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ScienceDirect

Procedia Computer Science 175 (2020) 411–418

Procedia Computer Science

www.elsevier.com/locate/procedia

The 15th International Conference on Future Networks and Communications (FNC)
August 9-12, 2020, Leuven, Belgium

# Intelligent context-based healthcare metadata aggregator in internet of medical things platform

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**Abstract**

The internet of medical things (IoMT) is relatively new territory for the internet of things (IoT) platforms where we can obtain a significant amount of potential benefits in terms of smart future network computing and intelligent health-care systems. Effective utilization of the health-care data is the key factor here in achieving such potential, which can be a significant challenge as the data is extraordinarily heterogeneous and spread across different devices with different degrees of importance and authority to access it. To address this issue, in this paper, we introduce an intelligent context-based metadata aggregator in the decentralized and distributed edge-based IoMT platform with a use case of early sepsis detection using clinical data. We thoroughly discuss the various aspects of the metadata aggregator and the overall IoMT architecture. Based on the discussion, we posit that the proposed architecture could improve the overall performance and usability in the IoMT platforms in particular for different IoMT based services and applications.



*Keywords:* metadata, machine intelligence; context based metadata aggregation; future networks and communications; internet of medical things; machine learning; deep learning

## 1. Introduction

The internet of medical things (IoMT) is a combination of different health-care applications and medical equipment [1]. To create a connection among different health-care information technology systems, IoMT utilizes different network technologies [2]. Intending to make the health-care system less costly, more individualistic, and more dynamic, currently, IoMT is expanding in different health-care sectors [3]. IoMT can reduce the workload in the hospitals by limiting the unnecessary hospital visits and can provide a secure data transmission network to exchange sensitive medical data among different medical sectors. It can provide the health-care data in rapid time to the medical professionals automatically, which in turn can be very useful to treat critical patients or quick interventions in such cases

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10.1016/j.procs.2020.07.058

[4]. It is worth mentioning that IoMT is not proposing a replacement of the current health-care settings; instead, the goal is to create an additional mechanism to provide valuable and relevant information by exchanging medical data in a secure, robust, and quick way [5]. Therefore it ensures a superior diagnosis and better treatment for the health-care professionals [6].

To make health-care data more useful, optimizing the current workflow in the health-care sectors, efficient management in the inventory, and robust integration of different medical devices are required [7]. IoMT can perform all of these in a very efficient and speedy way. As nowadays the health-care providers can get a large amount of data from this IoMT transition, therefore to provide a better service to a patient, the critical question we should resolve is, how we can turn this wealth of data into insightful information so that we can convert it to action in a real-time basis? Not only the useful utilization of data in the form of informative insights, data analytics and visualization with the help of artificial intelligence are also bringing the opportunity to suggest physiological anomalies, salient trends, and early prediction of the diseases to the health-care professionals without exhausting them with this overload of medical information [8]. It can help the existing diagnostic practices in the health-care sectors as it reduces the time to analyze all the information, and automatic processing of the medical data ensures that the typical workflow in the health-care settings is not getting affected by it.

To make the health-care data useful, then the immediate approach is to combine different types of health-care data from different IoMT devices efficiently. Therefore, interoperability among different IoMT devices in terms of data transmission is a vital concern here [9, 10]. Metadata can help us immensely to ensure interoperability in this scenario. Metadata is usually defined as "data about data." More elaborately, metadata could be defined as the information required to contextualize and understand a given data element [11]. Intelligent aggregation of metadata obtained from the IoMT devices could play an essential role in this aspect. In health-care, it is vital to accumulate and analyze information from all possible angles to get a more accurate summary. For example, a disease diagnosis may rely not only on the symptoms but also with the demographic and hereditary information as well [12]. Metadata about such information can ease the process. In particular, this could be useful if we want to have a machine learning analytics and data visualization component along with a decision support system application in our IoMT framework. An intelligent context-based health-care metadata aggregator component in the IoMT architecture could be a viable solution for this.

As IoMT is quite an emerging field, therefore little focus has been provided in the metadata aggregation aspect in the architecture. Utilizing the electronic health records and the conventions to ensure semantic interoperability, Löbe et al. discussed the usage of metadata in addition to the processes and tools [13]. To integrate the sensor and health data for diverse translational exposomic research, Gouripeddi et al. proposed a metadata-driven big data integration platform [14].

