J Supercomput
DOI 10.1007/s11227-009-0314-5

u-BabSang: a context-aware food recommendation system

Yoosoo Oh · Ahyoung Choi · Woontack Woo

Abstract In this paper, we propose a context-aware food recommendation system for well-being care applications. The proposed system, called u-BabSang, provides individualized food recommendation lists at the dining table, and is based dietary advice in the typical Korean medical text. Our proposed system receives a user's profile, physiological signals, and environmental information around the dining table in real time. To operate our system, we present a method for user specified analysis, and also describe time-division layered context integration which integrates the multiple contexts obtained from the sensors. Thus, our system recommends appropriate foods for each individual's health at the table in real time.

Keywords Context-awareness · Context integration · Personalized food recommendation · Well-being care applications

1 Introduction

With the increased interest in living a healthy or "well-being" diet and lifestyle, research into applications that assist people to improve their lifestyles have also increased [1–3]. This is particularly true with the development of systems and middleware which provide health care services utilizing various types of sensor information (e.g., sensing physiological signals). Typically, people who want to change lifestyle choices for better health and fitness, focus on their diets [4]. As such, further research

Y. Oh · A. Choi · W. Woo (✉)
GIST U-VR Lab., 1 Oryong-dong, Buk-gu, Gwangju, 500-712, S. Korea
e-mail: wwoo@gist.ac.kr

Y. Oh
e-mail: yoh@gist.ac.kr

A. Choi
e-mail: achoi@gist.ac.kr

Published online: 08 July 2009

into applications that can inform consumers about appropriate food choices and that take into account individual physiological status and environmental situations is required.

However, most previous works on well-being care applications have not considered user adaptive food recommendation systems that take into account the user's current situation. Most systems dedicate a specific sensor to a specific service for users in general, and do not apply personalized results to recommendations. This inflexibility makes it difficult to extend these services to make reliable and stable recommendation to individual users. In addition, previous studies did not permit their systems to obtain high level inference information. Little attention has been paid to personalized food recommendations based on sensing and analyzing current situations in real time. Hence, in order to utilize the information from multiple sensors, a system is required to understand signals of different formats and to deliver converted contexts to various services in a distributed network environment. Moreover, for higher level reasoning obtained from low level sensory signals, the real time integration of multiple contexts is also required. Our research is based on the premise that individualized context-aware food recommendations are needed to reflect personal needs in real time.

As a means of resolving this problem, we propose u-BabSang ("u" stands for ubiquitous computing enabled, and "BabSang" is the pronunciation of the Korean word for a dining table); a context-aware food recommendation system for a Korean-style dining table. At a Korean-style dining table, people sit around the table on the floor and share the food. We chose to use Korean food because can have both healthy and unhealthy characteristics, depending the individual's physiological status and dietary needs. In this paper, we present a method for user specified analysis in the proposed food recommendation system. We also describe the context integration of the proposed system in order to obtain high level inference information. Furthermore, we present a user adaptive food recommendation method which adaptively recommends appropriate food for each individual at the dining table in real time.

Our proposed system integrates multiple contexts obtained from user profiles (e.g., body figure, gender, clinical history, body constitution [5]), physiological signals (e.g., heart rate, skin temperature, sweat on palms), and sensed environmental information (e.g., intensity of illumination, noise level, temperature). By gathering and analyzing these contexts, the proposed system adapts a time-division layered context integration system that uses multiple layers for context fusion to improve overall system performance. Its primary characteristic is that it can infer high level information, such as behavior, physiological status, and intention. Moreover, the proposed system can recommend food to each individual by exploiting this context integration technology in real time.

The advantage of our proposed food recommendation system is that it enables the management of personalized well-being care in that it collects data from both personal and situational contexts at run time, and interprets these in a user-centric way. Also, the proposed system can provide valuable real-time feedback to users who have specific clinical histories, with additional analysis of daily external conditions (e.g., location, weather, etc.). This information is presented to users in an intuitive and convenient real-time display.

This paper is composed as follows. In Sect. 2, we survey cultural food customs and related work. In Sect. 3, we explain the proposed food recommendation system. We then describe the implemented food recommendation system in Sect. 4. In Sect. 5, we present our experimental results, discussions, and suggestions for future research.

2 Background

2.1 Cultural food customs

While cultural food customs vary widely from region to region, sharing food at the table is a widespread practice in Asia. This is particularly true in Korean, where sharing meals both at home and when eating out is the normal practice. Rice and soup are served for each person, but the main dishes and side dishes are shared among all persons around the table. Basically, all Korean dishes are placed on a dining table before eating. Thus, the proper time of food recommendation is after all the foodstuffs are placed on the table.

A dining table designed to provide the most suitable food for each person has an advantage over a general dining table. The body constitution is one of the categorization methods of human being in terms of physiological and psychological characteristics of the users [5]. These classification criteria can be extended to general users in the world. The Korean medical text, "Donguibogam" [6] states that food materials have certain characteristics suitable to each personal body constitution [7]. The nutritional aspect of food and the body constitution have genomic relationship [8, 9]. Therefore, knowledge of personal information including body constitution and physiological status are useful for selecting good foods. For example, because cucumbers can cause a cooling effect, users with normally low body temperature rates are advised to avoid food containing cucumber. In this work, we apply this theory to the ubiquitous computing environment where we obtain current contextual information of both the environment and the user. If a system can utilize contextual information including body constitution, personalized food recommendations are possible for each individual. This obviously provides benefits compared to a system where, for example, nutritionists would provide more general dietary advice in the same situation. If a system is able to obtain personal information, physiological status, and the sensed environmental information based on a typical Korean medical approach, the system could recommend appropriate foods for each individual by analyzing and inferring that information.

2.2 Related work

In future home-related research, there is increasing interest about wearable and mobile physiological sensors and applications which can both monitor the user's current health status, and prevent the disease [10]. The unconstrained bio-signal instrumentation system which has bio-signal measuring sensors embedded in such common household items as beds, doorknobs, urinals, and bathtubs has been developed [4]. Also, health care services which use bio-signal sensors attached to mobile devices are being developed and sold commercially. The algorithm which analyzes information, such as heart rate, blood pressure, skin temperature, and skin conductance is formed by wearable bio-signal sensors in a wearable platform [11].

A wide range of services are appearing on the market that allows consumers to manage their health, particularly in disease prevention and weight reduction. For example, an obesity management service is commercially available that monitors individual motion and energy, sensing the user's health status and movement from a device in the form of a bracelet [12]. Similarly, a sensor embedded in shoes can detect motion and analyzes data though an MP3 device [13, 14]. Much of this research is focused on food intake tracking, but they do not mention food recommendation. For example, as a well-being care application, a dietary monitoring method that can track a user's spoon and the weight of remaining dishes has been proposed [15, 16]. Other developments include a diet-aware dining table [15] that supports automated food tracking by weighing each individual's dietary intake. There is one system that offers recommendations: a shopping suggestion system [17] that identifies healthier food items on a shopping list by tracking the nutritional content of various foods. However, it is a different approach, and does not recommend the appropriate foods for each individual user.

