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Ontology driven interactive healthcare with wearable sensors

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Abstract Ubiquitous healthcare is the service that offers health-related information and contents to users without any limitations of time and space. Especially, to offer customized services to users, the technology of acquiring context information of users in real time is the most important consideration. In this paper, we researched wearable sensors. We proposed the ontology driven interactive healthcare with wearable sensors (OdIH_WS) to achieve customized healthcare service. For this purpose, wearable-sensor-based smart-wear and methods of data acquisition and processing are being developed. The proposed system has potential value in healthcare. A smart wear using wearable sensors is fabricated as a way of non-tight and comfortable style fitting for the curves of the human body based on clothes to wear in daily life. The design sample of the smart wear uses basic stretch materials and is designed to sustain its wearable property. To offer related information, it establishes an environment-information-based healthcare ontology model needed for inference, and it is composed of inside-outside context information models depending on the users' context. The modeling of the proposed system involved combinations of information streams, focusing on service context information. With the proposed service inference rules, customized information and contents could be drawn by the inference engine. In the established OdIH_WS, real-time health information monitoring was achieved. The results of system performance and users' satisfaction evaluations confirmed that the proposed system is superior to other existing systems.

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1 Introduction

Recently, interest has increased in disease prevention and health promotion, rather than disease treatment, and people's tendency to get various types of information from diverse media and applying them have also increased. Then, various and numerous health information sites have been developed and operated. However, they do not actually seem effective for users' health care and promotion not only due to the limitations of Web-based information, but for lack of customized services. In the current ubiquitous environment, health information support services have been generally developed in a format of inputting data on bio-information acquired into the computer for the existing network-based transmission. For that reason, in fact, such services are quite inconvenient and inefficient. In this regard, it is urgently required to develop a method for supplying customized information using an interactive system of acquiring context information and processing it in real time [11]. For healthcare service realization, context-aware computing-based services for high-quality medical care achieve better healthcare services by way of collecting context information and making intelligent inference according to ontology-driven context-aware computing and ubiquitous environment [14, 16]. For the existing healthcare support service using context-aware information, context-aware inference based services are provided by acquiring information from different types of sensors, or by leading users to directly input context information using computers or mobile devices [6]. However, until now, there have not been many studies on provision of healthcare support services, which acquire data in real time through wearable sensors, using health information in terms of diseases, which are judged to show higher incidence and popular interest, in addition to the relative relation to meteorological elements. Moreover, in the cases of asthma, yellow sand, dryness and allergy where the quality of life depends on meteorological condition, the current healthcare support services do not provide customized, individual services for disease prevention and health promotion. More effective and interactive healthcare support systems, therefore, should be developed with real-time bio-information acquired from wearable sensors, inference technology of medical support systems and context-aware computing technology. Accordingly, this paper proposes OdIH_WS, or Ontology driven Interactive Healthcare with Wearable Sensors, in order to achieve a more efficient solutions to mitigate these problems. The purpose of this system is to provide more satisfied healthcare services to users using their devices by acquiring environment information through wearable sensors in real time, defining environments for their healthcare services using ontological methods, and inference information and contents on health.

The rest of this paper is organized as follows. Section 2 provides the related research. Section 3 describes in detail the ontology driven interactive healthcare with wearable sensors. In Section 4, the design of an ontology driven interactive healthcare is presented. Experiments evaluations are given in Section 5. The conclusions are given in Section 6.

2 Related research

2.1 Wearable sensor based information

Smartwear, a fabric fashion product using IT convergence technology, is designed to allow essential digital functions to be ubiquitously used in future lifestyle according to the application of new signal-transferring textile technology to the product, equipped with various related digital devices. It can be also used as an information production device to provide main information necessary for context-aware computing to achieve interactive services. Likewise, for wearable sensor-based smart wear, new applications are under development, which are enabled by the development of new-generation IT convergence technology, and more efforts to improve its reliability have been made through enhanced accuracy of measurement. Moreover, numerous technologies applied to products have launched into the market.