Having this in mind, In this position paper, we are proposing an intelligent context-based health-care metadata aggregator component in the decentralized and distributed edge-based IoMT architecture. We discuss the utilization of this component in decision support systems for automatic and early sepsis detection [15] to show its importance. Our contributions can be summarized as follows,

- A novel intelligent context-based metadata aggregation component in the decentralized and distributed edge-based IoMT architecture.
- The integration of this component with the clinical decision support system to show the benefit of adding this component.

## 2. Different aspects of metadata

In this section, we discuss the different aspects of metadata in the health-care sectors. It is crucial to have an overview of these various aspects of metadata to understand the diversity and importance of the context-specific aspect of our proposed metadata aggregator.

### 2.1. Patient related metadata

The metadata can provide insights about the patient's individual information such as name, address, date of birth, contact number, marital status, age, demography, and so on. We can denote it as a patient's personal information specific context. It can be expanded as personal life related, and family relation related metadata. Physiological information, lab test results, case history of previous visits to different health-care facilities, diagnosis reports and biometric information related metadata can provide us a patient's health-care information specific context. If the patient uses any personal health monitoring devices or sensors, then the information can also be integrated using the patient's self-imposed health-care management related information specific context. Social media can also provide information about a patient's habit, hobby and physical activities, and social visits. We can denote the metadata in this aspect from a social media-specific context.

### 2.2. Healthcare provider related metadata

The institutions, companies, or health-care professionals usually record information about different aspects of health-care. The medical records of the patient is one such example. The detailed records of the hospital admission also provide essential insights about patients and demography. Medical text categorized according to different medical interests is also quite vital. The details about various clinical research studies are also quite important. Different regulatory reports regarding the process, maintenance, and update can provide us insights about health-care institutes. The billing reports for the care of patients and reports about the cost of various equipment can also provide us valuable information. We can find three contexts here. The information related to medical information can be viewed from a medical context. The information regarding the process and maintenance can be viewed as the management context. The information regarding the bills and costs can be viewed from an economic context.

### 2.3. Medication related metadata

Detailed information about drugs is quite crucial. It can provide us many insights regarding the patients. The data about pharmaceutical research to support this drug are also valuable. Usually, we get such kinds of information through clinical trials. The efficacy of a particular drug for a particular scenario is also a precious insight. The prescriptions provided by the health-care providers are also critical. Two contexts can be found here. One is patient-specific drug-related information. Another is general research-related information about medical drugs.

### 2.4. Healthcare payers related metadata

Health-care providers are paid by different organizations or individuals. The government is one major stakeholder in this regard. Different insurance companies are also responsible for paying. Most of the private companies are also responsible for paying for their employees to a certain degree of the amount. It is also paid on a patient's basis. We can summarize the metadata from three contexts here, the public aspect, the private aspect, and finally, the individual aspect. It is worth noting that the public and private aspects can have interactions as sometimes the government can pay using different insurance companies as well rather than providing a direct payment. The billing report, usage review from these payments can provide many insights.

### 2.5. Government regulatory services related metadata

Government regulatory services provide standards to protect the stakeholders in the health-care sectors, in particular, the patients and caregivers. It also ensures that no exploitation or harmful activities can be done in the health-care sectors. The data from these services provide us insights about the management process and future projection about this topic so that it can be improved. Two contexts can be summarized from here. One is the current status in the health-care sectors based on the reports from these regulatory services, and the other is the future improvement potentials.

### 2.6. Healthcare data service providers related metadata

Due to the advancements of information technology and big data, nowadays, several companies are providing data services for health-care providers. The improvement in taking medical notes using speech to text technology, the advanced insights on how to complete valid prescription, effective automatic integration of medical information related terminology and taxonomy are some of the examples of the different types of metadata from this category. The different software-based applications for analyzing the data can also be useful in this context. The vital contexts that can be drawn from here are the security and privacy aspect, interoperability aspect with other medical equipment to make it more robust and automatic.

### 2.7. Healthcare information service related metadata

Without a direct connection with the health-care institutes, there are individuals or companies who provide health-related advice or reports. Usually it is done to improve the situation and raise awareness among people. This is an excellent resource about the general version of the health-care information. We can get a brief idea about what are the most sought out medical topics that people are interested to know based on the availability or popularity of this information. We can find two critical contexts in this category. The precise information can be obtained from different authorized or verified channels or websites. The informal but most interacted information can also be found from social media. Therefore, we can get various aspects of information from these formal and informal contexts.

