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Geohashed Spatial Index Method for a Location-Aware WBAN Data Monitoring System Based on NoSQL

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Abstract

The exceptional development of electronic device technology, the miniaturization of mobile devices, and the development of telecommunication technology has made it possible to monitor human biometric data anywhere and anytime by using different types of wearable or embedded sensors. In daily life, mobile devices can collect wireless body area network (WBAN) data, and the co-collected location data is also important for disease analysis. In order to efficiently analyze WBAN data, including location information and support medical analysis services, we propose a geohash-based spatial index method for a location-aware WBAN data monitoring system on the NoSQL database system, which uses an R-tree-based global tree to organize the real-time location data of a patient and a B-tree-based local tree to manage historical data. This type of spatial index method is a support cloud-based location-aware WBAN data monitoring system. In order to evaluate the proposed method, we built a system that can support a JavaScript Object Notation (JSON) and Binary JSON (BSON) document data on mobile gateway devices. The proposed spatial index method can efficiently process location-based queries for medical signal monitoring. In order to evaluate our index method, we simulated a small system on MongoDB with our proposed index method, which is a document-based NoSQL database system, and evaluated its performance.

Keywords

Location-Aware, NoSQL Database System, WBAN Monitoring System

1. Introduction

With the exceptional development of mobile device technology and the miniaturization of mobile devices and the development of telecommunications technology, human biometric data can now be collected anywhere and anytime using several types of wearable or embedded sensors. Some sensors can even be embedded in the human body for several years in order to monitor vital signs and send the information to a monitoring center. These devices and signal receivers form part of the wireless body area networks (WBANs) with a bandwidth that is different from that of normal sensor devices [1,2].

As part of a ubiquitous healthcare system, WBAN can collect and send data that covers our daily life. In the WBAN system, WBAN sensors send this type of collected data to a gateway or coordinator node, and then the gateway or coordinator node filters, samples, and aggregates the data in order to resize them [3]. Subsequently, the cleaned data are sent to monitoring centers and medical experts. In this

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paper, the device that receives all of the vital signs of a patient and sends data to a medical center is referred to as the gateway device.

When WBAN sensors collect vital sign data, location data is also gathered [4]. Because body status can change in different environments the location information is a very important factor for health monitoring, and it is used in medical location-based analyses [5], such as disease statistics or health status based on location [6,7].

Currently, in the design of most health monitoring systems, gateway devices have to collect several types of data from several WBAN devices that measure different types of data, such as EEG, pressure, and toxins. The collection rate differs based on the device, and different devices define their data format. Some previous studies have attempted to convert row binary data from health monitoring sensors to XML-based data so that medical centers can analyze medical data from homogeneous devices in one integrated system [8]. However, these studies have only focused on one specific type of device. When mobile gateway devices collect data from different WBAN sensor nodes and send the data to the medical center at a different gathering rate, the position data can be repeated in different data packages [9].

In previous research, several medical monitoring systems that store and manage data in traditional relational databases have been proposed. However, traditional database management systems (DBMSs) focus on transaction management and consider almost all query functions. Therefore, when a DBMS processes high-throughput and high-frequency insert requests, real-time processing, and multi-client requests are negatively affected because of bottlenecks. In order to solve real-time analysis problems, researchers have proposed data stream management systems (DSMSs) that focus on continuous queries over massive online inserted data and busy data streams.

Healthcare and medical data from WBAN are very large data obtained when medical centers cover specific areas with a dense population. Moreover, the volume of WBAN data sent to medical centers differs based on time and day. During the daytime, WBAN data are collected more frequently than during the night. The current trend shows that over 1 billion diagnostic imaging procedures were produced in America in 2014. If other types of medical data were included from the “wild” WBAN, over 200 petabytes of data would be generated [10]. Therefore, in order to provide efficient medical monitoring services, systems have to support large-scale data processing, and system scalability has to be supported [11].