3 Context-aware food recommendation system

We present a context-aware food recommendation system that can inform users of available foods by applying contextual information obtained from sensed profiles, physiological signals, and environment conditions. The key technologies of the proposed system include three phases. The first phase acquires a user's sensed bio-signal information and converts this into a preliminary context. Then a time-division layered context integration for each user's behavior, physiological status, and intention is composed. Finally, the last phase creates a personalized food recommendation list and visualizes it by exploiting the integrated context. Figure 1 shows the system diagram of u-BabSang, which consists of various real sensors, a processing unit (Context Integrator), and a recommendation service. Each box of Fig. 1 is explained in the related chapter. By gathering various sensing information, the proposed system recommends appropriate foods to each individual user at runtime as shown in Fig. 1.

3.1 User-centric context generation

In this section, we introduce preliminary context generation. The proposed context generation is processed as a logical sensor that links with a physical sensor. It converts raw signals obtained from the sensors into the preliminary context in 5W1H [18] form. Figure 2 illustrates the steps for preliminary context generation. The steps for context generation are signal processing, feature extraction, and preliminary context generation.

The signal processing module supports basic filtering, such as IIR, FIR filter. According to the signal, developers can regulate the parameters, for example, filter size or window type (e.g., hamming window, rectangular window, Blackman window,

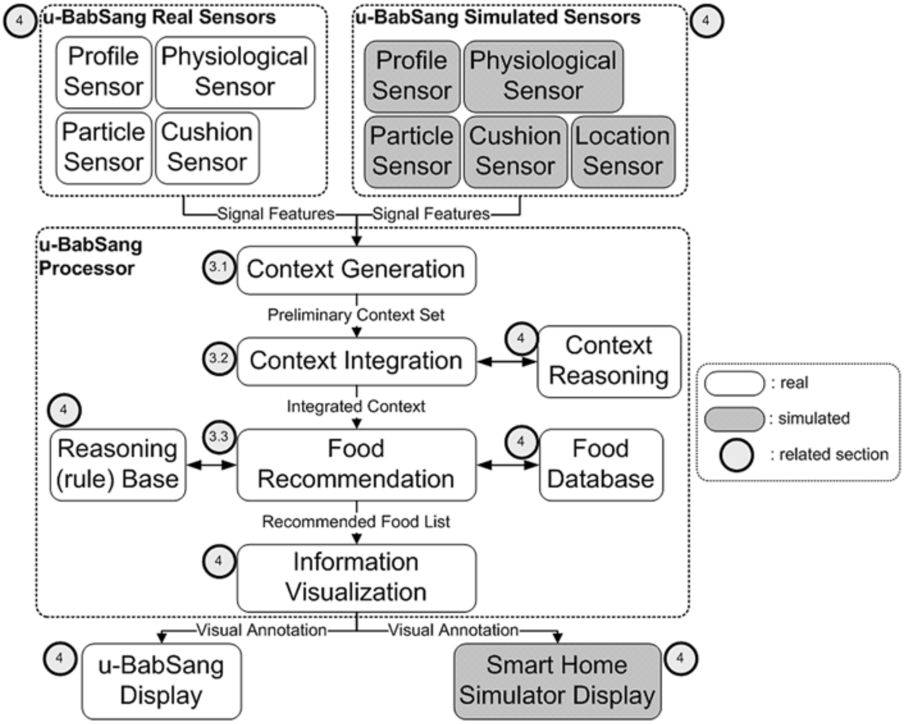
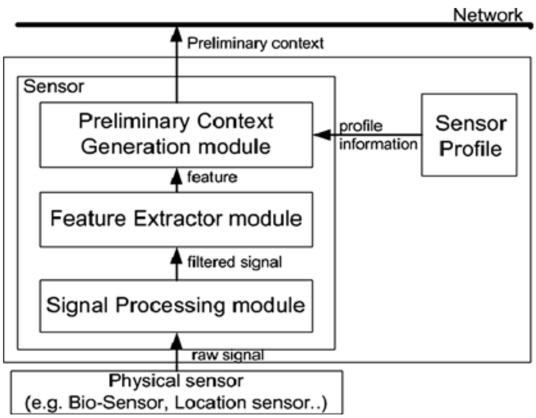


Fig. 1 u-BabSang system flow diagram

Fig. 2 Steps for preliminary context generation



Bartlett window). The filtered signal is then sent to the feature extraction step. The purpose of feature extraction is to extract features of the sampled signals by calculating their mean and standard deviation. Finally, the extracted features are converted to the preliminary context, which is an incomplete context form of the 5W1H context according to the sensor's ability. The preliminary context is generated by referencing the sensor profile described in XML format. Each XML field includes the value of the 5W1H context, a sensor ID, a sensor communication port, accessibility, a key, a type, a granularity, and a value [18].

The preliminary context is unified as it is formed in an XML document without regard to sensor type or sensor specification, obtained as a result of signal filtering and signal correction in the signal processing step. The data from each sensor has different ranges due to the use of different sensor types and specifications. Thus, to understand values and the range of validity in each measurement, data with different scales and granularity goes through a signal revision process.

For user-centric context generation, we composed the preliminary context by focusing on the "who" context (e.g., user I.D., profile, etc.) as the main component. This generation process supports user adaptive analysis for higher level feature extraction with the preknowledge of the "who" context. Using this user-centric context generation, multiple contexts obtained from the user's profile, physiological signals, and the sensed environmental information can be managed based on individual characteristics.

3.2 Time-division layered context integration

Context integration is the process of extracting contextual information that has high level meaning, achieved by collecting low level contexts from heterogeneous sensors. The integrated context is obtained by aggregating the preliminary contexts from sensors. The context integration implemented in u-BabSang collects a user's profile [e.g., body shape and condition (e.g., pregnant, student, etc.)], gender, clinical history (e.g., hypertension, glycosuria, etc.), body constitution (e.g., tae-yang, tae-eum, so-yang, so-eum) [5, 7], physiological signal information (e.g., heart rate, skin temperature, sweat on palms), and sensed environmental information (e.g., intensity of illumination, noise level, temperature). Then it analyzes the user's stress level, and captures the user's physiological status in its current situation.

