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## **Context-aware Inference in Ubiquitous Residential Environments**

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Abstract: Residential ubiquitous computing environments have focused on interconnecting environmental controls using a home network and the management of sensor data rather than a context-aware inference. Building upon previous research, this paper proposes a novel sensor-based context-aware system with a focus on three inference processes: rule, inference and pattern driven. Using pattern data derived from five families for a working week and establishing rules and inferences, the proposed context-aware system is demonstrated using electrical lighting as an example. The processes to develop an intelligent house are described so as to ameliorate personalized services in response to inhabitants' needs.

**Keywords**: Ubiquitous residential environment, context-aware inference, smart home, sensor network, lighting, intelligent environment

## **1. Introduction**

Ubiquitous computing (also known as pervasive computing) embeds microprocessors in everyday objects so they can communicate information. It relies on the convergence of wireless technologies, advanced electronics, sensor networks and the Internet. Within residential buildings, ubiquitous computing has manifested itself under the auspices of the 'Smart Room', 'Smart Environment', 'Intelligent Room', 'Intelligent Environment', 'EasyLiving', 'Aware House', 'Neural Network House' and 'Intelligent Space'. The application of ubiquitous computing in residential buildings has generally focused on establishing a home network and the management of sensor data rather than context-aware inference computation [1-7]. There is a need to investigate viable approaches to adopt context-aware inference in residential environments. Context-aware is an emerging computing paradigm that exploits information about the context of its users so as to provide improved services. A context is commonly defined as any information that is used to characterise the situation of an entity [8]. Through the context-aware inference, ubiquitous environments embedded with computing devices are capable of learning from users' behaviours and then suitable services (e.g., the diming of lights) can be provided accordingly.

In this research, we use the term 'ubiquitous residential environments (UREs)' for all kinds of residential buildings. UREs can incorporate a large amount of sensors to monitor residents' activities in order to anticipate their preferences and needs, and then provide them with some customized services. Some residents have negative experiences with the UREs as they feel that they are under surveillance. Understanding and justifying the use of sensors is a prerequisite for determining their optimal use for services. When implementing UREs, it is essential to recognise situations or contexts that confront residents and then determine appropriate services to be provided. The context in UREs is an intermediation that understands the situations of the space and reasons the behaviours of the residents, and connects the residents, the residential environment with the sensor data.

Liberman [9] defined context as 'everything' but the explicit input and output, which focuses only on implicit control. However, we suggest that a context should relate to explicit input and output simultaneously when the inference computation is operated. Further, changes in time and location of contexts should be considered so as to accommodate residents' services as the same sensor data may have different information according to changes in time and location [10]. The context can be any measurable and relevant information that can affect the behaviours [11]. In this research, the context (as represented by sensor data) in UREs includes the information that can derive customised services and meet the needs of residents'. Each type of the context is a distinctive element that is connected to the service. Moreover, to make UREs adjustable to residents' needs, services should respond to residents' behaviours. The role of interpreting the context and connecting it to a specific service can be taken through the context-aware inference. The aim of this paper is therefore to develop a novel framework for context-aware inference based upon residents' needs and behaviours in UREs. The context in our inference is the set of sensors and entity data that effects on the service.

## 2. Related Works

Context-aware systems require proper and effective inference processes about their contexts. These inference processes generally consist of context information from sensors and reasoning about situations. The inference methods are often referred to as the *who, what, where, when and why* (5W) and *how* (IH) [8, 10, 12]. Behaviour can be represented as a context information factor of user behaviour about 5W and used selectively for a given purpose. For example, the information about a resident, an object and a location (who, what, where) are considered for the most common contexts. In context-aware systems, an understanding of the residents' behaviours is drawn from their behaviour patterns captured through various sensors or cameras [13-15]. In the case of the Vivid room project [18], for example, behaviours are detected by numerous sensors (i.e., magnet sensors for doors and drawers, micro-switches for chairs, and ID tags for personnel). Thus, the context information is collected by a sensor server via a Radio Frequency (RF) tag system and local area network (LAN). To recognize meaningful behaviour, e.g., studying, eating, and resting, an ID4-based learning system is used. In cases of UREs, privacy issues and inaccuracies in interpreting the resident's behaviours can arise through the use of sensor or camera data [16].

