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A user experience environment model for human activity simulation

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Highlights for Reviewers

Article entitled: A User Experience Environment Model for Human Activity Simulation

Highlights

In this paper, we propose a user experience environment model to quantify the user experience information of a virtual space. Thus, it will be able to reduce the cost of obtaining the user experience information by composing a virtual space similar to the real space and predicting the user activity in this space.

It is the space in which user experience information is gathered. This data collection consists of the spatial model, the user activity model, and the object model. This information is recorded in a user activity dataset.
The simulation is a 3D game-like environment which is implemented using Unity 3D game engine. This simulator enables substitutional experience via the virtual space bolstered by the specificity of placing existing furniture depending on the spatial program within the real space.
The user activity prediction process based on the results of the learning process. And the simulation result of the predicted user activity from the learning result, based on the specified scenario.

From the simulation result, we can find a method by which to judge the accuracy of collected user activity information, implemented in a virtual space based on user experience environment information. We have also found a method of intuitively identifying the method of the learning result. These results signify meaningful experimental data.

A User Experience Environment Model for Human Activity Simulation

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Abstract

In this paper, we propose a user experience environment model for quantifying user experience information in a virtual space. This model consists of a spatial model, a user activity model, and an object model. The spatial and the object models represent a space containing the objects the user is using. The user activity model contains information on the experience information that a user accumulates while using the space. Experiments to quantify the user experience in the high complexity space require a lot of time and money. Thus, this approach can reduce the cost of obtaining user experience information by composing a virtual space similar to the real space and predicting the user activity in this space. In conclusion, we propose a simulator for collecting information on user experience environments and for predicting user activity through knowledge gained using the collected data.

Keywords : Human activity simulation; User activity model; Virtual space; Data collection; User experience;

1. Introduction

The various objects surrounding human beings to smart production environment to control a large amount of production volume from everyday life is based on the network infrastructure, through the connection between the data, not only the industry, causing a variety of changes across society and that is being a hyper-connected society.[1,2] The following terms are used to explain this networked social phenomenon: machine-to-machine(M2M), Internet of Things(IoT), and Internet of Everything(IoE).[3-5] Among the above terms, IoE is gaining the most traction. These terms represent an overarching concept that offers advanced connectivity for devices, systems, and services that goes beyond the concept of mere technology.[6] The purpose of IoE is to deliver real-world spatial information to the user in real time, and to deliver categorized information to a target site quickly and accurately with four components: human, process, data, and objects. The goal of this paper is to realize people oriented value using the process described above.

In order to do so, we need to understand the large amount of data generated from the experience environments surrounding humans.[7] This means that we should quantify the user experience for adequate analysis of both human behavior and spatial interactions. Therefore, we reviewed various studies on both the cognitive aspects of human-environment interactions and human-computer interactions. In doing this, we operated under the assumption that the concept of space cannot be explained without interactions with humans. These interactions can be explained using adequate amounts of data to understand human behavior. The contents and form of these data can correspond to the characteristics of each space. This means that each space may exist in a variety of forms through interactions with real-world information and human experience information.[8]

In this paper, we collect spatial information, which exists in an abstract form, and implement this information in the design of a virtual space. We then use this virtual space to collect information on user experience based on the design of a given virtual space. This experiential information from user interactions illuminates the complexity of the virtual environment. Therefore, collecting and analyzing user experience information with high accuracy is very important because of the potential difficulty in computing non-purified data. Accordingly, we have implemented a virtual space simulator to collect user experience information since collection of this information in real space is very difficult due to ethical and legal issues. Within this virtual environment, we can obtain the user experience information from timestamps in the past to predict those that might occur in the future. This methodology has allowed for simulation of the experimental environment using complex user experience information.

In Chapter 2, we review the technical requirements of the simulator by analyzing the related work on user activity simulations in a virtual space, using specific scenarios. In Chapter 3, we introduce the user experience environment model for a virtual space. In Chapter 4, we verify the accuracy of our design by analyzing the experimental results from using the simulation and applying the user environment model.

2. Related work

The representative research into virtual reality for scenario-based simulation includes platforms such as UbiREAL, SIMACT, and PerSim3D, among others.[9] UbiREAL is designed to simulate interactions between humans and devices in a context-based simulation for smart environments.[10] This simulator can specify the user's movement path using dedicated short-cut keys, which can select the movement path of an avatar. The avatar executes the specified interaction in real time. Appliances such as televisions, video recorders, stereo audio systems, and air conditioners are placed in the virtual smart space attached to sensors to detect contextual interactions. These simulated devices in the virtual smart space have similar functions to their real-world counterparts.