Figure 3 shows the context integration procedure which generates an integrated context in single fusion layer by aggregating preliminary context from a buffer of a

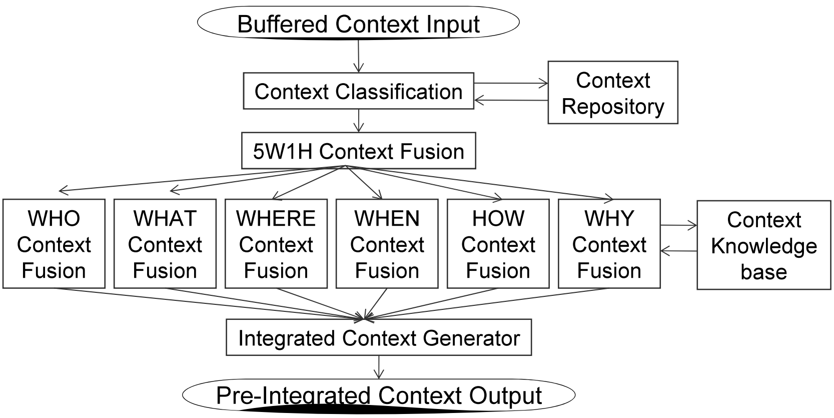


Fig. 3 Context integration procedure in each fusion layer

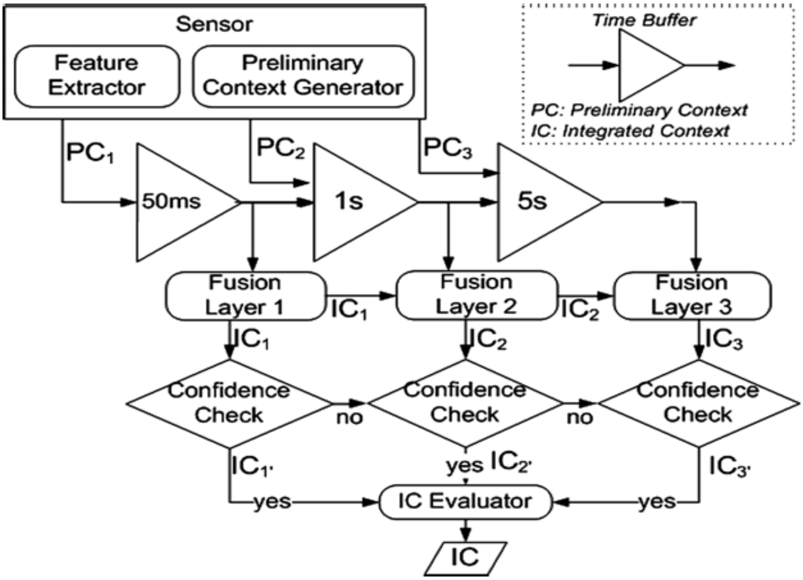
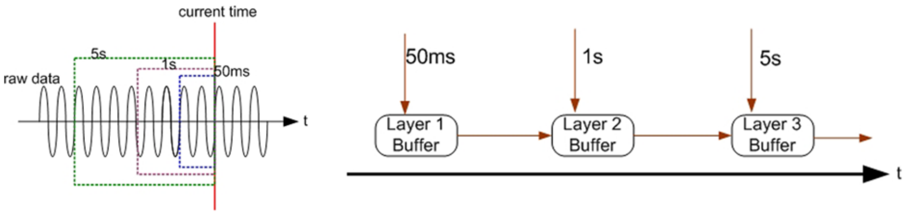


Fig. 4 Time-division layered context integration

layer. This architecture classifies inputted contexts according to individual users, and utilizes them by obtaining context history from a context repository. The 5W1H Context Fusion step classifies the inputted contexts as the characteristics of 5W1H (Who, What, Where, When, How, and Why), and integrates each component of 5W1H using each specified fusion method. Especially, the "why" context is reasoned out from the Context Knowledge base by exploiting JESS [19] or CLIPS [20]. Finally, the integrated 5W1H context is formalized in the Integrated Context Generator.

We designed time-division layered context integration, an improvement of single-layer context integration, as a means of evaluating semantic information by efficiently integrating various contexts from heterogeneous sensors. The proposed method stores contexts from sensors into the time-division buffer, and then applies the results to several context fusion process layers, as shown in Fig. 4. Each layer can be divided by the integration interval, and an integrated context is generated in the divided time interval. A typical method for using a time-division layered approach is as follows. First, the context integrator applies a time buffer to classify the continuous sensing data inputs at discrete intervals (Fig. 5(a)). Secondly, three processing layers (multiple context integrators) are created according to the stated integration interval (Fig. 5(b)). We applied three fusion layers as a prototype of multilayer context integration. Finally, contexts were integrated by moving the time window about the integration interval with the lapse of time in each layer. The movement of the time window has the effect of dynamically fusing the current preliminary context inputs and the past input context history. The integration interval was determined by sensing periods. We assumed that the minimum sensing period is 50 ms, and applied the other intervals orderly, such as 1 s and 5 s. The determined interval was for short-term integration of context.



(a) Buffered input division

(b) Time buffer

Fig. 5 Process of time division layer

The integrated contexts generated in each layer were then applied based on weighting factors, according to the type of sensing data. Next, each layer composed the weighted integrated context and the most reliable context was selected. As shown in Fig. 4, the preintegrated contexts resulting from each fusion layer were gathered in the IC Evaluator, and this evaluator determined the integrated context with the highest weight.

Time-division layered context integration is effective for aggregating heterogeneous sensing information, because it integrates multiple contexts by moving time windows reiteratively according to the time interval of each layer. This approach infers reliable integrated contexts by integrating multiple preliminary contexts at run time. Also, it is useful for developing a context-aware system because it is adaptable to changes (e.g., add, delete, replace) in various sensor environments.

3.3 Personalized food recommendation

The purpose of personalized food recommendation is to supply an appropriate food list that contains a diet that balances healthy and less healthy food items for each individual by exploiting the proposed context integration technology. Food recommendations for each individual are based on the traditional Korean medical text, "Donguibogam" [6], which describes ingredients of foods according to individual characteristics, environmental conditions, and chronic diseases. However, this book is not a scientific paper, and more detailed examples need to be regulated by a doctor or a nutritionist. Our goal is to make a framework/system to recommend appropriate foods for the user's healthier life by exploiting contexts. Our focus is the way how to deal with multiple sensory information and contexts, and how the contexts are used to recommend foods to the users. We expressed the correlation between the change of sensed data and foods based on the analysis of this book, and implemented the food database as an XML document. To verify the personalized food recommendations, we developed u-BabSang. This system processes contexts obtained from various sensors by applying time-division layered context integration, and suggests individualizes food lists. This system enables to check the list of healthy and unhealthy foods simultaneously. Final decision is given by users. If there are no appropriate foods to take, then a user can choose whether (s)he eats the food or not by adjusting the amount of food.