U.S. Accu Weather[1] [21] provides health information on pain, allergy and heart diseases, which are caused by meteorological and regional conditions. In this time, health information is given via 5 grades, Extreme, High Risk, At Risk, Neutral and Beneficial. This product, combined with the current weather information, predicts the incidence and durability of diseases expected in view of weather reports. Japan Weather News[2] [7] provides contents helpful to achieving a healthy lifestyle through weather information. It also makes analysis and prediction, based on field reports, inspection data and symptom reports from about 1.6 million supporter networks, in order to analyze, predict and support health information for more specific description of meteorological elements to influence health. However, unlike Accu Weather, it provides only simple data, instead of numerical grading information. Figure 1 shows U.S. Accu Weather and Japan Weather News.

The existing products are Heart Rate Monitor Sports Bra [20] of Textronics Inc.[3] and Smart life Health Vest [18] of Smartlife Technology.[4] They are embodied in the design form through human sensory functions using Smartwear. Textronics Inc. developed heart rate monitoring clothes designed as sports top bra for women with textile sensors. The heart rate can be monitored by sensors based on textile electrodes, which are attached inside the clothing. It was designed to allow wearers to continuously monitor their body conditions and burnt calories through a watch-type monitor. Smart life Technology developed Smart life Health Vest [18] to continuously monitor electrocardiogram, respiration and body temperature. It allows bio-information collected through electrodes to be transmitted to a computer, PDA or cell phone in real time, which leads wearers to continuously monitor their health conditions. Due to the development of IT convergence technology and diversification of the lifestyles of consumers, a greater interest in the wearable sensor-based Smartwear has been reported. In view of this trend, some studies have been conducted on designing eco-friendly user-oriented clothing similar to usual clothing, as well as the minimization and weight reduction of devices [2, 13, 17].

2.2 Semantic inference

Semantic inference is a method of implementing interactive processes with ontology as the knowledge base. Here, semantic is an adjective referring to “meaning” or “semantics.” In this regard, semantic inference conducts meaning-based inference [15]. It is an inference method that has come into the spotlight as the web Semantic network in earlier studies on artificial intelligence reappeared as semantic web. As grammar of the standard form of the language for defining ontology, there are OIL, RDFS and OWL [3]. Ontology is formed with knowledge on domains as a hierarchical structure model, which is embodied into domain instance. The instance can be represented into various types, for example, text, image, sound

[1] U.S. Accu Weather, http://www.accuweather.com
[2] Japan Weather News, http://www.weathernews.com
[3] Textronics Inc., http://textronics.com
[4] Smartlife Technology, http://smartlifetech.com

Fig. 1 U.S. Accu weather and Japan weather news

and complex events. An ontology-based inference engine performs a process of information retrieval and question and answer by receiving information on a specific instance. In an expert system, it can perform more complicated information retrieval by assistance to a rule-based inference engine. For example, in case of an adverse drug reaction judgment service, an ontology-based knowledge base can be used to detect possible adverse drug reactions when a patient with properties of specific disease takes medicine with along with another where adverse drug interaction does not occur. Of course, in this case, the knowledge base should involve that fact that the relevant medicine instance, the specific disease and gene information can actually cause adverse drug interaction [22].

Ontology is generally constructed by domain experts using tools for ontology construction. Moreover, as domain information is mainly written and stored in text format, various text mining techniques are embodied into programs. In other words, a process of recognizing ranges of concepts and individuals according to the analysis of natural language, and making relations between these individuals and standardized names into a database is automated. This methodology cannot achieve complete automation of the process of constructing an ontology-based knowledge base, but is saves the time and cost of passive construction.

3 Ontology based health information service using wearable sensors

This section describes healthcare models and inference rules for recognizing users' contexts, based on context information acquired by wearable sensors, and for applying to healthcare services to support healthcare. Accordingly, it allows modeling context information for healthcare support, based on the context definition of Dey [4], and developing ontology-based healthcare models for inference services in view of context.