Previous URE research has focused on sensor-based systems for implementing intelligent residential environments. For instance, in the 'Easyliving' project [17], where the URE can capture the residents' behaviours by identifying their location and requirements via tracking with motion sensors and cameras. The inference process is a simple response to a situation. Similarly, the 'Aware home' project undertaken by Georgia Institute of Technology focuses on URE using a variety of sensors that are installed indoors and can sense and capture residents' living activities in a real-time. The proposed system can learn from the resident's regular habits and behaviours, and thus provide suitable services to a situation whenever needed [18]. The 'House\_n' project at Massachusetts Institute of Technology utilizes 250 sensors and 12 camera sets in a purpose built 'Place Lab'. This laboratory provides an experimental space for recognizing residents' behaviours and monitors their activity patterns [19]. While previous research has placed increasing emphasis on the proof of concept for UREs systems and devices, there has been limited attention placed on formulating a context-aware method that acts as the back-bone for UREs.

Studies that have developed an inference method using the behaviour pattern database (DB) have been limited [24-27]. The 'adaptive house' learns from the residents' habits regarding lighting, room usage, water temperature and ventilation and then anticipates the residents' needs through the inference on the patterns of the controlling behaviours. Thus, it can provide preferred services to maintain a comfortable environment based on the assumption that there is already statistical pattern DB to conduct an inference process [20]. The 'Ubiquitous home' project by the National Institute of Information and Communication Technology (NIICT) is a URE embedded with sensors, cameras and microphones to monitor and record the residents' behaviours. The residents'

behaviour patterns are identified through the recorded data and then the service patterns to be provided are categorized accordingly. In reality, the pattern DB should be built initially based on accumulated monitoring of residents' behaviours. The 'MavHome' project, for example, aims to address this issue using three anticipation algorithms [21-23].

- (1) LeZi-update, which is used to predict residents' future movements by recording their previous movement history
- (2) Smart Home Inhabitants Prediction (SHIP), which is used to predict the sequential behaviour through the history of their past behaviours and
- (3) Episode Discovery (ED). ED could identify more important behaviour patterns that can be automated in the URE.

Recently, context-aware research is moving to web and mobile environments beyond locationbased services (LBSs). Many systems [24-26] use ontology for searching service and interpreting services. Hierarchical context ontology [25] structures a resolution model for context uncertainty, whilst a sensor-based system [27] adopts the standard Semantics of Business Vocabulary and Business Rules (SBVR). Service-Oriented Context-Aware Middleware (SOCAM) [26] and Context-Aware System considering User Preference (CASUP) [24] adopts both ontology and user-defined rule-based reasoning as a rule-based approach to support context-aware services. CASUP also adopts context history to inform proactive personalized services. In addition, context-aware recommend systems use an ontology-based query method such as APOSDLE [28] and DEPTHS [29]. These systems use rule-based inference for decision-making, but it continues to be difficult to seek and prioritize suitable solutions. The CARGO (Context-Aware Reasoning using Goal-Orientation) [30] combining rule-based and goal-based reasoning is a good example of a rule-based inference system.

Context-awareness plays an important role in the development of mobile systems [31], which deal with a verity of mobile services by context-aware proactive service discovery [24, 31, 32], context-aware trails [33]. Research challenges continue to lie on context awareness for ubiquitous healthcare [19, 34-36]. The Casattenta project [34] allows indoor tracking and identification of dangerous events, while Context-Aware Service Scheduling Framework (CASSF) [37] highlights service discovery based on heterogeneous and mobile devices. CASSF adopts both function and context matching to select suitable services. In order to provide healthcare properly, some research focuses on activity recognition [38-40] or behavior pattern [41, 42]. Varkey et al. [38] use 'window-based algorithm' to cultivate on-the-fly range of activities and fine movements, while Wongpatikaseree et al. [40] present the activity log to interlink the history user's and current user's context for activity recognition. The user-pattern analysis method utilizes the semantic data mining [41] ontology for activities, services and objects within a smart home. Kang et al. [42] have enhanced the method by combing the User-pattern analysis and Episode discovery method.

The context is an important component of the implementation of UREs, however, previous research has tended to describe technology developments from a computer perspective [8-10, 16, 43-46]. There has been a limited focus on the relationships between residents' behaviours and services for effectively structuring UREs. We therefore examine how context-aware techniques can serve residents' behaviours. To effectively provide tailored services to meet residents' needs, we integrate rule-based, case-based and pattern-based inference methods into a single suit. As a result this paper provides an ameliorated understanding of key inference components for facilitating UREs as a new approach to context-aware inference.