The combined information from all sensors generates a preliminary context based on individual specifications. Then the context integrator integrates those preliminary

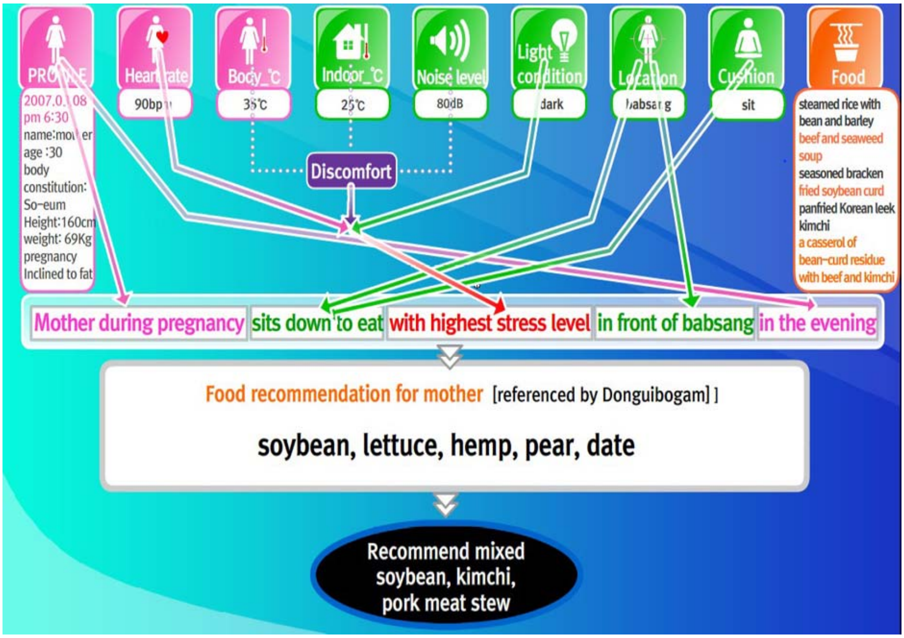


Fig. 6 An example of the food recommendation

contexts, and establishes each individual's behavior, physiological status, and intention. By exploiting all this information, u-BabSang can then recommend a personalized food list to each individual at the dining table. Then at the table, a food flash simulator displays common Korean foods; at this point, it is assumed that each food recognized can be obtained from the simulator. Foods on the table can be detected by RFID technology or by maker detection technology in cameras. In this case, we assume that foods on the table are detected by selecting from a menu in the implemented simulator for rapid prototyping. Every user around the table can directly see recommendation results and available dishes. The u-BabSang knows who is at the table and who is sitting where, by utilizing 4 direction cushion sensors and a simulated location sensor. Because the Korean food custom is to place all food on the table before eating and then sharing this among the diners, the appropriate time to recommend different food choices is when the user sits at the table. The process of food recommendation is shown in Fig. 6, which represents an example of the relation between sensors and the proposed context integration in u-BabSang system.

The process of recommending food from multiple preliminary contexts is operated by weighted sum [21], which calculates the recommended food list by the numerical integration of rule outputs. The weighted sum expresses the food recommendation rule by the following equation:

$$Rcommendation(X) = \sum_{x_1 \in X_1} W_1 \cdot f(x_1)w(x_1) + \sum_{x_2 \in X_2} W_2 \cdot f(x_2)w(x_2) + \sum_{x_3 \in X_3} W_3 \cdot f(x_3)w(x_3) \tag{1}$$

where X is a discrete set of the preliminary context (p-context), X_1 is a set of p-context for the profile, X_2 is a set of p-context for the physiological signal, X_3 is a set of p-context for the environmental signal, and W_1, W_2, W_3 are the weight constants for X_1, X_2, X_3. Here, $f(x)$ is a score function ranging from 1.0(bad) to 3.0(good) used for calculating recommendation rules, and $w(x)$ is a weight function where x is the subcontext. A set of the preliminary contexts is expressed as follows:

$$X_1 = \{x_1 | x_{figure} \cup x_{gender} \cup x_{clinical} \cup x_{constitution}\}$$

$$X_2 = \{x_2 | x_{heart} \cup x_{skintemp} \cup x_{sweat} \cup x_{stress}\}$$

$$X_3 = \{x_3 | x_{illumination} \cup x_{noise} \cup x_{temperature} \cup x_{temperature}\}$$

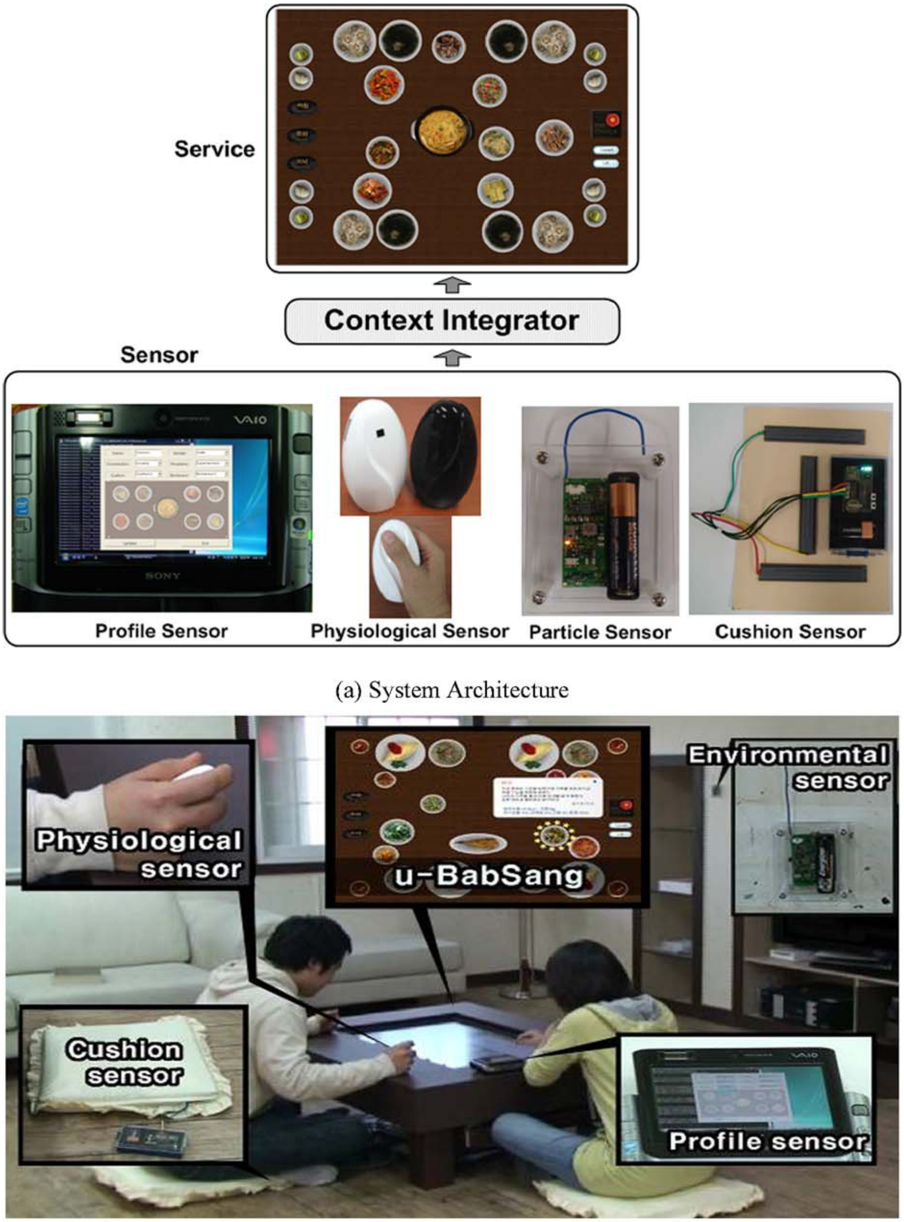
where all subcontexts x are obtained from heterogeneous sensors.