### 2.8. Health-care research related metadata

Healthcare research is a very active and rapid-changing field. A tremendous amount of information is generated daily, and in most cases, this information is open for all to access. The research data and reports provide brilliant insights into different health-care topics. It is worth noting that this information can complement the day to day practice and usage of the established methods or drugs in the health-care sectors. With the help of big data, IoMT, and analytics, therefore it could be immensely beneficial if such information could be integrated with the current establishment on an automatic basis. The contexts can be deduced to current research and future improvement predictions.

### 2.9. Medical device manufacturer related metadata

Medical device manufacturers are continuously working their devices to make it up to date and useful. They can also provide us much information from their point of view. These devices are directly integrated into the health-care sectors and, therefore, can provide us real-time information. From the device perspective, we can get much information regarding the usefulness, maintenance, resource usage, which will, in turn, will be valuable to maintain a robust IoMT setup.

In this section, we introduce the metadata aggregator component. It is worth mentioning that this section describes the different modules and sub-components of the proposed metadata aggregator. We discuss the different aspects of implementation and usability issues in section 4.

## 3. Intelligent Metadata Aggregator

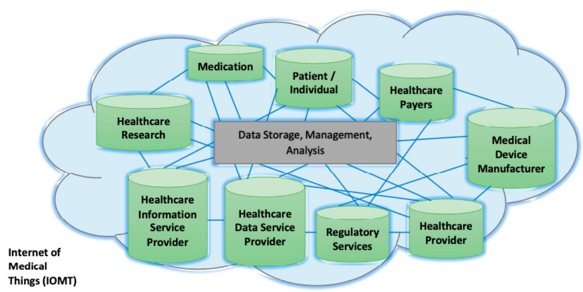


Fig. 1. Example of current cloud-centric IoMT platform.

Figure 1 is describing the example of current popular implementation of IoMT platforms where the primary data storage, processing, management, and analysis are done in cloud based middle-wire architecture.

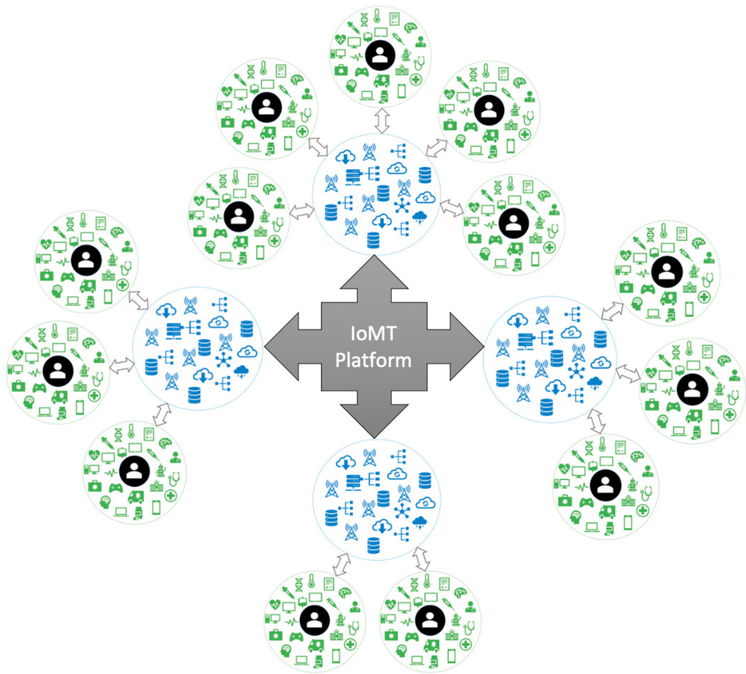


Fig. 2. Proposed edge-based IoMT platform.

Contrary to this, in figure 2 we are proposing a decentralized and distributed edge-based IoMT architecture. Different IoMT 'end devices' are connected with each other based on the context described in section 2 as shown in the green circles. These end devices are then connected with the edge(s) as shown in blue circles. These connections are based on metadata-centric contextual information. The edges are connected with each other in a distributed and decentralized fashion. Therefore efficient and intelligent aggregation of metadata using a specific component in the edge is crucial for the data collection process.