### 3. URE and the Context-Aware Inference

The research presented in this paper develops a framework of the context-aware system based upon previous research. For example, in the case of the 'adaptive house', which deals with four environment-related behaviours, our proposed system aims to produce the behaviour pattern DB by analysing all behaviours that occur within the UREs. The behaviour and movement patterns proposed by the 'MavHome' project and the behaviour pattern and the service pattern proposed by 'Ubiquitous home' are combined as a single living pattern in our proposed framework. This combination will enable resident's diverse characteristics and life styles to be accommodated. Further, our proposed system adopts rule-based and case-based inference methods in addition to the pattern-based inference method. The adoption of the rule-based and case-based inference methods enables the system to provide customized services to situations that are not identified as behaviour pattern. In addressing privacy and inaccuracies in interpreting the resident's behaviours through the use of sensors, we assume that typical behaviours can be matched to particular services using a mixture of reasoning and inference methods through hierarchical layers. In other words, a rule-induction algorithm and a case-based reasoning process can be used to determine a context-aware inference [47-51]. More specifically, a pattern-based inference process can be used to examine behaviour patterns, which makes uses of the log data from the sensors to infer situations, thus enabling explicit and implicit generalizations to be made.

#### 3.1 Structure of a Ubiquitous Residential Environment

Figure 1 depicts the URE created and driven by our context-aware system, which is comprised of physical and electronic environments. The physical environment has sensors and devices that can react to the physical conditions and provide services such as lighting, heating, ventilation, and air conditioning (HVAC) and television (TV). The electronic part of the environment consists of system modules such as working memory (i.e. RAM), agent modules and databases. A context-aware inference method is essential to provide effective services using agent modules in the electronic environment.

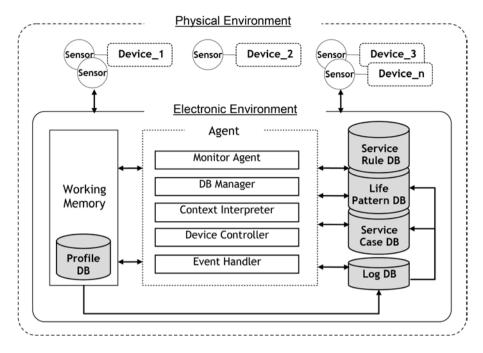


Figure. 1. Ubiquitous Residential Environment

A Monitor Agent refers to the Profile DB and the emergency sensing data for the indirect control. For example, information about user accessibility can be retrieved from the Profile DB. The Monitor Agent can check if sensing data periodically exhibit changes in their values. If there is any change in values associated with the emergency sensing data, the Monitor Agent will execute a command that copes with the situation. Furthermore, the Profile DB incorporates behaviour nodes that act as the cues to the Context Interpreter. For example, if the Monitor Agent detects sensing data of 'PIR1, on' and 'Bed\_Pressure, on' in the Working Memory, it will then send the behaviour status as 'Sleep' with the sensing data to the Context Interpreter.

The Context Interpreter is connected with the Service Rule DB, Service Case DB and Living Pattern DB which respond to various contexts. All commands are executed through the Device Controller, and the Log DB, which contain stored information about the residential context and service execution.

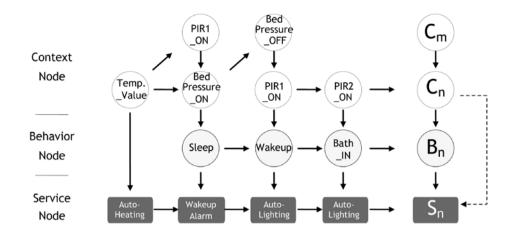


Figure 2. Three nodes of context-aware inference

Figure 2 illustrates the structure of the inference process. The context-aware inference consists of three nodes in the structural flowing of contexts, behaviours and services where reciprocal mapping is performed among the nodes. A URE can be considered as an environment that consists of three inference nodes. The components identified in Figure 1 for creating an inference are:

- a context node consists of one or more sensor data;
- the sensing data, which has a hierarchical tree structure making behaviour node (e.g. 'PIR(Passive Infrared Sensor) 1, on' and 'Bed pressure sensor, on' make 'Sleep' in Behaviour node.);
- behaviours have a sequential behavioural pattern such as sleep, wake up, bathing;
- service nodes that are customized by residential needs that match behaviour nodes.