3.1 Health information using wearable sensors

Context information is the technology of informationalizing and characterizing real context in virtual space by connecting between real and virtual space to provide a personalized interactive service [10]. It can provide an optimized service by proposing technical tools for representing all contexts of real world and applying interactive methodologies such as context-awareness, feature extraction and learning. Likewise, context is information used for characterizing the conditions of an individual. In a user's environment, it is represented as location, behavior, weather, conditions and others, and indicates values of information on individuals and their changes. Here, individuals refer to everything in relation to Human Computer Interaction, including users and the system itself. Recently, the importance of context information has been more and more emphasized in the computer field, in view of IT convergence, healthcare and AI. The reason is because consideration of context achieves enhanced adaptability and effective decision making, like inference through human thought [2]. Accordingly, in this paper, wearable sensors are used to provide a high-level abstract concept of context information. In order to provide customized healthcare, it leads to the analyses of users and their surrounding contexts and conversion into applicable forms. Using wearable sensors, Smart wear is designed to let wearers feel comfortable, in consideration of body curves, by application of their casual clothes. For its design pilot, a basic type flexible material was used. In this paper, a smart wear using wearable sensors was manufactured, as shown in Fig. 2.

The context sensor used in this design consists of various sensors such as temperature sensors, illumination sensors, humidity sensors, and wind sensors. It is a device that can be configured as a package with servers, which detect and manage various environments, as well as an RFID reader. It has been practically used in various applications from home networks to weather environment monitoring, agricultural and livestock product management, and environment monitoring. The smart wear is fabricated as an attachable and detachable pocket type in order to put the context sensor in the pocket, which is attached at an area that does not disturb movements. It aims to use the smart wear as a usual cloth while the wear is washed or does not require the sensor. Also, the sensor is to be fabricated as an embroidered type in order to safely fix the context sensor and apply it for various types of clothes. As small context sensors are connected as a way of wireless communication, an issue of complexity in the conventional smart wear can be solved through minimizing the use of wires. A 3.3V coin cell battery is used as a power supply of the context sensor and attached to the wear for enabling the change of the power supply. Radio communication between small-sized context sensors leads to the minimization of unnecessary wires, which gives solutions to a complex structural problem [1] of smart wear. It is manufactured to maintain wearing quality and wearability while keeping the appearance of clothing. Then, context information can be acquired to get life weather indexes such as heat index, food poisoning index, discomfort index, ultraviolet(UV) index, wind chill temperature index(WTI) and water pipe freeze possibility index; and health weather indexes such as the asthma index, the stroke index, skin disease index, pulmonary disease index, pollen concentration index and city high temperature index.

Fig. 2 Smart wear using wearable sensors

3.2 Ontology based context information model

In order to utilize the information generated from wearable sensors, context information models are needed, and context information models are defined by using the most effective method among the model representation methods. As the domain ontology, context information includes External Context Information, Internal Context Information and Service Context Information. The ontology is defined by using a triple pattern in OWL (Ontology Web Language) format. The top class is designed to infer context information in terms of services according to division into Internal Ontology, External Ontology and Service Ontology and to focus on extensity. Moreover, as healthcare support should provide new services with the integration of different information, a health care model is constructed via the combination of context information models and then embodied into a hierarchical ontology structure. In the hierarchical ontology structure, Service Ontology is the top-level ontology, with Internal Ontology and External Ontology as the lower-level ontology. In this regard, a service-oriented healthcare ontology structure is designed [17].

Figure 3 shows the integrated hierarchical classes of healthcare ontology and their relations. The External Ontology and Internal Ontology are context information for