When all $w(x) = 1$, all $f(x) = 1$, and $W_1 = W_2 = W_3 = 1$, $Recommendation(X)$ will be the maximum. The best weight parameters are preset-up manually in the XML file, and the weights assigned to different context are determined by reference to the traditional Korean medical text, "Donguibogam" [6]. The example in Fig. 6 is done by (1), and appropriate foods are recommended by the result of $Recommendation(X)$.

4 Implementation

Personalized food recommendation is realized by integrated contexts resulting from user-centric context integration. Figure 7 presents the implemented u-BabSang system overview. The implemented system consists of several heterogeneous sensors, the context integration architecture, and the food recommendation service. The components as shown in Fig. 7 are actually implemented. Figure 8(a) shows the relation between the context integrator and the knowledge base, and Fig. 8(b) represents a reasoning rule for a well-being care index (e.g., stress) implemented by CLIPS [20]. The integrated context from the context integrator is conveyed to facts in the knowledge base, and then the inference result from the rule based system is conveyed back to the context integrator. This inferred result represents lists of harmful foods and healthy foods. Also, the knowledge base reasons out the well-being care index by using users' physiological signal sensing devices, such as PPG (PhotoPlethysmoGraphy) sensors, SKT (Skin Temperature) sensors, GSR (Galvanic Skin Response) sensors, and external factors, such as noise level. The u-BabSang system table consists of a wood frame, an LCD display, and a laptop computer. The display of this table shows the food with the recommended content.

The u-BabSang recommends appropriate foods to each individual by integrating the preliminary contexts. User profiles (e.g., name, gender, body constitution (e.g.,

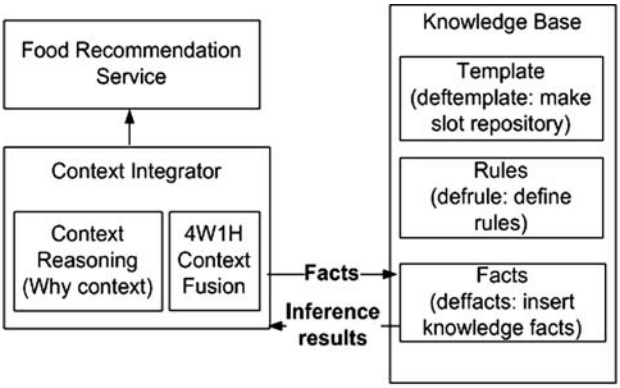


(a) System Architecture

(b) Implementation Overview

Fig. 7 u-BabSang system

tae-yang, tae-eum, so-yang, so-eum), clinical history (e.g., glycosuria, hypertension, pregnancy, etc.)), users' physiological signal sensing information (e.g., heart rate, skin temperature, sweat on palms), and sensed environmental information (e.g., in-



(a) Relation between the context integrator and knowledge base

```
;;<Define Functions>
;;Function for the Stress Analysis based on PPG/SKT/GSR/Outdoor Noise signal
(deffunction Stress_func(?ppg ?skt ?gsr ?noise)
        (bind ?belownormal (create$ low normal))
        (bind ?abovenormal (create$ normal high))
        (bind ?all (create$ low normal high))
        (if(eq ?ppg high)
                then
                (if(eq ?skt high)
                        then
                        (if(member$ ?gsr ?abovenormal)
                                then
                                (if(member$ ?noise ?all)
                                        then
                                        (bind ?out much_stress)
                                        (assert (inference (result ?out)))
                                                ...
```

(b) Well-being care index reasoning rule

Fig. 8 Context reasoning process in u-BabSang

tensity of illumination, noise level, temperature) are represented by context and are utilized for the personalized food recommendation because those information affect to the user's body. We implement the food database using XML based on the oriental medicine analysis given by the traditional Korean medical science text, "Donguibogam" [6] to express the correlation between the change of sensing data and foods. The sensory information which should be concerned depends on the target user. For example, we assumed the special use case for the users who need to take care of their food intake customs, such as a hypertensive or a diabetic, or a pregnant woman. We monitored heart related factors from the sensor and body temperature for detecting the basic condition of the users. These kinds of contextual information are related to the theory in "Donguibogam" which states foods with the description of the effects on organs and entire body status [6]. Figure 9 shows a part of the implemented XML code and weighting factors of the food ingredients.

```
<?xml version="1.0" encoding="ISO- 8859- 1"?>
<FoodBase version="3.0"
  xmlns="http://uvr.gist.ac.kr/UCAM"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema_instance" >
  <Header copyright="Yoosoo Oh">
    This is basic information for Food Recommendation!
    <Service name="Food Base" version="1.0" />
  </Header>
        <Service_Name>Food Base</Service_Name>
        <AttributeList>
          <FoodReference>
              <boribab>
                    <pregnancy>2</pregnancy>
                    <fatness>2.5</fatness>
                    <hypertension>2.5</hypertension>
                    <glycosuria>2</glycosuria>
                    <male>2</male>
                          ...
```

(a) XML code for the food database

Menu(dinner)		boiled barley			fried bean curd	roast beef			pineapple	pear
Ingredients		barley	rice	mean	bean curd	beef	onion	mean	pineapple	pear
Consideration	pregnancy	1	3	2	3	3	3	3	2	1
	student	2	2	2	3	2	2	2	1	2
Clinical history	fatness	3	2	2.5	2	1	2	1.5	2	2
	hypertension	3	2	2.5	3	1	3	2	2	3
	glycosuria	3	1	2	3	1	2	1.5	2	2
Gender	male	2	2	2	2	2	2	2	2	2
	female	3	2	2.5	2	3	2	2.5	2	2
Body constitution	taeyang	3	3	3	3	1	2	1.5	3	3
	soyang	3	3	3	3	3	1	2	3	3
	soeum	1	3	2	3	3	3	3	1	1
	taeeum	2	3	2.5	3	3	3	3	1	2
Body condition	much_stress	1	3	2	3	1	3	2	1	2
	little_stress	3	2	2.5	2	3	2	2.5	2	3

(b) Weighting factors of the food ingredients

Fig. 9 Food database

We applied the weights (from 1 to 3) concerning the healthy foods, the unspecified foods, and the harmful foods. The food database is based on a daily menu which contains the main ingredients and side ingredients found in a Korean normal diet. We selected the representative food ingredients in the food database and calculated the average weight of these ingredients. The u-BabSang has collected foodstuffs by the integrated context, and creates the personalized food list by the sum of the weight of ingredients. For instance, for a pregnant consumer, with the body constitution of “tae-yang,” recommended foods are a broad bellflower and a green onion.