The information hierarchy of the context, the behaviour and the service nodes are depicted as layers in Figure 1. Context nodes bring about a behaviour node based on the sensor sets. The behavioural node makes inferences about the service node by considering its continuity. In the proposed context-aware inference structure, the behaviour node is core to determining the residents' housing behaviour. The behaviour node is deduced from the context node that consists of the sensor data and induces the service node that provides customized services for the residents. It is assumed that there are certain patterns of behaviour during weekdays. As shown in Figure 1, a combination of several context nodes corresponds to one behaviour node and eventually matches a service node. The customized service node can be connected to the behaviour node, which can enable required sensors in the URE to be optimized.

A context node is comprised of one or more sources of sensor data. For this reason, a context node can be considered as a 'cue' [43]. The combination of sensors creates a hierarchical tree structure, which can be used to determine the behaviour from the sequence of information derived from multiple sensors and combined into a single percept. The data from sensors can be used to trigger the reasoning process or just used for the reference. The former is defined as a context node

whereas the latter is explained as a general context. The combination of sensors can be described as the number of sensors that are used for the reasoning. (e.g., 1Set, 2Set, 3Set, 4Set ...).

Sensor data can also be considered from the perspectives of the physiology, activity, and environment. When the sensor data are classified according to the distributed way, they can be analysed and applied as: fixed, removable or nomadic. Depending on the measurement method, sensor data can also be categorized as active or passive [52]. The sensor data within the URE that we propose comprises of the following sensors: activity, environment, fixed and passive. For example, the sensing information of 'PIR1, on' at bedroom in Figure 1 triggers the inference as a context node. A series of sensing data, 'PIR1, on' and 'Bed\_Pressure, on' deduce 'Sleep' as a behaviour node.

When a context node is activated, the inference system commences and sensor data through the process of reasoning are retrieved from a behaviour 'database' (DB). A behaviour node contains the information on behaviours, users, locations and time (i.e. who, when, where and what action(s)). One behaviour node enables the prediction of another one and only behaviours that can be mapped to the service node are considered. For example, 'Sleep' as a behaviour node in Figure 1 can be connected to a service node, 'Wake-up Alarm'.

A service node is a contact point that connects residents' needs (Figure 1). This can be also achieved without the mapping process to the behaviour node (e.g. temperature sensor (Temp) can be directly connected to the 'Auto-Heating') or to deduce behaviour nodes such as 'Sleep', 'Wake up' and 'Bath\_in'. For more efficient service systems, the service node should be constructed selectively. We have developed and proposed the following service systems in the URE: safeness, convenience, comfort, amusement, health, energy saving and sociality. For example, in terms of safeness, the following services are included: fire detection, gas detection, invasion robbery protection, automatic locking system, visitor monitoring, emergency call, and gas control.

## 4. A Mixed Context-Aware Inference

To use captured sensor data, we propose a context aware system that utilizes a mixed inference method comprising of three reasoning processes: (1) Rule-Driven Inference (RDI), (2) Case-Driven Inference (CDI), and (3) Pattern-Driven Inference (PDI). The reasoning method applied to the 1Set context node is the RDI which uses a rule-induction algorithm. In order to reason a behaviour node over with the 2Set context node, the CDI and the PDI are used.

## 4.1. Rule Driven Inference

The RDI is an inference method that can be applied to a device, if the condition of the sensor is matched to a rule. This reasoning method is similar to that of commercially developed home automation systems. The RDI is applied to the context node that has a structure directly connected to the service node. This inference method is made up of sensor data of the 1Set structure and is

applied without predicting and reasoning, if the condition (IF, THEN) is satisfied. Sensor data are studied and analysed in various forms to utilize them for the inference. In case of the RDI, fixed and passive sensors are considered. The RDI deals with environmental services such as HVAC and lighting. The 1Set structure in the RDI can be handled by one device though the sensor data, as the service trigger follows the context node that is constructed with the 1Set. Contrary to the other inference methods (e.g., CDI, PDI) the sensor data, which composes the context in the RDI, does not need to be in the sequence. The RDI simply needs to provide the services corresponding to the changes in values of the sensor data. Accordingly, the user, location and time do not need to be taken into consideration when providing the service.

In the case of lighting devices, a light will be turned on if a person enters a room. The sensors that are applied to the situation are the PIR and an illumination sensor. The structure of the Service Rule DB is constructed with the service names, devices, actions, sensing variables and values. To find an appropriate service, the Service Rule DB will be searched. If the device cannot be directly executed, the DB will search for the service. A rule within the Service Rule DB ensures that the Emergency Rule DB within the safeness system connects with the illumination service. The RDI mapping service includes the fire detection, gas detection, an invasion protection and a gas valve automatic isolation. Services that connect a context node with a service node directly are HVAC, illumination, ventilation and humidity control service. The RDI process is illustrated in Figure 3.