During the simulation, the avatar is programmed to exhibit the expected movements naturally as various scenarios are constructed by the user. The importance of such a simulation is that it attempts to implement a networked simulation using ubiquitous applications. However, it can meaningfully simulate only a limited amount of space as it is still in beta testing. Here, only one rule is applied to the devices and the avatar. As such, this configuration does not reflect the interactions between sensors and the complexity of each individual sensor. Accordingly, the differences between recognizable zones depend on additional sensors. Therefore, it is meaningful that we have implemented an environment that can use multiple sensors or objects to collect and analyze user-generated motion paths. UbiREAL can show only the relationship between human and device, not human activity. Our simulator searches various experiential variables via a model that records relationships between user activities, spaces, and objects.

A different model, SIMPACT, is a 3D smart home simulator with a form-based interface. After the user selects an object to place in a real-world space, the corresponding virtual scenario related to the object is constructed. As such, a user designs the structure of the scenario in this sysyem, and the designed scenario is saved as a script. Since there is no avatar in a virtual space, the system does not have a specific activity model. Instead, it classifies past actions and future actions, and verifies the input data through the simulation screen. It then adjusts the simulation values until the simulation is similar to the scenario. This systemic structure is one of the advantages of SIMACT.

SIMACT incorporates various methods of finding optimized scenarios by taking into user characteristics by virtue of very high flexibility within the system's structural design.[11] The system shows that objects and user activities are highly correlated using a method for configuring scenarios of user experience based on the environments and objects, not on human activity. However, the system does not consider the correlation between space and movement, nor does it consider interactions between people. Instead, it records and displays a scenario for each user.

Alternatively, PerSim3D is a simulator developed for the detection of human activity characteristics. It emphasize the optimization of user activity perception by constructing a recorded dataset of user activity, and expanding the dataset based on sensor information.[12,13]

The simulator uses this method to make the generation and re-combination of data easier by converting the data to a Sensory Dataset Description Language. Therefore, it is designed for computational encoding of human-environment interactions using a model of sensors and actuators for the recognition of the actions and locations of smart characters in a virtual space, as opposed to using high-quality 3D virtual space. The model also emphasizes the similarity between the character actions and the human actions in real space by enabling avatar mirroring in the simulation. This does not, however, mean that similar actions imply that every action in the simulation should be the same as in the real world. What it does is enable researchers to show natural actions in a space constructed using a data set implementation based on virtual sensors. Specifically, the system creates a space derived from user input and sensors placed by the user. The flexibility of such a system makes it easy to insert or remove other kinds of sensors. This is a major advantage of PerSim3D.

On the other hand, the complexity of the PerSim3D simulator is very high because it is based on a data collection sensor model. Within such a model, it is difficult to move a character actively because it is hard for the system to grasp the correlation among space, object, and user only using the dataset obtained from the target space. Thus, the system can predict a user’s actions only right after the specific user activity has been executed in real space, since it predicts user activity within a restricted action category. The system does not consider the prediction of user activity at a distant point in the future. Therefore, it needs to extend the data category for the prediction of user activity in daily life.

Finally, the Center for Advanced Studies in Adaptive Systems project is based on sensors within a real space. This system, uses various methods to visualize real-world sensor information.[14,15] Other research also exist regarding objectifying experiential information using the real space and user activity by recognizing user actions via mobile devices.[16-18]

3. User experience environment model

The user experience environment model utilizes a space in which an object is placed as well as the experiential information derived by the user from interactions with the object in other words, a space in which user experience information is collected. This data collection consists of a spatial model, a user activity model, and an object model. The spatial model contains the location of the user activity and the placement of objects. The user activity model contains information on the user’s interactions with an object in a specific location, which is recorded in a user activity dataset. The object model uses an object’s location in relation to the user activity as well as sensor information to recognize user actions. These actions can be represented by complex data since the system records a user's spatial usage pattern in relation to spatial characteristics and objects. Accordingly, the user experience environment information consists of a complex concept with various experiential metrics and environmental variables. Fig. 1 shows the relationships between the user experience and environmental components using overlapping spatial information, user activity information, and object information with highly related variables.