This type of large-scale system construction needs scale-out architecture where computing resources are distributed across a network. In recent years, many researchers have focused on NoSQL (sometimes known as “not only SQL”) database systems, which are non-relational, distributed, schema-free, and horizontally scalable, easily replicated database systems [12]. Most new NoSQL databases have emerged from several independent efforts to provide a flexible, scalable database alternative that can effectively support the needs of high-volume Internet applications. Furthermore, many such databases are built on extremely solid networking and distribution technologies, but have diverged significantly from traditional database techniques. Several popular NoSQL databases, such as Redis, Cassandra, MongoDB, Hadoop/Hbase, Cloudata, VoltDB, CouchDB, SimpleDB, and OrientDB, have been widely used in Web 2.0 applications [13,14]. Although these types of databases provide good horizontal scalability for simple read and write operations distributed over many servers, this means that neither key-value nor document-based storage has spatial support, including the spatial data type or spatial query required by most LBS applications [15,16]. Some researchers already do research on constructing medical based systems and have tried to store medical image data by using cloud data [17,18].

In this paper, we propose a scalable location-aware WBAN data monitoring system based on a document-based NoSQL database system that uses MongoDB. First, we analyzed the integrated data model from WBAN, and then designed the data model for our system. In order to support location-based WBAN data analysis efficiently, we propose a spatial index for the document-based NoSQL system.

The rest of the paper is organized as follows: in Section 2, we provide some related works, including the system architecture of previous healthcare monitoring systems and the WBAN data format. Section 3 provides an overview of the scalable geospatial data service based on the MongoDB NoSQL database that lies on top of MongoDB and describes the proposed index method for a location-aware WBAN system. In Section 4, we compare and contrast our system with MySQL in terms of response time and system resource usage. We present the conclusions and future works in Section 5.

2. Related Works

It has been reported that almost 98,000 patients worldwide die from medical errors annually, and many of those errors and adverse incidents occur because of poor quality medical data and late information analysis. In order to support a quick analysis response time for numerous medical requests and frequent large medical data inserts, we propose and construct a WBAN data management system with location data based on the NoSQL database.

Many types of medical or healthcare applications use WBAN data, but such applications are still limited in fully using the information gathered from the human body. Most of the current studies have focused on gathering information from WBAN, and analyze only medical factors such as ECG signals, nerve potentials, body temperature, blood pressure, and so on. However, when WBAN collects such data, it can also provide data concerning the location from where the data is measured [8].

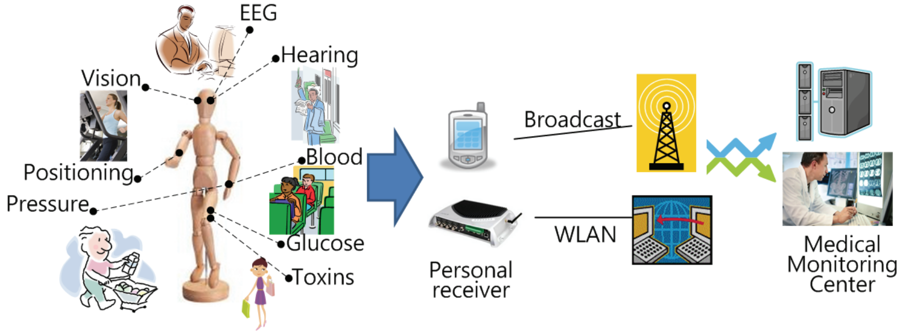

Fig. 1. WBAN health monitoring system overview.

WBAN connects wearable devices on the cloud or the human body through a wireless network; the wireless sensors measure data and send it to the gateway device. [11] describes a WBAN medical monitoring system, and in their design, mobile phones or PDAs collect data from wearable devices from one person serves as a gateway. Fig. 1 shows an overview of WBAN system architecture that collects and monitors data from individual wireless sensor nodes from a single human body via a gateway device. In this design, mobile phones are used as the gateway device in such a way that data measured using WBAN devices can be sent easily to medical centers while an individual works or shops, or are on their way home.

In a case study of CISCO location-aware healthcare solutions, WBAN was used in one hospital area to automatically measure the patients' vital signs in a timely manner [19] in order to allow the hospital to deliver high-quality patient care service at a low cost, increase staff efficiency, and reduce capital and operational costs. Medical experts were able to receive accurate information on patient status and the location of medical staff by using an automatic alert system. For this system, they used RFID tags and PDAs to track thousands of devices in the wireless network. When the monitoring area is larger than one hospital, such that the area covers one village or city, the amount of collected data is much larger than the capacity of the system designed for this hospital. Furthermore, the workload for the medical center server could be more than 100,000 records per second [6].