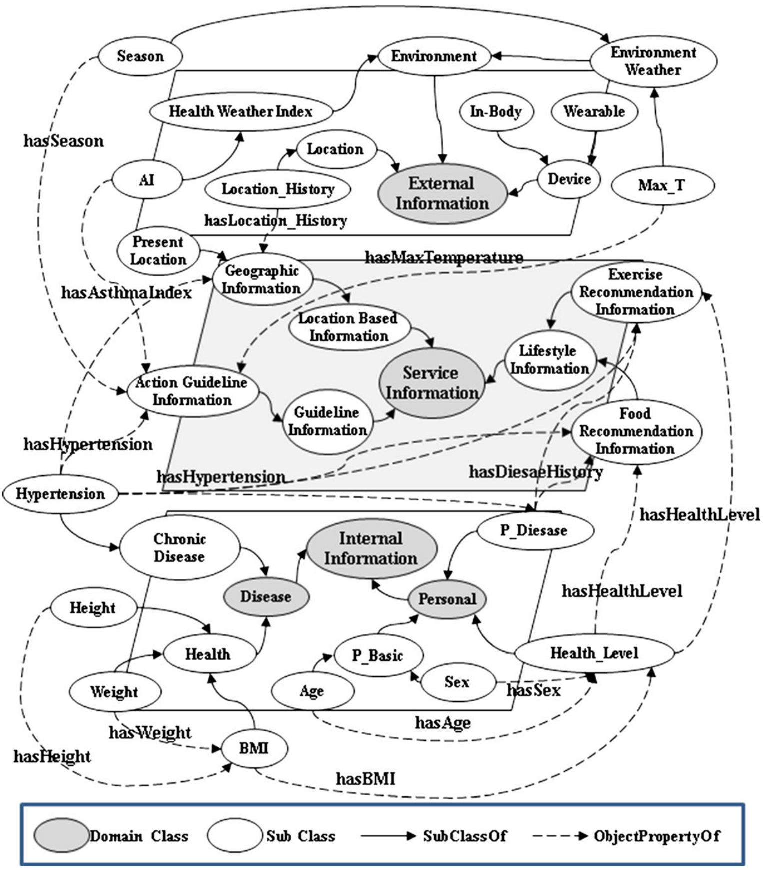

Fig. 3 Integrated hierarchical healthcare ontology class and relation

providing services, and information inferred from them, respectively, becomes inferred results of the Service Ontology. Healthcare ontology is constructed by using context information, and the relation between the Domain Class and the Sub Class of External Ontology and Internal Ontology is defined, based on the Service Ontology. To apply this healthcare model to the healthcare service, inference rules are required to infer designed Ontologies.

3.3 Service inference rule

Context information necessary for the service is derived by inferring the External Ontology and Internal Ontology, in addition to inference rules. For this, inference rules for the Ontologies are respectively specified, and those for service are then specified. The External Ontology is divided into the Device Class of acquiring information from different network devices, Location Class of indicating local information and Environment Class of acquiring environment information. Moreover, the Internal Ontology is divided into Personal Class based on personal information and Disease Class of indicating disease information. For both Ontologies, the main inference rules for context information are shown in Table 1.

The inference rules for service are used for inference information in relation to services using external context information inferred from the External Context Ontology and internal context information from the Internal Context Ontology. They are divided into Guideline Information of monitoring diseases, Location Based Information and Lifestyle information of providing information on exercise, diet and behavior. The inference rules for service are shown in Table 2.

Table 1 Inference rule of external and internal context information

Context info.	Inference info.		Inference rule
Health weather info.	Asthma index	Low	(?Health_Weather_Index ?AI) ∩ (AI<50) →(?Customer hasAI ?AI_Low)
		Middle	(?Health_Weather_Index ?AI) ∩ (AI >51) →(?Customer hasAI ?AI_Normal)
			(?Health_Weather_Index ?AI) ∩ (AI<=81) →(?Customer hasAI ?AI_Normal)
		High	(?Health_Weather_Index ?AI) ∩ (AI >81) →(?Customer hasAI ?AI_High)
Chronic disease	Hypertension	Period	(?Customer hasDisease ?Hypertention)∩ (?MaxBP>= 120) ∩ (?MaxBP<139) →(?Hypertention hasHypertention ?PreHypertention)
			(?Customer hasDisease ?Hypertention) ∩ (?MinBP>= 80) ∩ (?MinBP<89)→(?Hypertention hasHypertention ?PreHypertention)
		Primary	(?Customer hasDisease ?Hypertention) ∩ (?MaxBP>= 140) ∩ (?MaxBP<159)→(?Hypertention hasHypertention ?1Step)
			(?Customer hasDisease ?Hypertention) ∩ (?MinBP>= 90) ∩ (?MinBP<99)→(?Hypertention hasHypertention ?1Step)
		Secondary	(?Customer hasDisease ?Hypertention) ∩ (?MaxBP>= 160) →(?Hypertention hasHypertention ?2Step)
			(?Customer hasDisease ?Hypertention) ∩ (?MinBP>= 100) →(?Hypertention hasHypertention ?2Step)