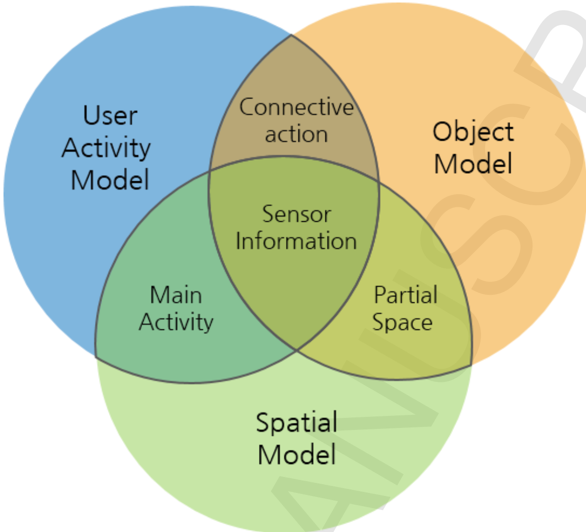

Fig. 1. The interrelation between user experience environment components

For example, if a user sleeps on a bed, the value of the corresponding spatial model would be 'bedroom', the value of the user activity model would be 'sleeping', and the value of the object model would be 'bed'. In this situation, the sensor information is a collection of sensor values. The sensors are used for the acquisition of spatial, object-based, locational information. For a highly realistic simulated appearance based on real space using a correlation of variables, the system needs to optimize the data construction model. This optimization is needed to characterize the highly complex and variable user experience. A high-complexity environment is one in which the number of environmental variables necessary to predict user actions is very high. As the complexity increases, the prediction of user actions becomes more difficult. Since it is hard to perform experiments in real space, we designed and implemented a virtual space with a highly realistic appearance using an optimized data construction model.

The spatial model presupposes an expert data model for a standard indoor residential area. In this residential area, various spaces are mixed, resulting in a uniform residential area. It is easier to model a specialized space as an interpolation of a high-complexity environment. The spatial model is designed to define a partial space based on the main activities in the space, the main furniture, sociality, objectivity, and specialized areas or to obtain information related to user actions. The main activity represents the actions that a user performs frequently. It also comprises information related to user actions in "normal" situations. The user actions may be specific to each person. The main furniture values will be assigned to values that are highly related to the user's main activities. Sociality and objectivity are related to the utilization of the partial space. The partial space, which is divided into personal and public areas. We can verify that the objects used and the main activities performed in a user's daily life may be different depending on the objectivity of the specific space. A specific area is defined by a specialized zone, retention zone, and comfort zone. Fig. 2 shows an example of a partial space and a living room, representative of the specific areas in this spatial model.

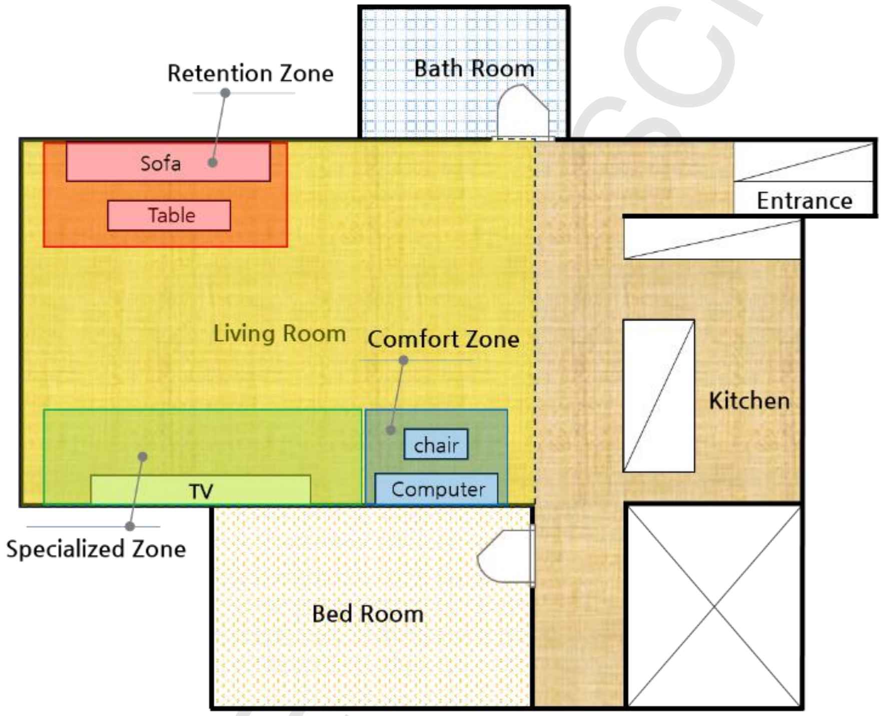

Fig. 2. An example of specific area in the spatial model

The specialized zone is the area in which the user performs his or her main activities. It is highly related to information derived from objects. The retention zone is the zone in which the user stays during a specific period. The comfort zone is the zone in which user activity occurs and the user utilizes objects for comfort in this zone.