Figure 3 provides an in-depth overview about this metadata aggregation aspect in our proposed IoMT platform. Our proposed platform consists of three modules. They are as follows,

The 'Data & Services' module is in the IoMT devices layer. To initiate any service or application from the user or to collect metadata or data from the end devices this module is used. The 'Metadata Aggregation' module is responsible for aggregating the metadata based on contexts and providing the data to the 'Data Analysis' module based on these metadata for further analysis. Both of these modules are in the edge layer. The 'Context Acquisition' sub-component of the 'Metadata Aggregation' module collects the context for a specific application or service requested by the 'Data & Services' module. 'Context Modeling' then models these contexts suitable for specific systems. 'Context Reasoning' then infers suitable contexts for any particular tasks. We are using distributed machine learning and deep learning for this sub-component, therefore, we can refer to it as intelligent context reasoning. The results of decisions are then used by the 'Context Distribution' sub-component which then in turn using the 'Data Collection' sub-component acquires the data from the end devices based on these metadata specific contexts. The data is then used in the 'Data Analysis' module for the analysis of the particular service or application. The result is then finally sent to the 'Services & Applications' sub-component to display the result in the end device(s).

Finally, to demonstrate the usability of this additional component, we are providing an example of early sepsis detection application based on medical data [15] in the IoMT platform. Early sepsis detection is a very crucial problem as early detection can save the lives of the patients. This 'Early Sepsis Detection' is one example decision support system application of the 'Services & Applications' of the 'Data & Services' module. It sends a service request to the 'Context Acquisition' sub-component (1). Based on the specificity of the task (sepsis detection in this case), 'Context Acquisition' sub-component then acquires the contexts from the end devices (2, 3). After modeling the contexts (4) the 'Metadata Aggregation' module then resolves the required contexts (5) with the help of the 'Data Analysis' module.

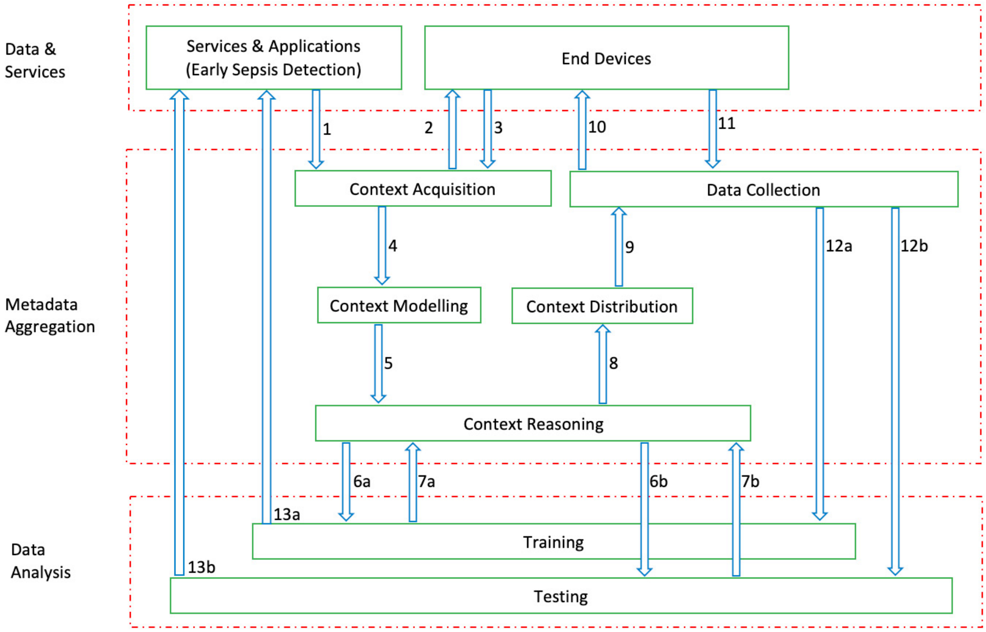


Fig. 3. Proposed intelligent context-based metadata aggregator in the decentralized and distributed edge-based IoMT platform.

If it is a request of training the data (specified in 1) then ‘Context Reasoning’ uses the ‘Training’ sub-component (6a, 7a) otherwise for inferring it uses the ‘Testing’ sub-component (6b, 7b). The contexts are then distributed through ‘Context Distribution’ sub-component (9) so that based on these the required data can be collected from the end devices (10, 11). The data is then provided to the ‘Data Analysis’ module for training (12a) or testing (12b). Finally, the results are sent (13a or 13b) to the ‘Services & Applications’ module to display to the user. It is also worth noting that using this setup we can make the whole process faster as we do not have to rely on unnecessary data searching in all the sources, and it is integrated with different sources. Therefore this architecture is beneficial for real-time deployment in health-care settings for early detection of sepsis.

## 4. Discussion

In this section, we discuss the presently available and standard IoMT enabling technologies for the implementation of our proposed intelligent context-based metadata aggregator based decentralized and distributed edge-based IoMT platform.