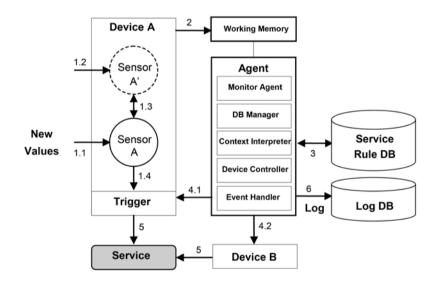


Figure 3. Rule Driven Inference

For example, new values in context node are perceived to the sensor A of the Device A (1.1), and then the information is delivered to the trigger corresponding to initial setting condition (1.4) and is then executed (5). If the Sensor A refers to the Sensor A's information (1.3), the transaction is conducted in the Device A and the service is executed.

If the process refers to the condition, except device A, the reasoning method is requested through Agent (2), the RDI method is adopted and the Service Rule DB is retrieved (3). If the Device A is

searched and mapped, the Trigger is executed at (4.1) and serviced at (5). If the Device B is searched, the trigger of the Device B is executed at (4.2) and serviced at (5). Finally, the log of the new values in context is saved for further reasoning. For example, the sensing information of 'PIR1, on' at bedroom requests the reasoning process through the Agent. The Service Rule DB is retrieved and the following data in Table 1 is transmitted.

Table 1. T	The Service	Rule DB
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Service Name	Device	Variable	Conditi	ion1	Condition2
Visitor	Monitor	DID 1 on	Image	sensor,	_
monitoring		1 11(1, 011	on	on	-

While condition 1 in the Service Rule DB of 'Image sensor, on' in the Working Memory is matched, the 'visitor monitoring' service is retrieved and the device of 'Monitor' is executed.

#### 4.2. Case Driven Inference

The information of users, spaces and time are the important elements that are associated with services in the CDI. The core of the CDI method is its learning capacity and ability to undertake probability assessments. The processes of the CDI are denoted in Figure 4.

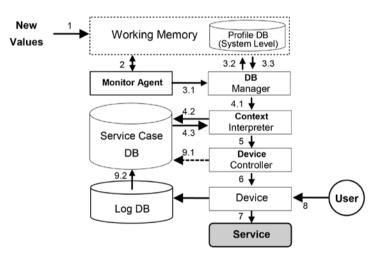


Figure 4. Case Driven Inference

The CDI is the inference method that enables a residence to learn from routine operational situations. The more frequently an action is observed, the more likely the user is to need the corresponding service. In the initial period, the recognition of the services that the user needs may not be initially accurate as there may be a lack of the information accumulated in DB. Over a period time, the system will accumulate data, which will enable a better determination of probabilities and the ability of the residence to learn from users' habits.

A primary characteristic of the CDI is the behaviour node. The behaviour node is the combination set of the context node. The behaviour B1 forms the context node like 2Set ={Sensor A, Sensor B}. In addition, the behaviour may be constructed with the context node such as 3Set ={Sensor A,

Sensor B, Sensor C}, though for the purposes of this research we believe this is not required for this simple process. If a Context node in behaviour B1 considers the ordering sequence, the case of 2Set ={Sensor B, Sensor A} creates another behaviour node. For example, if 2Set={Sensor A, Sensor B} is A(entrance's PIR)and B(entrance's door switch sensor), {Sensor A, Sensor B} means 'go-out' and {Sensor B, Sensor A} means 'come-home'.

Consideration of time and the sequence are the fundamental to CDI. The behaviour and service nodes have particular patterns and sequences over a 24 period. Moreover, CDI evolves continuously from the patterns and sequences that are accumulated. The frequencies of reasoning and service execution make inference about their probability. This information and the probability values determine to trigger for the service that has been accumulated to the Service Case DB where it can be matched. Thus, the Service Case DB is created automatically as the residence is operated, and the user's habits are learned and service executed.