Table 2 Inference rule of service context information

Service	Inference info.		Inference rule
Location information service	Emergency info.	Danger	(?Customer hasEmergency ?Emergency) ∩ (?Health_Level(?emergency,Lvel5) ∩ (?Locations,Danger) ∩ (?Health_Weather_Index(?Location,Danger) ∩ (?Life_Weather_Index(?Location,Danger)) →(?Emergency ?Danger)
		Warning	(?Customer hasEmergency ?Emergency) ∩ (?Health_Level(?emergency,Lvel3) ∩ (?Locations,Warning) ∩ (?Health_Weather_Index(?Location,Warning)) ∩ (?Life_Weather_Index(?Location,Warning)) →(?Emergency ?Warning)
Guide line	Environment advice alarm	Allergic disease	(?Customer hasDisease ?allergicDisease) ∩ (?Environment_Weather hasSeason ?Summer) ∩ (?Environment_Weather hasHum ?Hum<50) →(?ActionGuidelineInformation ?allergicDiseaseAdvice1)
		Influenza and bronchial tubes	(?Customer hasDisease ?bronchitis) ∩ (?Environment_Weather hasSeason ?Summer) ∩ (?Environment_Weather hasHum ?Hum <50) →(?ActionGuidelineInformation ?bronchitisAdvice1)
	Activity guideline advice	Humidity low	(?Environment_Weather hasSeason ?Summer) ∩ ((?Environment_Weather hasMax_T ?Max_T<22) || (?Environment_Weather hasHum ?Hum <50)) ->(?ActionGuidelineInformation ?ActionAdvice1)
		Humidity high	(?Environment_Weather hasSeason ?Summer)∩ ((?Environment_Weather hasMax_T ?Max_T>24) ∩ (?Environment_Weather hasHum ?Hum >60)) ->(?ActionGuidelineInformation ?ActionAdvice2)
Life pattern info.	Food	Diabetes	(?Customer hasHealthlevel ?Health_Level) ∩ (?Customer hasDisease_History ?Diabetes) →(?FoodRecommand hasFoodRecommand ?Food_Diabetes)
	Exercise	Hypertension	(?Customer hasHealthlevel ?Health_Level)∩ (?Customer hasDisease_History ?Hypertension) →(?ExcerciseRecommand hasExerciseRecommand ?Exer_Hypertension)

4 Design of ontology driven interactive healthcare

The configuration of Ontology driven Interactive Healthcare with Wearable Sensors (OdIH_WS) is shown in Fig. 4. A Context Collection Layer and Context Layer are the processes of acquiring devices, personal information and external data and converting them into Ontology format and data necessary for inference.

The Context Collection Layer is a module for collecting context information. A process of collecting internal context information is achieved by creating an SQL query, after