The user activity model is designed to extract the characteristic values related to user activity in daily life, based on information defined by the user's actions in the real space. We have reformed the user activity model to implement a simulated environment easily based on a conceptual frame that classifies the actions described in a user survey distributed by the Korea National Statistical Office. First, we divide user activity into complex actions and connective actions. A connective action consists of sitting, walking, laying, standing up, object selection, object usage, etc. It is essential to predict complex action, which is the totality of connective actions. A complex action is classified as daily activities such as eating, applying makeup and watching television. The characteristic values in the user activity model are applied to the user activity information. We can then obtain the following information previous complex activity, current activity, type of activity, object information, event space, activity area, retention time, etc. Fig. 3 visualizes an intuitive simulation that applies the user activity model.

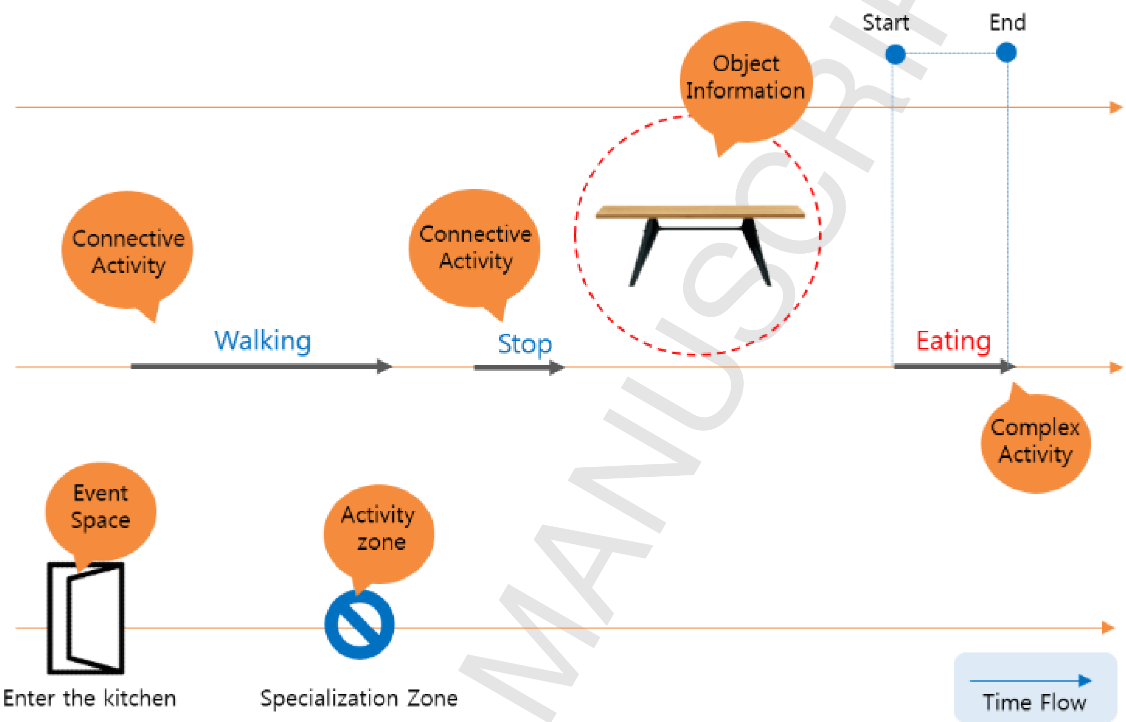

Fig. 3. An example of the user activity model application

The characteristic values of this model are populated when user activity occurs. We use the virtual simulation described above as a design method for modeling user experience information, since a simulation of the same type can be verified using the right methodology to find variables representative of the user's actions.