As noted in Figure 4, if new values of Context nodes are perceived (1), the Working Memory constitutes the Profile DB to operate the URE by transmitting the sensor value detected in the physical environment to the Monitor Agent (2). The Monitor Agent triggers the DB Manager Task (3.1). The DB Manager searches for the context (sensor value) at the system configuration level in the Profile DB and constructs the system operation level (3.2). The system operation level is saved to the Working Memory (3.3) and transmitted to the Context Interpreter (4.1). The Context Interpreter search for the Service Case DB (4.2), and acquires the information on the service and the frequency of the cases (4.3), and then calculates the probability of the service node. If the probability of the service node is greater than the value set up by the resident, the execution command is transmitted to the device (6) and the service is executed (7). The frequency of the service reasoning is saved in the Service Case DB (9.1). Furthermore, user's direct and explicit control (8) executes the service (7) as well as save the frequency in the Service Case DB (9.2) and then make it use for the later inference. For example, the sensing information of 'PIR1, on' at bedroom requests the reasoning process through the Context Interpreter. The Service Case DB is retrieved and the following data in Table 2 is transmitted. As the frequency of the information is calculated, the 'Schedule manager' in the Service Case DB is accepted and the device of 'Monitor2' is executed.

Table 2. The Service Case DB

			Refore	Refore Curre		Frequency operat infere Trigg Termi			
Service name	Device	Varia ble	Behav iour	nt Behav iour	t av operat ir <sup>ion</sup>	infere nce	Trigg er	Termi nate	
Schedule manager		PIR1, on	sleep	get up	7	8	1	0	

#### 4.3. Pattern Driven Inference

In demonstrating the use of the PDI, we observed five families' behaviours over a period of five days excluding weekends. To collect the data of families' behaviours, we asked them to complete daily activity templates for periods of 30 minutes. In addition, we conducted detailed interviews about their daily activities. We observed consistent patterns of behaviour, which enabled us to develop living patterns (e.g. Table 3). The collected patterns of behaviour pattern set consists of a minimum 2Set and a maximum 12Set. Contrary to our expectation, the behaviour of the families was found to be consistent, and therefore invoked the reasoning process to adopt the behaviour DB.

Table 3. The Living Pattern DB

Service	Device	Location		User	Time		Behaviour
Service Name	Device	HouseI D					Behaviour
Lighting service1	Light1	103	bed1	husba nd	Mon	06:30	get up

The consistent sequence of behaviours that arose each day was then divided into 2, 3, or n combinations. We extracted the living patterns by calculating the frequency of the combination of behaviours. The behaviour nodes were: (a) awaking, (b) going to the toilet, (c) face washing, (d) folding laundry, (e) going out, (f) cooking, (g) household activities and arrangements, (h) meals, (i) watching TV, (j) reading the newspaper, (k) showering, (l) using a computer, (m) cleaning, (n) laundry, (o) study, (p) going to sleep, (q) exercising, (r) conversation. Understanding the common types of inhabitants' behaviours is fundamental for determining the services that are provided.

The PDI is similar in nature to the reasoning structure of the CDI. A notable difference, however, is that it directly connects the user, time, space, behaviour and service for providing a customized service. The combination of user, time, space, behaviour and service are also fundamentals for living patterns to be determined. The service that is provided in the pattern considers the mapping method of the space and the behaviour. The awareness of PDI behaviour is derived from the analysis of the sensor data and provides the service only if the condition of the space and time is matched with the user's behaviours. When the case of the PDI is constructed as a pattern, the probability of the service execution for the pattern becomes 1. That is, if a case is regarded as a pattern, the corresponding service will be executed. The information inferred by the CDI is saved in the Living Pattern DB, which is used by the PDI later. The mapping table, which provides the appropriate service to residents, is created automatically.

The primary difference of the PDI from CDI is that the Context Interpreter searches for the Living Pattern DB (5.2) to determine the required service in the PDI. The Context Interpreter executes the service that is found in the Living Pattern DB without calculating the probability of the service

execution as the probability of the service execution is already 1. The Living Pattern DB is built on the CDI, thus it cannot be created at the first construction in the URE. However, setting the residents' behaviour pattern in a generalized way, without the CDI, can be considered for the care of a dependent person or someone is elderly. The values of the behaviour pattern that was investigated through the observation research can be applied to the initial setting of the Living Pattern DB. For example, the sensing information of 'PIR1, on' at bedroom requests the reasoning process through the Context Interpreter. The Living Pattern DB is retrieved and the following data in Table 3 is transmitted. When the pattern of location-user-time-behaviour-service corresponds to the service, 'Lighting service1' in the Living Pattern DB is accepted and the device of 'Light1' is executed.