Previous research [12] proposed a medical monitoring solution based on the cloud-computing paradigm that can be processed by expert systems and/or distributed to medical staff. [12] focused on a service platform design. In addition, [15] conducted research on a solution for processing a high volume of medical images. Such research focused on scalability and maintenance issues with the healthcare providers' onsite picture archive and communication system and network based on cloud computing. [15] used Microsoft Windows Azure to manage store/query/retrieve requests and provided an image indexer that parses metadata and stores them in a SQL Azure database. [13,14] conducted research on a mobile cloud for assistive healthcare infrastructure for efficient resource sharing and planning that addresses security, privacy issues, and quality-of-service on the P2P cloud. This type of research considered a large volume of data and requests for medical services in the future, but did not consider location-aware medical data from WBAN in real-time [16].

In our previous research [20], we designed and constructed a large continuity of care record (CCR) data stream server with DSMS and DBMS in electronic medical record (EMR) systems to monitor CCR data streams and store the processed results with high efficiency. The system allows users not only to query stored CCR information from DBMS, but also to execute continuous queries for real-time CCR data streams. However, the single DSMS and traditional database system cannot support non-fixed data schema processes.

Previous research [7] showed that the data from WBAN systems could not be used if the schema is not defined and shared with relational database systems. Therefore, a new data management system has to be designed and developed for different WBAN devices [21].

In recent years, a new trend of NoSQL databases has been started [18,22]. Such non-relational databases are significantly different from classic relational databases because the former often do not require fixed table schemas, avoid join operations by storing deformalized data, and are designed to scale horizontally. Most non-relational databases can be classified as either key-value stores or document-oriented databases. In contrast, traditional database products have comparatively limited or no ability to scale horizontally on these applications.

Most new NoSQL databases have emerged from several independent efforts to provide a scalable, flexible database alternative that can effectively address the needs of high-volume Internet applications [9]. Moreover, many are built on extremely solid networking and distribution technologies, but have diverged significantly from traditional database techniques. Some popular NoSQL databases, such as Hadoop/Hbase, Cassandra, MongoDB, Redis, VoltDB, CouchDB, OrientDB, and more, have been widely used in many applications [23,24]. Although these type of databases neither key-value system nor document-based storage system didn't fully support spatial data, and thus cannot support medical location-aware services.

In order to support location-aware services in WBAN monitoring systems, a spatial index is required for a short response time and efficient location-based analysis. A spatial index is a special access method used to retrieve data from within the datastore [2]. This allows users to treat data within a datastore as existing within a two-dimensional context, and many researchers have developed a variety of tree structures, including B-trees, R-trees, Quad trees, D-trees, and more [5]. As a spatial indexer, R-tree is used to identify candidate pairs of zones with overlapping bounding boxes [25]. R-trees are fast and efficient for general spatial searching, but the additional overhead of checking polygonal boundaries can be high when there are many zones. For a key-value based cloud computing system, a 2-dimension-based tree is not efficient to generate a spatial data key value, so in this paper we propose a geohash-based index method to support WBAN data.

3. Geohash-Based Spatial Index Method for a Location-Aware WBAN Monitoring System

The main property of our framework is to provide location-based medical analyzing based on a cloud system. In this section, we first overview the proposed location-aware WBAN monitoring system architecture, which can support location-based analyzing, such as location-based aggregation functions. And then we describe the proposed geohash-based spatial index method for the system in detail.

3.1 Location-Aware WBAN Monitoring System Architecture

According to research, location awareness refers to user services that are based on the location information provided by suitable devices or software. Therefore, we believe that location-aware WBAN monitoring systems should not only monitor and analyze location-based healthcare data and vital signs, but also support location-dependent medical services, such as providing local disease rates, the addresses of local healthcare facilities, successful medical treatment cases, and local health risks and hazards based on local WBAN data statistics and analysis. Such systems should also be able to predict possible diseases for any given user based on the user's location. For example, for those living in a specific mountain area, it could predict potential problems caused by a specific plant that could be dangerous to humans. In order to provide this type of services, location-aware WBAN monitoring systems have to quickly store WBAN data, including spatial information, and detect individual dangerous situations on time.

Consequently, we designed the location-aware WBAN monitoring system architecture, shown in Fig. 2. As can be seen in Fig. 2, our proposed location-aware medical monitoring system receives WBAN data from numerous users with the measured location data. The inputted data is inserted based on MongoDB distribution mechanisms. Before the data is inserted, the Location-Aware Patient Manager module generates the data format that could be inserted into MongoDB and controls the data distribution in cloud nodes. When it's received the user query with location-aware analyzing, it will pass the spatial query and then gather the results from parts of MongoDB.