Lastly, the object model in the resident area needs to encode information from furniture and electricity, which influence the user's actions as well as the definition of a partial space. We also utilize the object model to design the user experience model. We then construct an object database, focusing on frequently used objects in daily life, excluding specialized smart devices using the recent information technology. We classify objects into fixed and non-fixed categories depending on the mobility of the object. A refrigerator, television, and washer, for example, are classified as fixed objects. A TV remote control and a smart phone are examples of non-fixed objects. The elements within the object database consist of an object ID, object mobility, object usage, object identification sensor ID, placed space, and usage time. Importantly, the database contains virtual sensor information to confirm the identities of object, usage, user entrance in the partial space, user action, etc.[12,18] Table 1 contains the information sheet classifying sensors by type and functionality. Sensors are classified as follows: physical detection sensor, logical detection sensor, and environmental sensor.

Table 1. Information sheet for sensor type

Category	Sensors	Purpose
Physical detection sensor	Entrance sensor	To determine if a person enters the partial space
	Pressure sensor	To identify sitting or standing
	Camera sensor	To enable the detection of a specific area, object, and user activity area
	Contact sensor	To determine if a user contacts any object
Logical detection sensor	Temperature sensor Humidity sensor Luminosity sensor	To obtain information for environmental information control in a specific space
Environmental sensor	Clock/watch Calendar Weather information	To obtain the starting point for a user's actions within an environment

The system requires a detailed model of the characteristics, types, and functions of the sensors, since the characteristic values of the object model contain the sensor type and sensor value. We consider the sensor values as the parameters of each object model, instead of using the sensor values to define the dedicated sensor model.

4. Experiments

Experiments were performed to evaluate the accuracy of the proposed user experience environment model. In the experiments, user experiences were emulated using a simulator. The overall process of the experiments is depicted in Fig. 4.

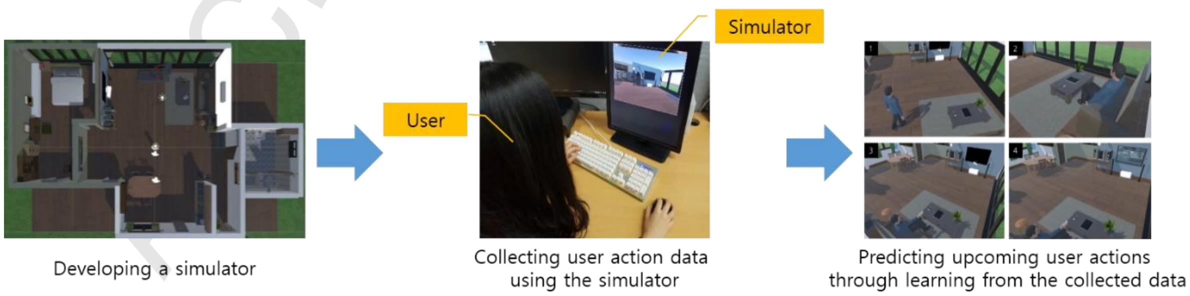

Fig. 4. Data collection mode

The developed simulator provides a virtual environment in which actual user experiences can be collected. The data collected using the simulator represents how people behave in the real world. That is, the user's daily actions are captured via a character (avatar) in the simulator. The behavioral data collected over a certain period enables the simulator to predict upcoming user actions. The simulator makes predictions on user actions by learning from historical behavioral data, and outputs the predicted user action at a specific future time in the form of a snapshot.

We implement a virtual space in a simulator based on the design information for partial spaces in reference to real spatial information from the spatial model. This simulation is a 3D game-like environment implemented using the Unity 3D game engine. This simulator imports the frame of a functional game. In doing so, it enables substitutional experience via the virtual space, bolstered by the specificity of existing furniture placement depending on the spatial program within the real space. This simulator is designed to obtain information related to actions collected to replace these in the real world giving a high presence to the user. Keys on a keyboard are used to control detailed connective actions. The implemented simulator has the following features.

The functions of the simulator are divided into a data collection mode and a scenario configuration mode for simulation. In the data collection mode, the simulator obtains information on a user's characteristics based on demographics such as age, gender, job, etc. It then stores this information under a user ID number, while user experience information is stored under a data ID. Fig. 5 shows the input window for the data collection condition in data collection mode.

