Sensing Learner Access to the Knowledge Spatially Embedded in the World

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***Abstract*—Real-world learning is an important application domain of mobile computing technologies. Real-world learning offers valuable opportunities for encouraging learners to acquire knowledge through experience in the world. Formative assessment by constant monitoring of intellectual achievement is an effective means of providing learners with adaptive support according to their situation. However, it is difficult to measure behavior and knowledge acquired in the real world, and no methodology has yet been developed to allow a formative assessment of learners in a real-world learning field (e.g., the natural environment). In this paper, we demonstrate that knowledge is three-dimensionally embedded in the world, and show a method for estimating how learners access such real-world knowledge. Our technology recognizes characteristic stay behavior and the associated body posture of learners, three-dimensionally estimates the target of their interest, and identifies the learning situation at any given time. As main achievements of our data analyses, we found that real-world knowledge is not only region dependent but also height dependent. We also showed that the learning topic of interest can be identified with wearable sensors (e.g., positioning sensors, 3-axis accelerometers, 3-axis gyroscopes, a barometer). These results are fundamental for realizing adaptive learning support based on systematic formative assessment.**

Keywords–mobile application; mobile learning; behavior recognition; context-aware service; real-world knowledge

I. Introduction

The ubiquity of computer technology is changing our daily activities and creating a next-generation society. Human intellectual activities in such a changing society are becoming more diverse, and more real-world oriented. To develop engineering technologies to enhance human activities, it is of fundamental importance to understand the dynamics of human knowledge processing. This paper focuses on people who interact with and learn in the real world, and makes a proposal for understanding how they access the knowledge that exists in the world.

A. Learning in and from the world

A cognitive architecture has traditionally been considered to be a process for forming a structured internal representation of the cognitive behavior of a person. In contrast, the theory of situated cognition postulates that a learner's cognitive process is embedded in the world, and proposes a cognitive architecture for acquiring knowledge through human interaction with the world [1], [2]. Real-world knowledge is embedded in situations [1], [2], and learners need to interact with the world, to have diverse experiences, and to autonomously investigate, find, and acquire real-world knowledge. Discovery learning through bottom-up knowledge acquisition is an important requirement of real-world learning. Environmental learning in nature is a typical example of real-world learning, and is selected as our model case.

B. Formative assessment of real-world learning

Formative assessment by constant monitoring of changes in learning situations is an essential factor for realizing adaptive learning support. Periodically testing the achievements of learners is a conventional method of formative assessment that is generally used in the case of desktop learning in a classroom. Learning management systems (LMS) assess learners' understanding by analyzing access logs of the LMS, and reviewing the results of tests and reports [3].

The main difference between desktop learning and real-world learning is that the effects of real-world learning depend on the outdoor experience of the learner. However, it is difficult to measure behavior and knowledge acquired in the real world, and no conventional research on real-world learning has proposed a methodology for carrying out a real-time evaluation of a learning situation that changes from moment to moment. There are no techniques to assess what real-world knowledge has been adequately acquired, and whether real-world learners have carried out meaningful activities for understanding their surroundings. These are problems that limit the effect of real-world learning.

The following are goals of the formative assessment method that we consider in the present research: (1) assessing how learners expand the areas that they are interested in, (2) assessing the time-series change in the degree that learners are occupied in conducting important learning activities, and (3) assessing the time-series change in the learning topics that learners are interested in and examine. Such formative assessment can dynamically provide learners with dedicated learning support that is well tailored to each individual learner, and will refine the conventional methodology for supporting real-world learning.

C. Research objective

Real-world learners interact with the world, select from a range of possible actions, and then execute an action. The final output of the brain is behavior, and the intellectual state of real-world learners is to some extent physically reflected by their body. Although it is not possible to directly observe

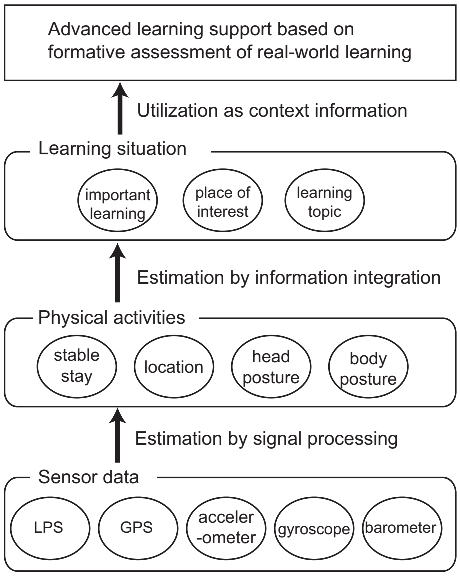

Fig. 1. Estimating learning situation by sensing physical behavior.

the thinking process of learners, their interaction with the world can be observed from outside, and can be a clue to understanding learning situations.