The Spatial Query Manager finds one insert query, and then collects the user's average life area and stores it in the matched node. At the same time, the spatial index is constructed, and the spatial index is described in the next section in detail. The Location-Aware Filter is connected to the Expert System, gathers real-time local medical and disease information, determines whether the user might be experiencing a complication, and then alerts the user if it discovers a potential problem. The Spatial Index Manager is the most important part of this system because, since version 2.0, MongoDB has supported a simple spatial index, but it is limited only to specific points and simple nearby queries. Therefore, we are proposing a new spatial index for NoSQL systems. A given medical expert system could be connected to other systems in order to gather real-time medical news and provide predictive information. In addition, the Map DB has to store and update the monitoring area map information in real time. In the next part, the proposed geohash-based spatial index method is described in detail for this kind of location-aware PHR (personal health record) system.

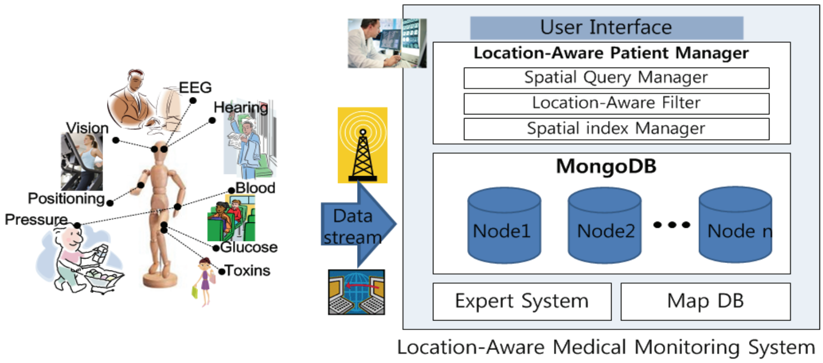

Fig. 2. Location-aware medical monitoring system architecture.

3.2 Spatial Index for Location-Aware WBAN

Every individual has a personal life area and only resides in a specific area. For the spatial index for location-aware WBAN, we focus first on rapidly inserting large volumes of data from WBAN networks. Second, we focus on efficiently supporting personal location-aware services that include aggregations, queries, or other types of queries that have to use historical data. Therefore, we are proposing a new spatial index for location-aware WBAN systems that uses the R-tree [26] and allows nested minimum boundary rectangles (MBRs) and a geohash-based B-tree.

Each node of the R-tree-based global tree includes its MBR, and in its hierarchical structure, the MBR of parent's node could cover the MBR of child nodes. So when the patient moves into the area of one of the leaf node's MBR, then the patient's data will be added into the leaf node.

The NoSQL database data model is a key-value model, and it cannot support multi-key searches. For example, when we find one location, the coordinates of this location have to be transferred to one-dimensional data first. Consequently, MongoDB uses the geohash method to transfer the two-dimensional location data to one-dimension data, and then inserts them by using the B-tree index. In addition, non-spatial data are stored based on B-tree index.

In our proposed index method, in order to support patient location-aware services more efficiently, we separated each patient's life area and stored it in different nodes based on the living area. Fig. 3 shows the structure of our spatial index for location-aware WBAN.

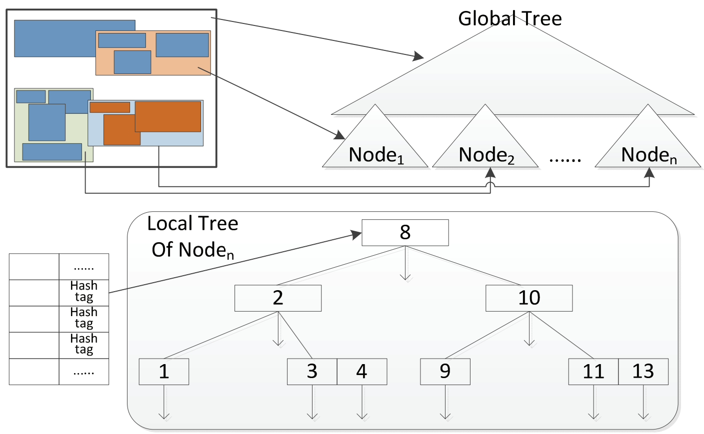

Fig. 3. Spatial index for location-aware WBAN system.