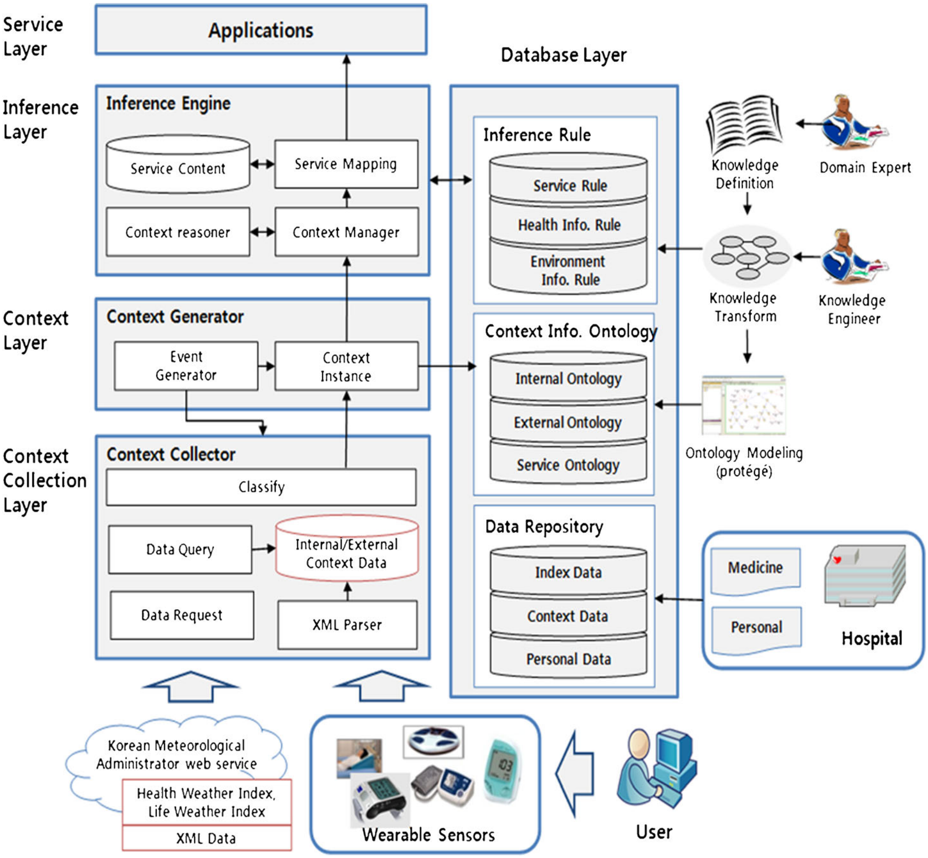

Fig. 4 OdIH_WS system architecture

generating an event from a context generation module of the Context Layer, and collecting user information from database. The user information may be personal information or disease information, and data can be collected from medical institutions. This collected information is classified as format that is convertible into OWL files. External context information is collected by requesting data to get necessary external information from the web, after generating an event and acquiring data from sensor devices. Meteorological environment information is achieved by collecting XML data, which are processed in RSS format by Korea Meteorological Administration [12]. The requested data are collected from the web in XML format, and classified as format convertible into OWL files after a parsing process. For a Context Instance of the Context Layer, a query is created for inference, and the classified context information is converted into a triple pattern in OWL format and then inputted as data into the Internal and External Ontologies. In case of input completion, a Context Manager of an Inference Engine is called. An Inference Layer is a section of inferring health contents through the Inference Engine and a Database Layer and providing the most suitable service for user environment. For knowledge modeling, when new context information is generated, domain experts define knowledge on new context and knowledge engineers process data into Ontologies and inference rules in processable format in systems. Moreover, Ontologies perform ontology modeling using Protégé [5], the OWL guide. The Context Manager of the Inference Engine infers the