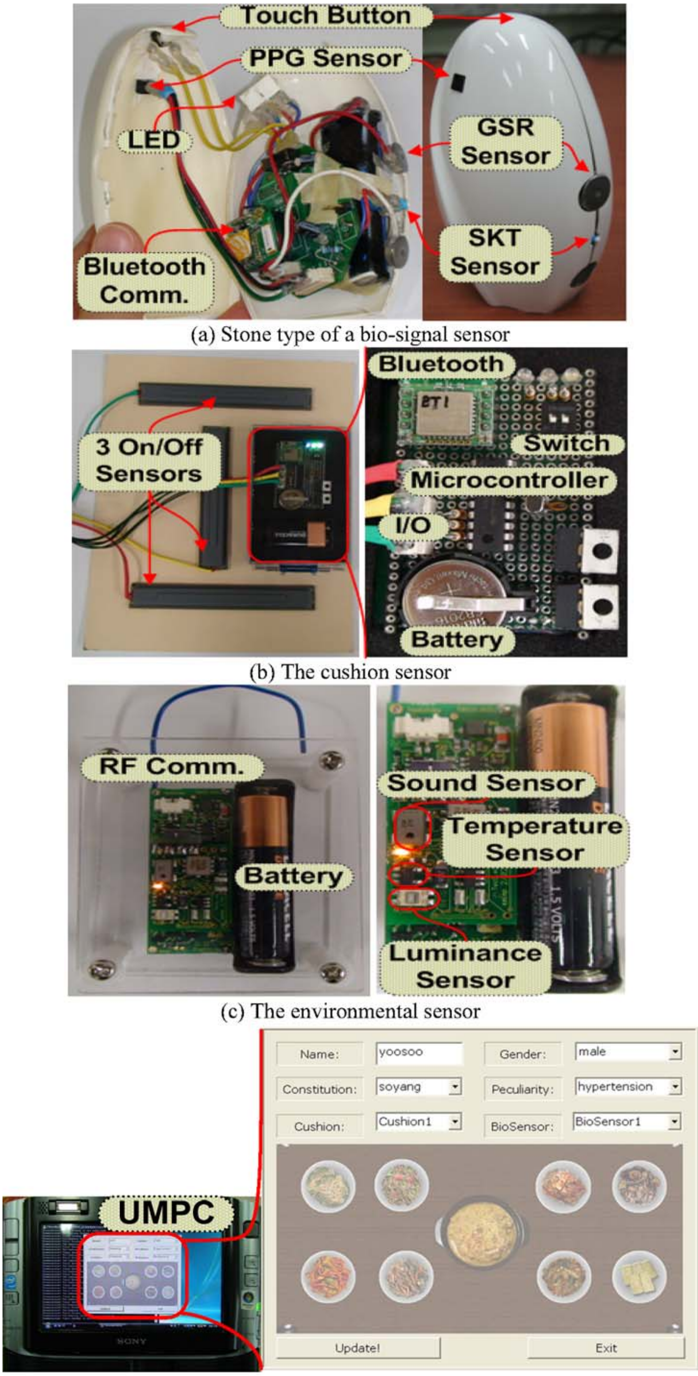
The u-BabSang system was realized by both simulated and real devices for rapid prototyping. For more diversity, we additionally implemented the smart home simulator which contains many simulated sensors and actuators, as shown in Fig. 10(a). This simulator has replicas of the actually implemented sensors and actuators, and also has more simulated sensors (e.g., location sensor) and actuators (e.g., air-conditioner, TV, audio). Figure 10(b) shows the display of the implemented u-BabSang. By exploiting this simulator, we are able to test the proposed system and add many simulated sensors.

(a) The smart home simulator

(b) u-BabSang display

Fig. 10 The implemented simulator

The implemented sensors include a profile sensor, a physiological sensor, an environmental sensor, and a cushion sensor. The name, gender, body constitution, and clinical history of each user are obtained from the profile sensor. Heart rate, body temperature, and the amount of sweat on the palms are obtained from the physiological sensor. The physiological sensor basically includes three kinds of sub-sensors: GSR, PPG, and SKT sensors (Fig. 11(a)). Heart rate is computed by inversion of the peak to peak variation of the pulse signal. We identified the body temperature average value with 100 sample windowing. From the GSR sensor, we used the amount of GSR value which is also obtained from the average of GSR intensity. The sensing device transmits the signal in a wireless manner, in this case, Bluetooth communication. The sampling rate of this sensor is 100 Hz which meets the Nyquist sampling rate of



(a) Stone type of a bio-signal sensor

(b) The cushion sensor

(c) The environmental sensor

(d) The user profile sensor

Fig. 11 The developed real sensors

heart rate variables. The sequence of transmitted signal includes carriage return value (1 byte), GSR value (2 byte), heart rate value (2 byte) and temperature value (2 byte). Power is controlled by a tag switch which supplies power only while the users hold this sensor. The user has to hold the physiological sensor while eating in order to obtain a real time food recommendation service but in practice, most physiological conditions do not frequently changed. Therefore, users need only to hold the sensor for a few minutes before eating. Additionally, a cushion sensor detects whether or not a user is sitting on a cushion in front of the dining table (Fig. 11(b)). This cushion sensor converts the user's movement into preliminary context and transmits the context to the context integrator through Bluetooth communication. An environmental sensor measures light intensity, temperature, and noise level in the ambient environment (Fig. 11(c)). The environmental sensor is based on a Particle Computer [22], and it delivers sensing data to home servers or personal devices through RF communication of the Particle Computer. The user profile sensor manages the user's name, gender, body constitution, and a clinical history, and conveys this information to devices (cushion sensor and bio-signal sensor) or the system (Fig. 11(d)).