## 5. Case Illustration of Context-Aware Inference

Drawing upon the rules established from the five families the 'context awareness' in our proposed system is realized using three mixed reasoning methods. The Agent performs the role of selecting appropriate reasoning methods. The service extraction is reasoned by using the Service Rule DB (for the RDI), Service Case DB (for the CDI) and Living Pattern DB (for the PDI). As described in Figure 2, when one context node executes the Agent and searches for the Profile DB in the Working Memory, several services and reasoning methods can be searched.

To provide more suitable services, the three reasoning methods are blended into the various sequences as shown in Figures 5 and 6. The smaller number of sequences that are chosen, the more private services within the URE would be provided. If we select the sequence of number 6, the URE will be provided with more supportable services but will require more sensors. In demonstrating the context-aware inference we presented a case example for the sequence number 1 (RDI, PDI, CDI) for the privacy.

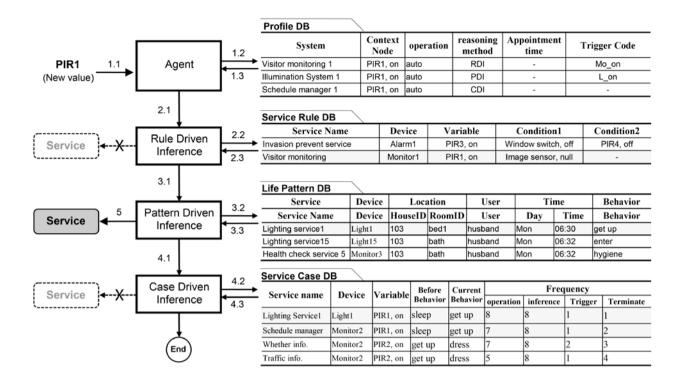


Figure 5. Example of Context Awareness

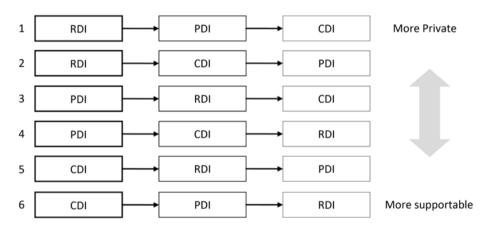


Figure 6. The Various Sequences of the Mixed Inference Applications

#### 5.1. The Case of Bedroom Lighting Service (Monday, 06:50 AM)

The Monitor Agent detects the sensor value (PIR1, on) in the bedroom from the Working Memory (1.1). The contexts of this case consists of 'Bedroom' for Location, 'Smith' for User, 'Monday, 06:50 AM' for Time, 'get up' for Behaviour in Working Memory. The Monitor Agent triggers the DB Manager Task. The DB Manager searches for the PIR1 at the system configuration and operation levels in the Profile DB (1.2) and obtains the data (1.3).

Figure 6 show the process of the mixed context-aware inference using three reasoning methods that have been proposed. If a new sensor node is detected, the Monitor Agent searches for the applicable information to the three inference methods in the Profile DB. As a result, 'Visitor monitoring 1' using RDI, 'Lighting service 1' using PDI, and 'Schedule manager 1' using CDI are identified. According to the orders of the three inferences, customized services provided will be significantly different. This case uses the RDI as the first inference method as follows.

#### <RDI Process starts>

As the visitor monitoring system is operated by the RDI method, the results can be obtained by searching for the Service Rule DB (2.3). When the key value of 'Service name' is searched, the RDI checks the device, variable and conditions. As shown in Service Rule DB, the variable of PIR, in case of the 'Visitor monitoring' Service, is corresponding to the current sensor node but the condition 1 is not satisfied since the value of image sensor in Working Memory is null. Therefore, the setting of the 'Visitor monitor' Service is not completed so this RDI service is not executed.

<RDI Process ends> <PDI Process starts>

As the Lighting service 1 is run through the PDI method, we can obtain the results by searching for the Living Pattern DB (3.3). This case uses the living pattern of four context elements, location-user-time-behaviour. If a living pattern is identified by all of the six context elements, 5W1H, the information can be more accurate but the computation in Working Memory would become more complicated. If some services do not need to consider the user context, they can be provided using the pattern constituted by the contexts of location and behaviour. This paper uses the living pattern considering the four context elements, location-user-time-behaviour, since our PDI method intends to suggest more customized services. The contexts of location and user are detected and recognized by special sensors while the context of behaviour is interpreted by the set of sensors in a sequence. Therefore, our system identifies the behaviour from our behaviour DB in Working Memory. Also, the context of time needs to set a permissible range at the initial setting. This paper sets the permitted range with  $\pm 30$  minutes to the average time for detecting behaviours in our system.