The ’Services & Applications’ sub-component of the ‘Data and Services’ module can be implemented using conventional embedded operating systems such as TinyOS, Contiki, LiteOS, Android, and Riot OS. The typical transmission protocols can be used here with REST (Representational State Transfer) or RESTful technologies so that the devices ensure interoperability [16]. The key issues that are needed to be investigated are, availability, management, reliability, interoperability, scalability (large-scale deployment and integration), security (authentication, access control, configuration management, antivirus protection, and cryptography), and privacy [16].

’End Devices’ sub-component can be described as a collection of real-world entities and virtual entities with capabilities such as actuation, sensing, identification, interconnectivity, and connectivity with communication networks through different communication protocols to connect with the ’Machine Intelligence’ module. Different sensors and actuators are an example of real-world entities [4]. Virtual entities are different embedded software to ensure operability and connectivity with the ’Machine Intelligence’ module. The software architecture should be OAP (the open application platform) based, and to ensure modularity and open access, open APIs (application programming interface) should be provided for sensors and other devices. The IEEE 802.15.4 standard based WSN (wireless sensor networks) are the most common solution in this case [17]; however, memory, processing, identity management, and connectivity are still critical issues that we need to resolve for the sensitive health-care data [16]. Distributed cognitive internet of things could provide us great insights in this regard as decentralized edge-centric or fog computing centric architecture can be more suitable in this regard [10].

The communication between the 'Data and Services' module and the 'Metadata Aggregation' module can be implemented using the most common TCP/IP (Transmission Control Protocol / Internet Protocol) based protocol stacks. Interoperability is a vital issue here among different network technologies; therefore, a standardized approach is necessary [16]. This module is a very critical one as this module is responsible for efficient data aggregation through metadata aggregator; therefore, to ensure real-time processing fault tolerance and delay management is critical issues here [4]. The current cloud-centric architecture dominant in the various IoT platforms should be customized because of this [9]. We will explore on edge or fog based solutions to minimize this issue [18, 19]. Intelligence agent-based sub-components in this module could ensure authenticity, accuracy, and security [20]. Context-aware platforms can decide the required information and services required for a particular task. The main aspects of the process are context acquisition, context modeling, context reasoning and inference, and context distribution. Different rules, logic, and machine learning-based approaches can be used here [21]. Context acquisition should be based on the five factors as described in [22], (a) the acquisition process, (b) frequency (c) responsibility (d) sensor types, and (e) source. Uncertainty modeling should be used for the context modeling as healthcare metadata quality should be estimated based on 'confidence, coverage, freshness, accuracy, resolution, timeliness, and resolution' [23]. Different supervised and unsupervised learning-based techniques should be used for context reasoning [22]. In the healthcare metadata context, the context distribution mechanism should be similar to the context acquisition process. We will explore this aspect deeply as 'Context' is one of the key features in our proposed platform architecture.

As the 'Data Analysis' module is mostly responsible for analyzing the data; therefore, a high computational capability with a significant amount of storage system is usually required here. The most common implementation of this module is, therefore, different cloud-based solutions such as AWS IoT Platform, IBM Bluemix Platform, Microsoft Azure, Google Cloud Platform, ThingWorx, and Xively [24]. As we have mentioned, although it ensures robustness and maintainability, in terms of real-time operation, security, privacy, and latency, it needs to be improved for IoMT platforms [25]. The critical challenge is to ensure advanced level machine learning and deep learning, but customizing the storage and computational complexity from a centralized viewpoint to a distributed and decentralized viewpoint. Distributed machine learning with the integration of edge computing can help us in this case [26]. The use of federated learning is promising in these cases as it enables the training on the end devices which ensures privacy and full decentralization of the distributed edge-based systems while retaining the efficiency of deep learning. The shared model then can be aggregated in the edge server nodes [27]. The other similar and supplementary techniques are aggregation frequency control [28], gradient compression [29], deep neural networks splitting [30], knowledge transfer learning [31], and gossip training [32].

## 5. Conclusion

We proposed a novel intelligent context-based metadata aggregator component in the decentralized and distributed edge-based IoMT platform and discussed the different implementing and usability related aspects of it with a use case of early sepsis detection using clinical data. We posited through our discussion that efficient usage of this component could benefit the data-centric IoMT platforms in various healthcare sectors for different use cases. In the future, we will implement such a platform to demonstrate the practicality of integrating this component.

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