checkups or the patient needs in-home care e.g. elderly people. The sensed data is then stored to the system for future processing.

As these devices consistently generate data, thus there are many issues and challenges to handle such an explosive data. The data becomes more complex as BSN consists of multiple heterogeneous sensor sources, so for the efficiency of BSN applications the use of data fusion is non-trivial. The concept of multi-sensor data fusion is not new. It can be compared with the use of senses of human body. In daily routine, we use multiple senses together to understand the environment more accurately. Sometimes a single sense doesn't provide enough information, e.g. we use smell, sight and taste sense to assess food quality; even sometimes we need to touch it. We use sight and hearing sense altogether to be aware of some threat. Likewise, wireless sensor nodes are deployed to observe an environment, combining these sensor readings is known as sensor data fusion.

It is a technique to integrate data from heterogeneous sources. It combines the common characteristics of datasets from multiple sources to produce better results. Sometimes data from one source may not be sufficient for taking decision in real-time environment. Data fusion supports representation of data in a way that helps decision makers in decision process [10]. It is a process that transforms data to help taking correct decision on time. There are several definitions of data fusion in literature but most widely used definition is from JDL. According to Joint Directors of Laboratories (JDL) workshop [11] Data fusion is defined as

> "A multi-level process dealing with the association, correlation, combination of data and information from single and multiple sources to achieve refined position, identify estimates and complete and timely assessments of situations, threats and their significance."

The aim of multi-sensor data fusion is to understand the environment and act accordingly. When more than one sensor is used to gather more accurate and additional data, sensor fusion is used.

The use of a single sensor or multiple individually considered sensors can cause many limitations to any physical measurement system. Likewise, a Health IoT application may also suffer from several problems, such as [12]

- Sensor deprivation: in case of a node failure, that specific observation will be lost.
- Restricted coverage: normally a single sensor covers a limited area or a restricted body part.
- Imprecision: accuracy of individual sensors is limited to only those specific elements.
- Uncertainty: an individual sensor may not determine all aspects of an incident, hence causes uncertainty.

These challenges urge the need for context-aware data fusion. In this paper, a novel approach has been proposed to solve these issues. The rest of the paper is organized as follows. Section 2 discusses related work. Section 3 presents context-aware data fusion in healthcare and describes data management steps for context-aware healthcare systems. In Sect. 4, a context-aware data fusion approach is proposed. Finally, Sect. 5 concludes the paper.

2 Related work

Sensor data fusion is well-known research field and there is variety of techniques available in research literature but still there are many challenges that need to be addressed. Two main approaches are possible for the process of data fusion, namely centralized and distributed/decentralized [9, 13]. In the centralized data fusion approach, the fusion process is performed at a central node called fusion center. All the sensor nodes pass their data to the fusion center which is responsible for overall fusion process. The benefit of this approach is that it provides global vision of environment; while the major drawbacks are; first the overall fusion process depends on a single node, causing network congestion on that node and may be sometimes more information is received than its capability. Second, in case of fusion node failure it affects the overall system. In the distributed or decentralized approach, the fusion process is distributed over some dedicated nodes. Those nodes receives data from surrounding nodes and sends locally fused information to next module for decision level fusion and global analysis. In this case, the node failure doesn't affect the overall system, as other fusion nodes can continue their work. So, the fusion process can be performed on raw data (centralized approach) or on pre-processed data (distributed approach).

The use of context in sensor fusion is becoming essential part of the real-time interactive systems. Gravina et al. [9] provides a comprehensive survey on multi-sensor fusion in body sensor networks and identifies the future research issues as autonomic, context-aware, collaborative, and cloud-assisted body area networks. Abowd et al. [14] categorized features of context-aware applications as (1) presentation of information and services to a user; (2) automatic execution of a service; and (3) tagging of context to information for later retrieval.

De Paola et al. [15] proposed and evaluated three-tier architecture of a context-aware self-optimizing adaptive system for multi-sensor fusion. They used Bayesian network for inferring the state of the world and using contextual information to improve reasoning accuracy. Hong et al. [16] proposed a framework for information management in smart homes to support decision making process of activity recognition. They used equally weighted sum operator and Dempster–Shafer theory of evidence for uncertainty of sensor data.