New sensor data of PIR1 generates the RDI, the PDI, and the CDI methods through the Monitor Agent. Each inference method needs to obtain additional data beyond the PIR1 for inference. The RDI in this case checks the value of image sensor in Working Memory for confirming the condition in the Service Rule DB while the PDI needs to acquire the value for the contexts of location, user, time, and behaviour. As a result, the PDI uses more resources in Working Memory than the other inference methods. The residents' pattern of location-user-time-behaviour-service in

Working Memory that matches the Lighting service 1 is bed1-Smith-Mon, 06:30- get up respectively, then Lighting service 1 can be triggered (5).

<PDI Process ends> <CDI Process starts>

Though the PDI executes the service, the process of the CDI is continued since there may be additional services related with the CDI method. The CDI searches for the database in the same way as the other inference methods. By searching for the service Case DB, results can be produced (4.3).

The CDI uses the probability made by frequencies considering before and current-behaviour for the inference process. First of all, the CDI confirms a matching service from the behaviours in Working Memory and then decides whether the service is executed or not by computing the probability of the service. The probability is computed by the CDI using the part of frequency in the Service Case DB. The frequency data accumulated for a long time provide more reliable probability. The computation of the probability is made by the frequency of Operation by Inference and the frequency of Trigger by Terminate. Additionally, the conditional probability about the behaviour set could be considered. The formula for probability is:

 $\label{eq:probability} Probability = (Operation/Inference) \times (Trigger/Terminate) \times P \ (current-behaviour \mid before-behaviour)$ 

We set up our system to provide a service only if the computed probability is above the value of the initial setting. The critical value of the current system is 0.8. Furthermore, as we mentioned in the previous section, if the information of the contexts is related with the service, the probability of the service execution is 1. Then it can be stored in the Living Pattern DB used by the PDI method. For example, the Lighting service 1 is provided by the PDI where the probability of the service execution is 1. Then, the second result of the 'Schedule manager' service is searched but the service is not executed because the probability is under 0.8 (the initial setting value).

<CDI Process ends>

The service searched through the three reasoning method is executed and the status of the device operation is saved as the Log DB. As shown in the example of the context-aware inference, three reasoning methods are complementary and can be constructed in an independent way according to residential needs. Therefore, as the reasoning method is constructed in the customized form, it is possible to enhance the performance of context-aware inference and optimize the UREs.

## 6. Conclusion

The development of frameworks for optimizing the reasoning process and constructing sensors & devices in UREs is an area that has received a considerable attention. The URE in this research can be explained as an environment constituting three layers of context node, behaviour node and service node in the built environment. Three layers systematically illustrate the residential computing environment. This showed how to provide a suitable service from contexts and behaviours. The nodes guided us across the complex ubiquitous system from Service node to Context node. This enabled us to readily understand the UREs and to optimize the required services systematically.

We described the context-aware inference used to construct the UREs. Our framework enabled us to understand and explore the intricacies of software as well as hardware in the UREs. This also allowed us to optimize the reasoning process and construct the UREs with the appropriate sensors; as well as obtain a practical way to enhance the performance of context-aware inference and customize the UREs in accordance with resident's needs. Furthermore, our proposed framework uses the unique reasoning method referred to as Pattern Driven Inference to focus on the behaviour of residents, which forms a core focus of the framework. The Behaviour Node especially acts as an important reasoning factor in the CDI and the PDI which happens with the continuation of the behaviours. In addition, the probability of the service execution is applied and the regular patterns of the resident behaviours form the Living Pattern DB through the method of the PDI.

To apply the reasoning system into reality, further research is required needed. The calculation of probability of the behaviour continuity, decentralization systems, sensors, and device composition are major key factors for the URE. General residential behaviours could be interpreted in various ways using the data that have been accumulated for a long time considering the social and cultural contexts. Also, our inference suggests the way of blending the RDI, the CDI and the PDI. The reasoning methods could be applied selectively by either using the RDI or both the RDI and the PDI in accordance to the situation. In case of the aged or the disabled, who need a high level of assistance, it would be effective to constitute the residential environment by applying the mixed inference of the RDI, the PDI, and the CDI.

This research can provide the direction of design and the guidelines of system development for the UREs. However, the presented framework was not completely verified and implemented in real residential contexts. As for future research directions, we envisage to implement the framework with more complicated scenarios and construct the UREs with a verified context-aware inference system

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