In order to track the patient's location information for one day or a week, the estimated life area for the patient needs to be detected easily. Therefore, the location information collected for every patient for a given duration can construct one MBR, and the rectangle can display the patient's life area. Within the same area, the patient's data is stored in the same MongoDB node, and thus, it can support efficient location-based analysis.

A global tree is constructed based on the R-tree, and the patient's base and location data are stored in the global tree. Each patient lives at a different location point, but has his/her own life pattern based on his/her lifecycle. When we collected the location history data, we detected and calculated the patient's base location. When we found the patient's life area changed, we were able to adjust the patient's location to the other node.

The global index structure is stored in the Spatial Index Management Module, shown in Fig. 1. The global index determines the patients' data that is stored in a given cloud node in the cloud distributed system. Moreover, within the distributed system, the global index simply uses the geohash B-tree index method to first transfer the location coordinates that were initially transferred to the geohash cord, and then stores them in each node.

In the Spatial Index Management Module, all of the user's location is managed by using the global index structure, as Fig. 3 shows. By using the patient location data the global index decides the separation in the distributed system. And in each distributed system, it uses a geohash value calculated from the location data as the key value and stores them in the B-tree index structure in each node, first to transfer the location coordinator transferred to the geohash coordinates, and then it stores it in each node. When analyzing a medical problem based on location information, because the data of patients who live and work in the same zone are stored in the same cloud node, our proposed index method can provide efficient and quick location-aware analyzing services. When the node is full in the distributed system, the data node will balance with other cloud nodes and store the patient's historical medical data.

When the expert system alerts the medical problem at a specific location, the global tree finds the MBRs of those included in the medical problem area, and then sends an alert directly to the patients. Consequently, there is no need to scan whole distributed nodes, and by using the proposed index method the system can support quick responses for location-based queries. Our proposed system fits the needs of emergency medical systems very well.

4. Experimental Results and Analysis

In this section, we present out experiment results for the proposed index method based on the proposed system framework, and we compare our method to MySQL and MongoDB-based systems without a spatial index for location-aware WBANs.

The proposed system was constructed using MongoDB version 2.1, and the spatial manager was implemented using a multithreaded programming method in JAVA and combined with MongoDB for the spatial index data. Making the plug-in highly concurrent requires a way of avoiding a lock argument when multiple threads or users access the node level index tree structure simultaneously, as shown in the insert process. Thus, we deployed a separated location-aware spatial index to each insertion thread in order to reduce the hotspot that results from locks competing for one index tree. Moreover, each thread is shared with one process in a modern operating system mapped to use one CPU in the system. Thus, we can use the system to be fully loaded by increasing the number of threads. Our spatial index is designed as a plug-in for the MongoDB system, and thus, we can use the MongoDB connection model and return the search results format in JSON.

In this evaluation, we sampled medical WBAN data based on the data format shown in Fig. 4.

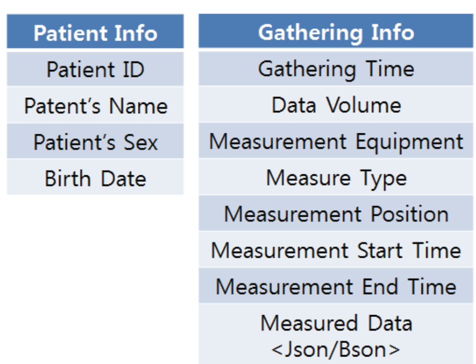

Fig. 4. Sample data format used in evaluation.

We evaluated our location-aware WBAN service based on a MongoDB NoSQL database by using GPS traces (130 million location data) taken from OpenStreetMap, which is an open GPS trace project. In order to evaluate the scalability of our design, we compared the response time with the most popular database, MySQL, for only two basic operations: check-in and nearby search. MySQL implements spatial extensions following the specifications of the Open Geospatial Consortium. This evaluation compares the performance of check-in/nearby, but does not perform a functional comparison. For each test, we sampled 1 million check-in data from 130 million GPS trace points. Table 1 describes the test environment. Furthermore, the MongoDB sharing nodes were constructed in other desktop computers by using the same test environment described in Table 1.