Real-world learners use their body to interact with the surroundings, and in this way obtain knowledge about the world. A learner's body can be considered to be a sensor for obtaining information about the real world, and also an actuator for manipulating the world. Therefore, in the present research, as a fundamental approach for achieving advanced intellectual support based on systematic formative assessment of real-world learning, we developed a sensing technology that can identify the behavior of real-world learners, and estimate the nature of their intellectual activity in real time. The system recognizes physical behavior using low-level signal processing, integrates the recognition results, and thus forms an understanding of learning situations at a high level of abstraction (Figure 1).

D. *Table of contents*

Section II shows our sensing technique to precisely determine the time series of important learning activities in the world. Section III focuses on the spatial structure of a real-world learning field, and demonstrates that knowledge is three-dimensionally embedded in the world. Section IV proposes our sensing technology to determine the learning topic that a learner is examining, and to understand how learners access knowledge that exists in the real world. Section V discusses our contribution and potential applications. Section VI concludes this paper with a brief summary of our achievements.

II. Time series of important learning activities

A. *Important learning activities and unimportant activities*

Determining how real-world learners carry out important learning activities is useful for forming an understanding of how they access knowledge embedded in the world. Based on past research [4], we can divide environmental learning activities into two categories: important learning activities and unimportant activities. We can define important and unimportant activities as follows:

- Important learning activities
  - **Observation**: An activity for acquiring knowledge through interaction with the world (e.g., observation or survey focusing on a certain target, such as touching plants and soil, or writing field notes while inspecting an observation target).
  - **Knowledge exchange**: A conversation activity for interactively solving a problem through externalizing and exchanging knowledge (e.g., cooperative thinking through conversation and discussion). Trivial chat is not regarded as a knowledge exchange.
  - **Intellectual investigation**: The most important activity, involving simultaneous observation and knowledge exchange (e.g., cooperative thinking and discussion through a collaborative field survey). Physical and internal experiences mutually influence each other. Real-world knowledge embedded in a situation [1], [2] is maximally utilized by intellectual investigation.
- Unimportant activities
  Lack of observation, lack of conversation, idle talk, rest, and so on.

B. *Determining intellectual activity through real-world behavior*

The time when a learner carries out a learning activity is meaningful information for understanding knowledge acquisition. Although human behavior can be estimated from sensing data [5], [6], [7], [8], [9], it is conventionally difficult to estimate the intellectual state of a learner by using sensors. To begin with, sensors are tools for measuring physical quantities (e.g., velocity, acceleration, angular velocity, signal strength) associated with body movement. Conventional research uses such sensors to recognize human physical behavior. A typical example is identifying the location of humans at a given time [5]. Other examples include recognition of daily activities (e.g., walking, ascending stairs) [6], and abnormal activities (e.g., slipping on a wet floor) [7]. This has recently been extended to the ability to sense human activities using consumer devices such as mobile phones [8], [9]. However, few studies have attempted to determine the relationship between the physical behavior and intellectual state of humans. Hence, even if we measure real-world activities using sensors, it is quite difficult to infer the internal intellectual state of the learner. Thus, we conducted field surveys to investigate the relationship between learner behavior and important learning activities, and obtained the following significant results [10].

1) When learners walk carelessly about in an environment, they rarely have enthusiastic discussions and obtain only superficial information about the environment.