Fig. 5. Data collection mode

The data collection mode can be activated at a specific location to begin collection of user activity information in a virtual space. The mode can be deactivated when the collection is finished. For the user's convenience, the data collection works per complex activity unit module. A user does not need to turn the simulator off and on again whenever he or she wants to collect the activity data specified in the data collection condition input window. The simulator decides whether the data collection is activated depending on the activation of a data collection condition input window. When a user specifies the data collection condition, he or she must input information about his or her previous activity when collecting the data. The activity information is used for predictions of user activity. In other words, the activity information is the link between a broad range of present and future actions. This enables the prediction of the user's future activity.

A user can also select whether he or she wants to use an object or not in the data collection mode. Usage of the object is visualized by the avatar in a virtual space. Fig. 6 contains a screenshot of the identification and actions of an avatar using an object.

(a) Object usage selection window

(b) Multi-object selection window>

Fig. 6. An example of object selection

Fig. 6 (a) is a screenshot of an object usage selection window. If a user does not select the <USE> button, the conditional value will be "Do not use object". Fig. 5 (b) is a screenshot of the selection of one object from a set of objects. To leave the data collection mode, the simulator shows a dedicated conditional input window to select the leaving condition manually. This window consists of the period of collection for the specified action from the conditional input window in the data collection mode.

Fig. 7. The scenario configuration mode

The results of the simulation will be shown after the learning phase. To identify the end of this phase, we select a user action scenario in the scenario configuration mode and view the results. Fig. 7 shows a screenshot of the scenario configuration mode. In this mode, we can configure up to five actions in a given scenario. The scenario configuration mode has the same interface as the data collection mode. A user can call the pop-up window as needed. This mode contains the value configuration function for the user action as well as the user action to simulate. A user can insert or delete an action and time stamp per action, as he or she desires.

In this scenario-based user activity simulation, it is important that the predicted user activity is shown as a user scenario configuration. Specifically, the collected user activity data forms clusters representing each complex action and connective action related to the distinguished complex action using the Support Vector Machine. The learning of collected data can be described as the prediction of a user's action at a given future point using the collected historical data. It also includes an event reconstruction at the past point by accumulating historical data. A character in a virtual space creates new action data as the predicted result with the classified data through a learning process based on a given scenario. The simulation results may be different depending on the result of the learning process, even though they simulate the same specified scenario. An unexpected user activity value may be shown in the simulation result, because the characteristics of a user's action may be reflected in the user activity value even though it is not defined in the set of specified scenarios.

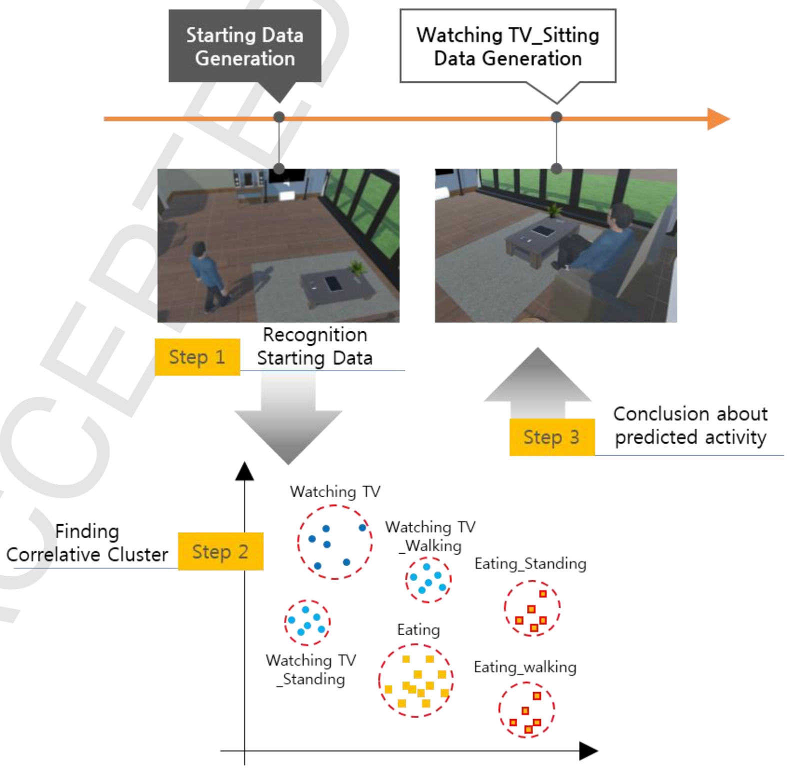

Fig. 8. User activity prediction process based on the learning results

Fig. 8 shows the user activity prediction process based on the results of the learning process. In step 1, we let the simulator recognize the data by inserting the starting data created in the scenario mode as the learning result. In step 2, we find the cluster closest to the characteristic value for the recognized starting data. At this point, the cluster is distinguished as one action for the user-specified actions in the data collection mode for a given scenario. Each cluster contains the characteristic value for a current action at the point of data collection and is labeled with the name of the next action. These may be different depending on the data storage method at the point of data collection during the system-structural learning process. Therefore, the data structure should be designed taking into account the learning process from the data collection stage.