5 Experiments

An evaluation of the proposed system was conducted as follows. To evaluate the suggested system, we calculated the accuracy and the reliability of the context integration and evaluated our system using a menu of common Korean foods for breakfast, lunch, and dinner. Evaluating the accuracy and the reliability of the context integration is to verify the proposed food recommendation system. The experimental setup used the following equipment: a laptop for the context integrator with u-BabSang (Windows Vista, Intel Core2 Duo 2.4 GHz, 2 GB RAM), 3 UMPCs for 3 users' profile sensors (Windows Vista, Intel Core Solo 1.33 GHz, 1 GB RAM), a PC for 3 cushion sensors (Windows Vista, Intel Xeon 2.4 GHz, 2 GB RAM), 2 PCs for 2 environmental sensors (Windows XP, Intel P4 2.8 GHz, 1 GB RAM) and 3 PCs for 3 physiological sensors (Windows XP, Intel P4 2.8 GHz, 1 GB RAM). We surveyed each user's original intention to the food recommendation. We chose four intentions closely related to the food recommendation process and which were dominant because each item of the intention has a repetitive variation; the selected intentions were expressed as each component of the 5W1H context [18] for the three users. We calculated how accurately the integrated context was generated by the proposed system by measuring the correspondence of a user's original intention and the system's output (the integrated context). Figure 12 shows the mapping results of the users' original intentions and the system's integrated contexts. We analyzed the correspondence of each component of the 5W1H context for 100 trials, meaning that one hundred integrated contexts were used where each correspondence is expressed based on a 0 to 6 score. In Table 1, type A and type B express User-1's original intention; type C is for User-2, and type D is for User-3. Average of degree of mapping correctness in Fig. 12 is calculated by the following equation:

$$\mathit{Average\ of\ degree\ of\ mapping\ correctness}(T) = \frac{\sum_{i=1}^{100} D(i)}{N}$$

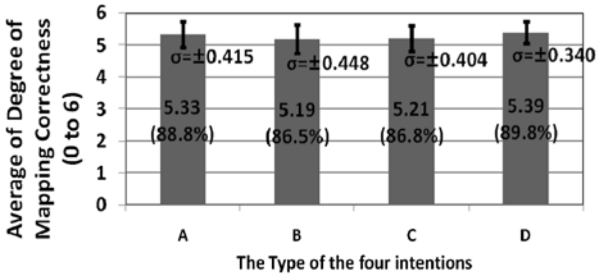


Fig. 12 The results of mapping of the users' original intentions and the system's integrated contexts

where $D(i)$ is the degree of mapping correctness per trial, and N is the total trials (a hundred).

As a result, the total average degree of mapping correctness for the four users' original intentions was 5.28 (88%) and the minimum average degree of mapping correctness was 5.19 (86.5%) in single-layer context integration. We evaluated the stability of the integrated context through the measured standard deviation of +0.340 to +0.448. From the results of a high mapping degree (88%), we can conclude that our system is reliable, which implies that our system can be reliably recommended. Only 12% is a failure of the recommendation. This is acceptable because the failure just represents the wrong order of foodstuffs in the recommended food list. That means the fundamental foodstuffs are not changed. Also, users can accept this failure because final decision for food selection is given by the users. Also, our results demonstrate that our system supports personalization, as based on the results of type C and type D. Both have a different "who" contexts (e.g., name, gender, body constitution, a clinical history), but simultaneously have all the same additional information (e.g., "what," "where," "when," "how," and "why" contexts). As a result, we confirmed the personalized recommendation that expressed different foods suitable for each user.

In order to verify the context-aware food recommendation method, we measured the required creation time and the CPU usage of the context integration method by increasing the fusion layer. We also calculated the reliability of the integrated contexts by measuring the success rate of the context integration. For consistency, we reused the user's intention-Type D in Fig. 12. Table 2 shows our results: the creation time is the time required to generate one hundred integrated contexts. The CPU usage rate is measured based on the average CPU usage for 60 seconds.

Based on these results, we see that the creation time for the integrated context did not dramatically increase, even when subsequent fusion layers were added. This implies that time is not affected by the addition of a fusion layer. In the case of the CPU usage rate, when two more layers are added, the CPU usage rate increased, though system performance is still guaranteed. In Fig. 13, we can see that the success rate of the context integration increased as the number of layers was increased. This success rate was calculated in the same way as the mapping experiment case, i.e., based on percentage.

In the case of the three layers, the success rate was 95.2%, with a small variation of the standard deviation (+0.287). Hence, we can ignore increases of the CPU usage rate due to the high performance of the degree of mapping correctness. Thus, based

Table 1 The context representation for four intentions

5W1H	Sub-context	Type A intention	Type B intention	Type C intention	Type D intention
WHO	Name	Yoosoo	Yoosoo	Ahyoung	Kiyoung
	Gender	male	male	female	male
	Peculiarity	glycosuria	glycosuria	pregnancy	student
	Body	tae-yang	tae-yang	so-eum	so-yang
WHAT	Positive contents	seasoned young pumpkin	seaweed soup	broiled walnut and peanut	seasoned spinach, baked mackerel
	Negative contents	adlay tea	None	None	None
WHERE	Location	ubiHome, dining table	ubiHome, dining table	ubiHome, dining table	ubiHome, dining table
WHEN	Time	breakfast	dinner	lunch	lunch
HOW	Ambient light	normal	normal	high	high
	Outdoor noise	low	low	low	low
	Temperature	normal	normal	normal	normal
	Heart rate	low	high	normal	normal
	Sweat	no	little	little	little
	Skin temperature	normal	high	normal	normal
	Activity	Sitting on a cushion	Sitting on a cushion	Sitting on a cushion	Sitting on a cushion
WHY	Stress	no	significant	no	no
	Intention	Wants the food recommendation	Wants the food recommendation	Wants the food recommendation	Wants the food recommendation
Description		User-1 wants to get the food recommendation in ubiHome in a normal situation	User-1 wants to get the food recommendation in ubiHome after exercise	User-2 wants to get the food recommendation in ubiHome in a normal situation	User-3 wants to get the food recommendation in ubiHome in a normal situation

Table 2 Measurements based on the addition of subsequent fusion layers

Evaluation item	1 Layer	2 Layers	3 Layers
Creation time	5 s	4 s	5 s
CPU usage rate	10.67%	24.50%	24.74%

on the verified time-division layered context integration, we can conclude that our system is efficient. From the above experiments, we can reliably state that our system can effectively recommend appropriate food for users in real-time. Further evaluation in the form of a usability test can be performed after confirmation of the operating system.

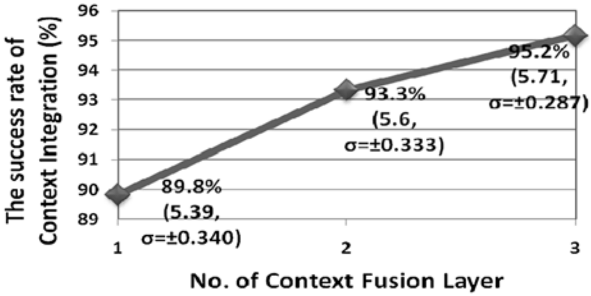


Fig. 13 Results of the reliability of the integrated contexts

6 Conclusion

In this paper, we proposed u-BabSang that recommends appropriate foods in real-time to each individual by utilizing each individual's profile, physiological signals, and sensed environmental information. The advantage of the proposed system is that it enables the management of personalized well-being care by integrating user contexts with other contexts during run time, and interpreting these contexts in a user-centric manner. More specifically, by analyzing their personal situation (e.g., physiological status, eating custom, weather, location, etc.), the proposed system can monitor the health of individuals with specific clinical history.