An appropriate data fusion technique helps in building intelligent systems. Chetty and Yamin [17] presented a smart fusion framework, based on hard and soft sensor fusion, for combining heterogeneous, multimedia, multimodal real-time big data streams to achieve actionable intelligence from the computer based decision support systems. Jain [18] presented implementation for telecommunication fraud detection using data stream analytics and neural network classification based data mining and compared the accuracy of both techniques. The results of this research can provide a basis for big data analytics and mining.

Based on above considerations, we propose a context-aware data fusion model for health-IoT. The novel concept in this model is focus on dynamic management of context and vital sign sensor data and it also includes user refinement and preferences.

3 Context-aware data fusion in healthcare

For any health system, the accuracy and reliability of data is most critical issue. Sometimes wearable sensors do not provide sufficient information to build the situation. For the reason, additional sensors are needed for context information. By combining data from multiple heterogeneous sensors, sensor fusion creates complete picture of the situation which enables context awareness. Health IoT applications has huge potential benefits using context-aware sensor fusion, e.g. a pulse sensor measures an increase in the pulse rate of a person; there may be some situation where it is normal like if the person is running or doing some physical workout at gym, otherwise this may be an alarming situation. By combining the location and motion (for activity) sensors, a context can be built to protect false alarms.

Abowd et al. [14] defines context as it can be any supporting information to define the situation of objects that are related to the interaction between a user and an application including them. So the context can be defined as location, environment, time and identity of user. This identifies what is happening in the situation. Context plays vital role in real-time systems. The sensor fusion method is supposed to deal with the changes in context, as they highly affect accuracy [9].

The healthcare systems generally consist of heterogeneous data sources that exhibit explosive data. Although, due to massive data from sensors and other devices, data management is the main concern for many researchers; but still there is no agreed upon definition [19]. The steps for data management highly depend on nature of data and the application used for.

To manage heterogeneous IoT data a multilayered approach is shown in Fig. 1, which includes data preprocessing, context-aware data fusion, and data processing and storage.

Data is collected at physical layer. Then, at data pre-processing layer necessary cleaning and filtering is applied to remove outliers (irregularities or unexpected values).

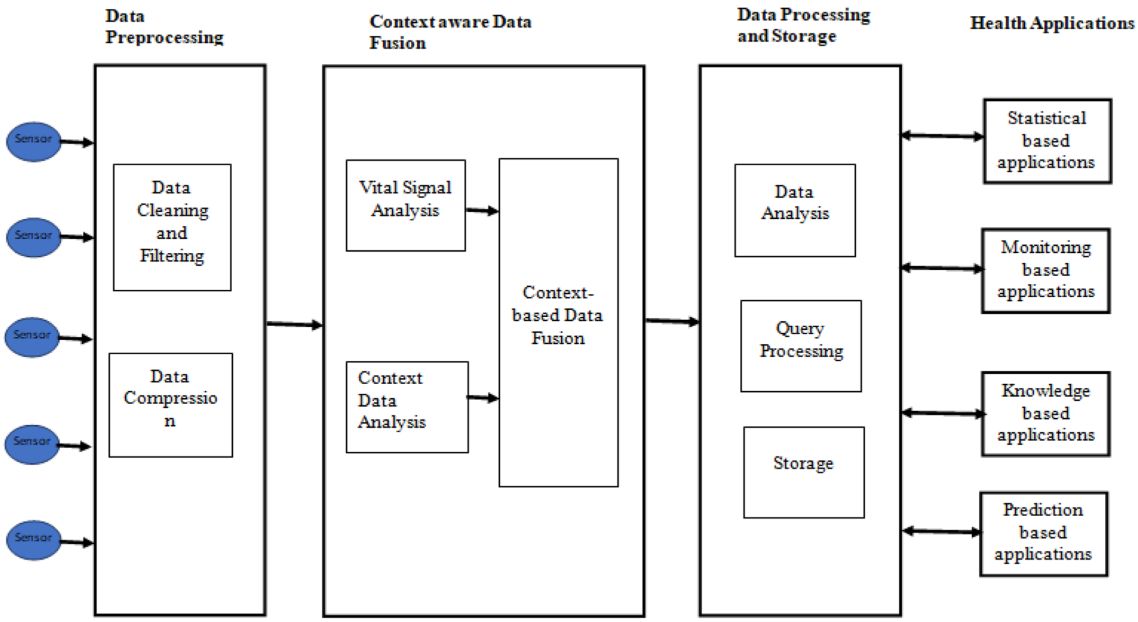

Fig. 1 Data management for context aware healthcare systems

Sometimes collected data contain redundant data which must be compressed to reduce storage and communication overhead. The next step is context-aware data fusion. This layer shows two types of data blocks, one is vital signals such as pulse rate, blood pressure, electrocardiogram (ECG), body temperature etc., and the other is context data. Context data contains additional information such as location of object, or environment temperature. The context source varies according to the situation. Intelligent data fusion techniques combine heterogeneous data and extracts context information which enables health applications to react accordingly.