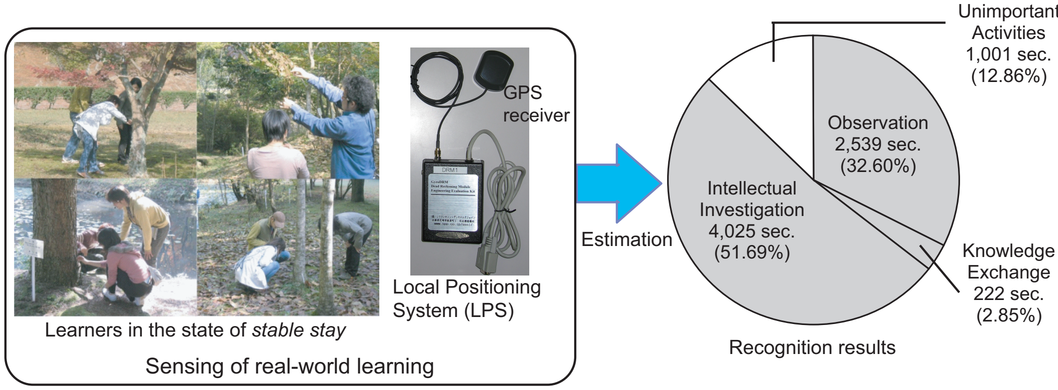

Fig. 2. Automatic accurate identification of important learning activities (precision=87.14%).

2) When learners engage in important learning activities (i.e., observation, knowledge exchange, intellectual investigation), they display a characteristic stay behavior. We call this behavior *stable stay*. Stable stay is defined as a condition that extends for T_t [sec] or more, in which a fixed body posture is adopted (horizontal angular rotation of T_θ [deg/sec] or less) and movement is restricted to a velocity of T_v [m/sec] or less. Stable stay includes the state of crouching down. The learners in Figure 2 are exhibiting stable stay behavior.
3) When learners are not focused on a specific learning topic and casually look around, their body orientation in the horizontal plane is not fixed, even if they are not walking.

C. Recognizing important learning activities by sensing stable stay conditions

Under stable stay conditions, the possibility that important learning occurred was found to be 3.12 times higher than for other conditions [10]. On the grounds that important learning activities and stable stay conditions frequently co-occur [10], each learner was given a wearable local positioning system (LPS) (255 g, 111 x 82 x 39 mm, Figure 2) to be placed on their lower back in order to determine the time series of important learning activities. The LPS is a sensor for recording the local movement and body orientation of a learner. Important learning activities were identified based on the detection of stable stay conditions with three threshold parameters (T_t = 15.00 [sec], T_v = 0.10 [m/sec], T_θ = 60.00 [deg/sec]). These values were determined by pre-evaluating sensor data for two experimental learners and inspecting the data distribution of physical movements associated with both important learning activities and unimportant activities. The data for these two learners were not used in the subsequent experiments for evaluating the recognition accuracy.

We evaluated the accuracy of the recognition method using ground-truth data for the time series of stable stay conditions and important learning activities (18,000 sec; data for five groups representing 15 learners). As shown in the pie chart in Figure 2, the recognition results mostly fell into the important learning category. We confirmed that the method could accurately recognize the time when important learning occurred (precision = 87.14%) by automatically analyzing the LPS data for the learners.

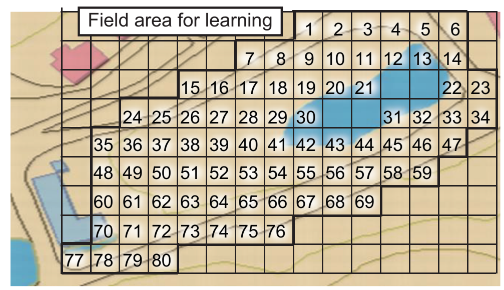

Fig. 3. Region map of Kamigamo Experimental Forest, Kyoto University.

III. Knowledge three-dimensionally embedded in the world

A. Regional dependence of learning topics

As shown in Figure 2, learners exhibit a wide variety of behavior such as looking at various parts of the environment, touching objects at various points with their hands, and observing objects while crouching down. However, whatever each learner actually notices, observes or investigates, stable stay behavior is commonly displayed when important learning activities are performed. This is an important finding concerning the common structure of diverse learning activities.

Important learning is a learning activity for accessing knowledge embedded in the real world. By sensing stable stay conditions, an accurate estimation can be made of how such important learning occurs in a learning field. Moreover, by tracing the location of learners with a GPS receiver, both the places of interest and the time spent engaged in important learning activities can be determined. Although this is an advanced approach to determining the time sequence of important learning activities, it is still difficult to estimate what a learner actually learns.