We used the data insert and nearby search requests to test the performance of our system. Insertion and nearby searches were performed in the same network environment because the response time is affected by the network conditions on the client side. Thus, it is more accurate to test the system's processing performance on the same network while the test clients perform bulk requests to each system.

Table 1. Server-side hardware information

MySQL version	5.0
MongoDB version	2.1
Operation system	Windows 2007
Memory	4 G
CPU	Inter Core-4
HDD	1000 G
Network	1000 M

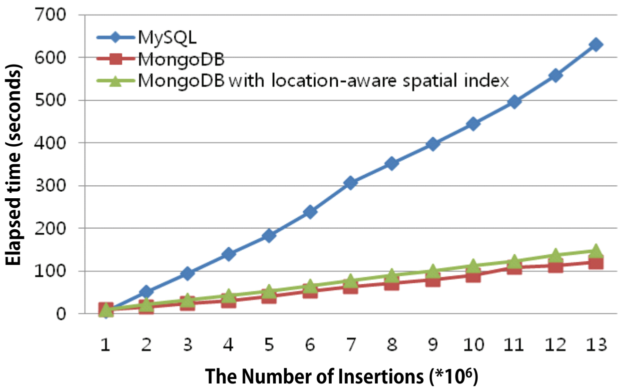

Fig. 5. Data insertion performance comparison.

Fig. 5 shows the results of the insert requests. In this performance test, we compared our system to the MySQL and MongoDB versions without our proposed index structure.

MySQL and MongoDB both use a B-tree-based tree for their index, and thus, both systems performed a similar indexing data process and stored data in each system. However, MongoDB reduces the size of the spatial indexes with the centroids of clusters and the capacity.

Fig. 5 shows the time elapsed for inserting location data into each system. The insertion benchmark program is a single-threaded standalone program that checks each system's spatial index complexity. As the figure shows, the response time for inserting up to 1,000 entries is almost the same. However, for a larger number of entries, MongoDB outperforms MySQL. Moreover, MongoDB with location-aware spatial index is slightly slower than MongoDB because it requires additional time to construct the global spatial index.

We measured the performance of the aggregation search of each system with a different number of clients to revise scalability. In this paper, the aggregation search was based on location data, such as average health data in a specific area. Fig. 6 shows the performance of the aggregation query, which is an SQL expression similar to SELECT AVG (body temperature) FROM check_in WHERE ST_D within (the_geom, Geometry From Text ('POINT (–123.000 32.000)', 4216), 0.01). This means "obtain average blood data within 1 km of the location's coordinate," which in this case was (–123.000 32.000). This point location is selected randomly from the check-in point data.

Fig. 6 shows that when the average query is evaluated and the search area is larger than 1 km to 9 km, because of the spatial index intended for WBAN data monitoring, the proposed method slightly outperforms the original MongoDB. Moreover, MySQL is much slower than MongoDB.

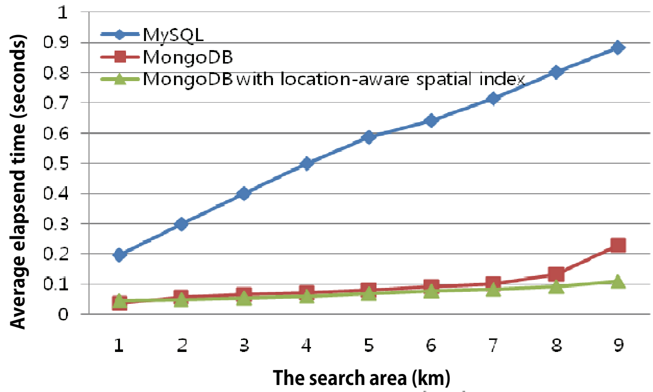

Fig. 6. Average query evaluation performance comparison.

5. Conclusions

We proposed, designed, and constructed a geohash-based index method for the NoSQL-based location-aware WBAN data monitoring system. Current WBAN systems didn't consider location-based medical analyzing. In order to support location-aware services, we have proposed a new spatial index algorithm for a document-based NoSQL database. We used the algorithm to focus on high insertion rates and average searches based on spatial data, which are a common characteristic of mobile applications. We simulated and implemented a medical location data service based on the MongoDB database by using our indexing algorithm. In the future, we will add many more spatial data types, such as polygons and multi-polygons, so that our method can propose more functions. In addition, we will test more location-aware services for WBAN healthcare monitoring systems in order to improve our methods.

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