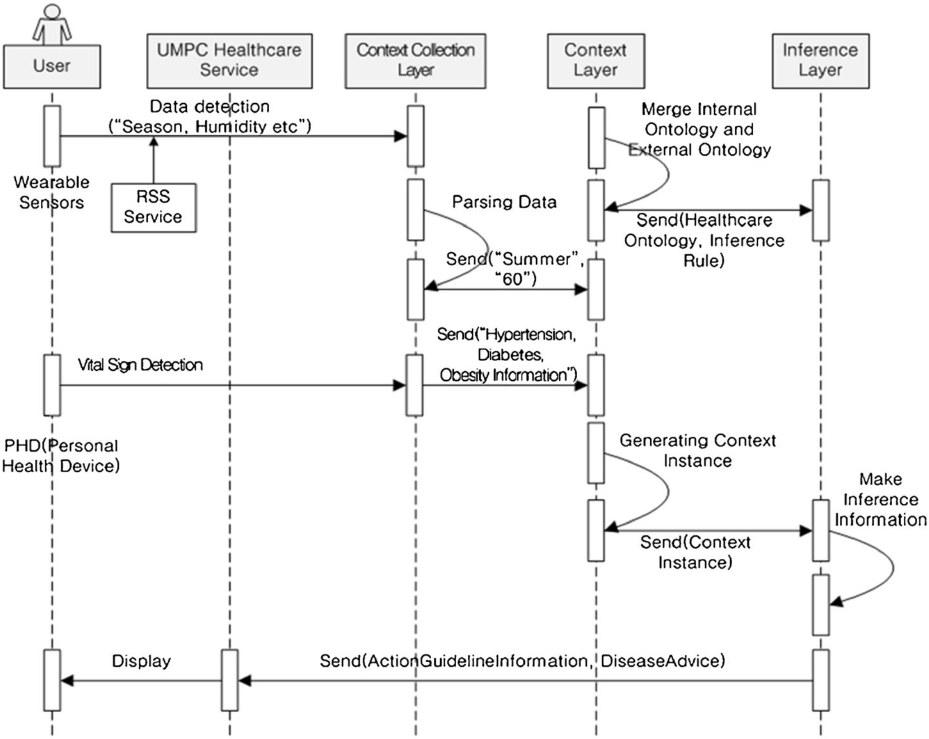

Fig. 5 Process of providing ontology-based health information with sensors

users' health conditions, disease conditions and health contents, on the basis of context information collected through the Context Instance and also create an internal query. For inference, the Context Manager's Triple Translator calls all Ontologies, the Internal, External and Service Ontology. A Context Reasoner, an inference module through rule chains, performs inference through a query, prepared by a query manager, with reference to the Interference Rules defined in Chapter 4, Context Information, Ontology and Data Repository. Moreover, the Inference Engine performs OWL inference using Jena API [8, 19]. In Service Mapping, for determining the format of the inferred results of service, data are converted into a format required in each application through the predetermined service content database. Finally, users can use the customized service through the Service Layer.

Figure 5 shows a process of collecting internal and external data through the proposed system and providing health information generated from the processed data. When

Table 3 Group query

Group	Query	Number of inference rule
1	{Health Level, Obesity}	{2,1}=3
2	{Health Level, Disease}	{2,6}=8
3	{Health Level, Obesity, Disease}	{1,2,6}=9
4	{Health Level, Life Index, Disease}	{2,6,5}=13
5	{Health Level, Obesity, Life Index, Disease}	{1,2,5,6}=14

Table 4 Result (Record 50)

Group	Inference result	TP	FN	FP
1	1000	216	284	500
2	864	216	284	364
3	638	303	197	138
4	724	362	138	224
5	500	500	0	0

environment information and bio-data are acquired from users, the Context Collection Layer generates information through parsing, and the Context Layer creates the Healthcare Ontology and the Context Instance and transmits the Interference Rule to the Inference Layer. The Inference Layer derives behavior guide and disease recommendation information through the transmitted information and provides them to the users via user devices.

5 Experimentation evaluation

In this paper, two experiments were conducted to evaluate the Ontology driven Interactive Healthcare with Wearable Sensors (OdIH_WS). The first experiment was conducted to verify the accuracy of the healthcare ontology model and the inference engine according to the evaluation of precision, recall and F-measure in the service provision information with 500 random context information records. The context information consisted of bio-information, life weather index, health weather index and healthcare information. Each experimental group was measured by using 500 context information records. For measurement, queries were determined for 5 groups to evaluate Precision, Recall and F-measure, and an inference value to each query was compared with the inference value to be actually provided [9]. Table 3 shows the types of queries for 5 groups and the number of inference rules used.

As queries, health status, obesity, life index and query statements related to diseases were used. Table 4 shows the experimental results of query statements. TP(True Positive) refers to a correctly inferred value among referred values, whereas FN(False Negative) refers to an incorrectly inferred one.