The proposed system has the potential to be extended to various other fields. For instance, this system can be extended to menus besides Korean menus. In particular, it can recommend food types and quantities based on the user's food preference, constitution, clinical history, and current climate conditions. Also, if we embed our system into personal devices (e.g., UMPC, mobile phone, etc.), the proposed system can be extended to recommend appropriate food items at point of purchase, e.g., supermarkets, restaurants, and other public places. In this way, users are able to protect personal information while accessing recommended products (e.g., foodstuffs, groceries, merchandise, etc.). Additionally, the proposed system could be utilized by athletics or medical services.

For future work, we will evaluate our system in real environments such as homes, restaurants, and stores. After obtaining the user study, we will hope to improve convenience of using sensors and display on the table. Another possible area to explore is to track and integrate the history of users' eating habits.

Acknowledgements This research is supported by Korea Creative Content Agency (KOCCA), Ministry of Culture, Sports and Tourism (MCST), under the Culture Technology (CT) Research and Development Program 2009.

References

1. Bruno F, Alois S (2001) Happiness and economics: how the economy and institutions affect well-being. Princeton University Press, Princeton
2. Michael S, Charles C (1992) Effects of optimism on psychological and physical well-being: theoretical overview and empirical update. Cogn Ther Res 16(2):201–228
3. Dennerstein L, Smith AM, Morse C (1994) Psychological well-being, mid-life and the menopause. Maturitas 20(1):1–11

4. Toshiyo T, Tatsuo T, Mitsuhiro O, Mikiko Y (1998) Fully automated health monitoring system in the home. Med Eng Phys 20(8):573–579
5. Han C, Inkyoon L, Soojin L, Sonhae C, Hyunsu B, Moochang H, Minkyu S (2003) An alternative way to individualized medicine: psychological and physical traits of Sasang typology. J Altern Complement Med 9(4):519–528
6. Jun H (1999) Donguibogam. Rubin Publishers, New York
7. Zhenzhen Z (1998) Do-it-yourself Chinese medicine: the hot & cold food cure. Nat Health 27(1):90
8. Jim K, Raymond R (2004) Nutritional genomics: the next frontier in the postgenomic era. Physiol Genomics 16:166–177
9. Cherlho L (2007) Harmonization of eastern and western health knowledge; nutrigenetics and Sasang typology. Food Sci Technol Res 13(2):89–95
10. Christopher LR, Sean C, Janice K, Frederick M, Yongmin K III (2002) Asynchronous web-based patient-centered home telemedicine system. IEEE Trans Biomed Eng 49(12):1452–1462
11. Sung M, Marci C, Pentland A (2005) Wearable feedback systems for rehabilitation. J Neuroeng Rehabil 2:17
12. Sensewear, BodyMedia Inc (2008) http://www.bodymedia.com/pnt_over.asp/. Accessed May 2008
13. Nike + iPod, Apple Inc (2008) http://www.apple.com/ipod/nike/. Accessed as of May 2008
14. Nuria O, Fernando FM (2006) MPTrain: a mobile, music and physiology-based personal trainer. In: Proceedings of the 8th conference on human-computer interaction with mobile devices and services (MobileHCI 2006), Helsinki, Finland, September 2006. ACM Press, New York, pp 21–28
15. Kenghao C, Shihyen L, Haohua C, Jane H, Cheryl C, Tungyun L, Chiehyu C, Polly H (2006) The diet-aware dining table: observing dietary behaviors over a tabletop surface. In: Proceedings of pervasive 2006. LNCS, vol 3968. Springer, Berlin, pp 365–382
16. Oliver A, Mathias S, Paul L, Gerhard T (2005) Analysis of chewing sounds for dietary monitoring. In: Proceedings of Ubicomp 2005. LNCS, vol 3660. Springer, Berlin, pp 56–72
17. Jennifer M, Gary H, Hochak H, Sharon L, Elizabeth N (2002) Using low-cost sensing to support nutritional awareness. In: Proceedings of Ubicomp 2002. LNCS, vol 2498. Springer, Berlin, pp 371–376
18. Dongpyo H, Hedda S, Woontack W (2007) Linking context modeling and contextual reasoning. In: Kofod-Petersen A, Cassens J, Leake DB, Schulz S (eds) Proceedings of the 4th international workshop on modeling and reasoning in context (MRC2007), pp 37–48
19. Jess, Sandia National Laboratories (2008) http://herzberg.ca.sandia.gov/. Accessed May 2008
20. CLIPS, Sourceforge.net (2008) http://clipsrules.sourceforge.net/. Accessed May 2008
21. Weight Function, Wikipedia (2008) http://en.wikipedia.org/wiki/Weight_function/. Accessed June 2008
22. Particle, TECO (2008) http://particle.teco.edu/. Accessed May 2008

Yoosoo Oh received his B.S. degree in the Department of Electronics and Engineering from Kyung-pook National University in 2002 and M.S. degree in Information & Communication Engineering from the Gwangju Institute of Science and Technology (GIST) in 2003. He is currently working towards his Ph.D. degree in School of Information and Mechatronics at GIST, Korea. His research interests include context fusion and reasoning, context-awareness for ubiquitous computing, human computer interaction, wearable computing, smart home, etc.

Ahyoung Choi received her B.S. in Electronics Engineering from Ewha Womans University (Seoul, S. Korea) in 2004 and her M.S. (advisor Prof. Woontack Woo) in Information and Communications from Gwangju institute of Science and Technology (GIST, Gwangju, S. Korea) in 2005. She is currently a Ph.D. student at School of Information and Mechatronics in Gwangju Institute of Science and Technology (GIST), S. Korea. The main thrust of her research has been physiological signal sensing and analysis in pervasive/ubiquitous computing environment, context awareness, and affective recognition and interaction.

Woontack Woo received his B.S. degree in Electrical Engineering from Kyung-pook National University in 1989 and M.S. degree in EE from POSTECH in 1991. He received his Ph.D. in Electronic Engineering from the University of Southern California in 1998. During 1999–2001, he stayed at the ATR Media Integration & Communications (MIC) Laboratory of Japan as an Invited Researcher. Since 2001, he has been with the Gwangju Institute of Science and Technology (GIST), where he is an Associate Professor at the Department of Information and Communications and Director of the Culture Technology Institute (CTI). His research interests include 3D computer vision and its applications including attentive AR and mediated reality, HCI, affective sensing and context-awareness for ubiquitous computing, etc.