The following shows the simulation results for User 1 (subject of experiment). In this experiment, the real-life actions of User 1 were collected in the simulator, and the “watching TV” scenario was selected in scenario mode. Fig. 9 shows the data classification from the accumulated user activity data learning results.

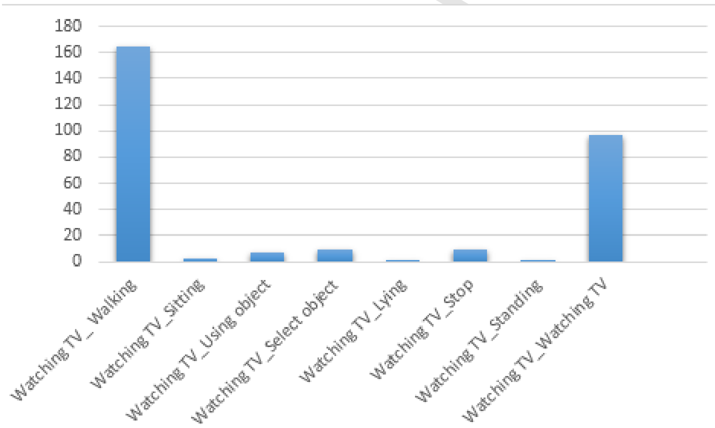

Fig. 9. User activity data learning results

In step 3, the simulator recognizes the representative characteristic value for the next action value after a decision has been made regarding the predicted next action.

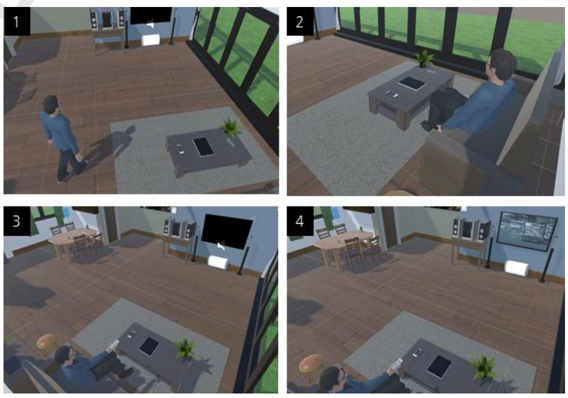

Fig. 10. The simulation result of the predicted user activity

Fig. 10 displays the simulation result of the predicted user activity from the learning result, based on the specified scenario. From the simulation result, we can identify a method to judge the accuracy of collected user activity information, implemented in a virtual space based on user experience environment information. We have also found a way to intuitively identify the appropriate method for the learning result. These results signify meaningful experimental data.

5. Conclusion and future work

In this paper, we proposed an efficient model for collecting information on a user experience environment with regard to the spatial interactions indicative of specific daily life patterns. We also verified the system's potential utility by implementing a simulator capable of predicting a user's actions. Using the system, we can collect user activity data from multiple users, yielding a large amount of user experience information. The ultimate goal is to create a simulator that can utilize data representing a long period to make long-term predictions as well as short-term predictions using big data methods. These predictions can be executed by dividing the user's actions along a given path as executed by an avatar in a virtual space. The user activity prediction is simulated automatically based on the simulator's learning results from the collected data. This paper provides an efficient method of using a virtual space to overcome the difficulties of reproducing real world events by utilizing real-world data in a virtual space. In doing so, we hope to inspire related work in the future.

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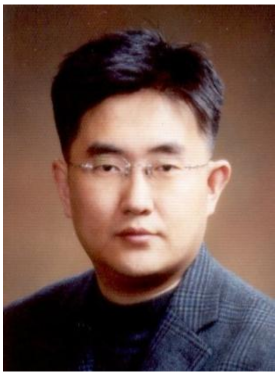

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