Moreover, the methods for accuracy evaluation include precision, recall and the F-measure that is a unit of combination of precision and recall. Here, while precision refers to the rate of correct judgment on the total inferred values, recall refers to the rate of correct judgment on all data of a population. The F-measure refers to the reliability of the inferred results and is defined as Eq. (1). The comparative evaluation of precision, recall and

Table 5 Result of the evaluation

Group	Precision	Recall	F-measure
1	0.302	0.432	0.355
2	0.372	0.432	0.400
3	0.687	0.606	0.643
4	0.618	0.724	0.666
5	1.000	1.000	1.000

Table 6 ACCU_W and OdIH_WS paired samples statistics

	Mean	N	Std. deviation	Std. error mean
ACCU_W	3.0425	94	1.12561	0.11610
OdIH_WS	4.2872	94	0.78456	0.08092

F-measure on the context information records were conducted by using Eq. (1). The results of the evaluation are shown in Table 5.

$$\begin{aligned} \text{Precision} &= \text{TP}/(\text{TP}+\text{FP}) \\ \text{Recall} &= \text{TP}/(\text{FN}+\text{TP}) \\ \text{F}-\text{measure} &= 2*\tfrac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \end{aligned} \tag{1}$$

As shown in Table 5, the higher number of inference rules led to higher values in precision, recall and F-measure. In other words, more context data and a higher number of inference rules are required to provide customized and suitable services to the users. Accordingly, it shows that more context information and the higher number of related inference rules, instead of the existing service such as simple monitoring, would allow more customized services for users through the inference engine [2, 17].

The second experiment evaluated the satisfaction level under the uses of the existing Accu Weather (ACCU_W) and OdIH_WS for 94 users. The evaluation was conducted via a five-step Likert score, 1 to 5. In the score, a score of 1 denotes a very negative answer for the surveyed item, and a score of 5 denotes a very positive answer. A *T*-test was applied to statistically verify the difference in evaluation data. The hypothesis H0 signifies “there are no statistical differences in service satisfaction between ACCU_W and OdIH_WS”, and H1 shows that “there are statistical differences in the service satisfaction between ACCU_W and OdIH_WS”. Table 6 shows the average and standard deviation of the evaluation data of the service satisfaction for ACCU_W and OdIH_WS, where the difference in the average is 1.24. Table 7 shows the results of the corresponding sample *T*-test for ACCU_W and OdIH_WS. As the significant level, α, was determined by 0.05, the values for making a decision are Sig. < 0.05. Because the values of Sig. were presented as $0.00 < 0.05$ in the *T*-test of the evaluation data in this paper, the Ho was neglected and the Ha was then accepted. Thus, there were some differences in satisfaction between the ACCU_W and OdIH_WS services. Also, it was verified that the satisfaction of the OdIH_WS service showed a high level of 1.24, which is the difference in the average value of the evaluation data, compared to the ACCU_W service.

Table 7 ACCU_W and OdIH_WS paired sample *T*-test

Paired differences					t	dr	Sig (2-tailed)
Mean	Std. deviation	Std. of the mean	95% confidence interval of the difference				
			Lower	Upper			
1.2446	1.4344	0.1478	0.9508	1.5384	8.414	93	0.000

6 Conclusions

This paper proposed and developed the ontology-driven interactive healthcare (OdIH_WS) to apply real-time information acquired from wearable sensors to services. For the healthcare service, the information necessary for the service was derived through the context information model and intelligent, and customized services were provided using health information and management rules. Moreover, the service was provided to personal portable devices to provide directions and measures for health information by stages in real time according to requests of various users. Moreover, for evaluating the performance of the proposed methodology, two experiments were conducted. First, the first experiment was conducted to verify the accuracy of the healthcare ontology model and the inference engine by using F-measure, a unit of combination of precision and recall. As a result, the higher number of rules related to context information were shown to provide more suitable information to users through the inference engine. Then, the second experiment was conducted to create a comparative analysis of service satisfaction of the proposed method (OdIH_WS) and Accu Weather (ACCU_W) using Paired *T*-test. According to the analysis results, the proposed method was shown to achieve higher satisfaction than Accu Weather. Accordingly, in order to generalize the results of this study, more extensive studies are required by extending the ranges used in the above experiments. Moreover, actual construction and application of healthcare systems, based on the results, will surely provide more diversified health information services to users and make a great contribution to disease prevention policies in the view of impending aging societies. According to the results, future studies are also expected to expand the medical information service market through the specific launching of healthcare related products and achieve higher added value.

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