Once fusion process is done and context is build, next step is to process that data. The data processing and storage phase includes three sub-blocks, i.e. data analysis, query processing and storage. All of them are huge fields at their own, and are beyond scope of this paper. Healthcare applications can access and store that processed data.

4 Proposed context-aware data fusion approach for health IoT

This section discusses our proposed context-aware data fusion approach for healthcare applications. The approach is based on JDL [11] data fusion process model. Our aim is to design a model to fuse vital signal data with context data to better understand situations. The model consists of three phases, context acquisition and filtering, situation building, and reasoning and intelligent inference as shown in Fig. 2.

The first step in context acquisition is data collection from physical devices. Then, measurement preprocessing is done by applying filtering and estimation techniques to remove noise and other measurement outliers. After that, data from multiple sources are associated to extract context information. Finally, appropriate data fusion algorithm, depending on the application, will combine data.

Situation building phase deals with the analysis of situational and relational information. It also tracks historical data to validate current data and predicts future situation. This level presents a virtual image of objects with their position and relationship.

Reasoning and inference completes overall target of the system. It indicates how to interact with physical infrastructure and according to the requirement of applications; it adjusts measuring parameters of sensors. It also includes user input to help increase system performance and decision process; this is known as user refinement. Blasch and Plano [20] revised JDL model by including level 5, i.e. user refinement, which supports user interactions to improve decision process.

Different intelligent techniques may be used to boost the decision process such as Dempster–Shafer theory, Bayesian network, artificial intelligence, and fuzzy logic etc.

5 Conclusion

The advances in pervasive computing trigger the use of IoT in healthcare. Due to which developments in wearable sensors and their use in health industry are also increasing

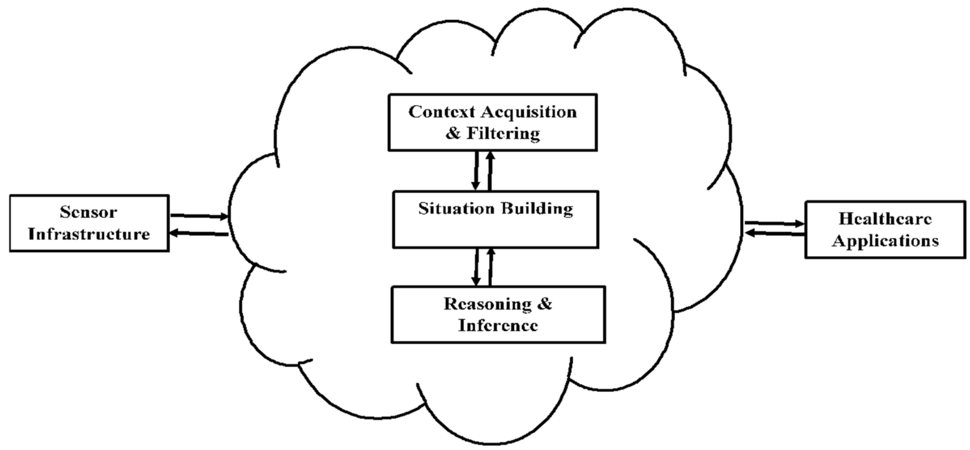

Fig. 2 A context-aware data fusion approach for health IoT

very fast. Multi-sensor data fusion is emerging research field with sound future scope to provide reliable data. This paper has aimed to provide basic concepts of IoT in healthcare and context-aware data fusion. Data management steps for healthcare systems are also described, which includes preprocessing, context-aware data fusion and data processing and storage. A layered approach for context-aware data fusion for health IoT has been proposed, including context acquisition and filtering, situation building, and reasoning and intelligent inference. This explains how context-aware data fusion is performed by following multiple subtasks.

As future consideration, we will work on specific techniques and algorithms for each phase. This framework will help us in creation and realization of intelligent algorithms.

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