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Fig. 4. Learner behavior in a natural ecosystem with a multi-layered hierarchy.

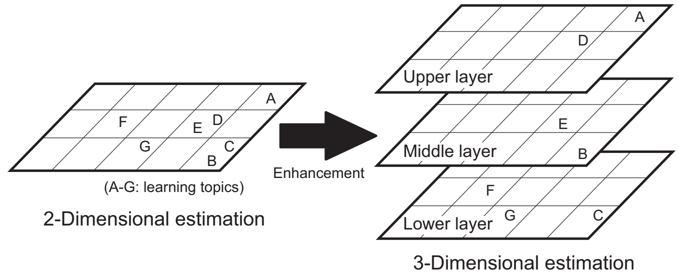

Fig. 5. 3D determination of the learning topics that a learner examines.

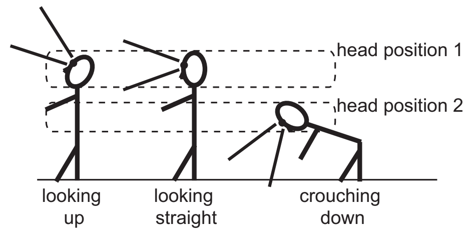

Fig. 6. Observation target and posture.

By identifying the targets on which important learning activities are focused, we hope to be able to clarify the associated content and the knowledge acquisition process. Here, if "what is learned" is related to "the position of the learner", the range of learning topics can be narrowed down based on location. To determine whether this is the case, we conducted experiments in a part (130 x 50 m; Figure 3) of Kamigamo Experimental Forest, Kyoto University, with 15 learners in March, 2010. We found that the learners considered a total of 142 topics. These included, for example, "the symbiotic relationship between mushrooms and moss", and "the relationship between pinecone features and the growth environment of pine trees." We divided the field using a 10 x 10 m grid, and defined 80 different regions (Figure 3). We found that the topics that the learners considered tended to depend on their location. Specifically, on average, each topic was considered in 1.71 regions, and 2.16 topics were considered per region. The topics and the locations are closely related, which illustrates the uniqueness of the physical information in each region.

B. Height dependence of learning topics

Based on the regional dependence of the learning topics, two-dimensional (2D) positional information is useful for narrowing down possible learning topics. However, in regions where more than one learning topic exists, 2D place information is insufficient to uniquely identify the topic of interest. We therefore need to consider additional information for the determination of learner context. We note that a natural ecosystem generally has a multi-layered hierarchy. As shown in Figure 4, learners behave differently even if they stay in the same place. They sometimes look up and sometimes crouch down, and their posture changes according to the learning topics that they consider. We therefore performed a 3D classification of the 142 topics learned in the experiment. We found that the topics were not only region dependent but also height dependent and could be categorized into the following three layers:

- **Upper layer**: Objects above the level of the learners' heads (e.g., tall trees, branches and leaves, light sources). The topics in this category are often examined when a learner is looking up.
- **Middle layer**: Objects at eye level (e.g., tree trunks, bushes). The topics in this category are often examined when a learner is looking straight ahead.
- **Lower layer**: Objects at ground level (e.g., mushrooms, moss, soil, undergrowth, aerial roots, mountain stream, pond). The topics in this category are often examined when a learner is looking down or crouching down.

What a learner examines depends on the region, and each region offers only a small number of topics. Moreover, this research also found that each layer of an ecosystem contains different knowledge, and height is therefore another factor influencing the knowledge that a learner can obtain. Even if more than one topic occurs in the same region, we found that height information is useful for distinguishing such topics. If the learning topics cannot be distinguished in a 2D space, it is possible to distinguish them in a higher 3D space (Figure 5).

IV. Determining the Currently Examined Topic

Stable stay is a condition that is defined in a horizontal 2D plane and can be used for robust identification of an important learning activity. As discussed in Subsection III-B, the posture of learners reflects their interests at that time. We therefore extended the technique for recognizing stable stay behavior to also identify the posture involved, thus allowing the 3D position of the topic of interest to be determined.

A. Wearable sensors

Using an eye-mark recorder, it might be feasible to track the gaze direction of a learner. However, such devices are currently large and heavy, and restrict the movement of learners. Furthermore, when learners move, their location and head direction constantly change without constraint. This makes it difficult to use data from an eye-mark recorder for automatic

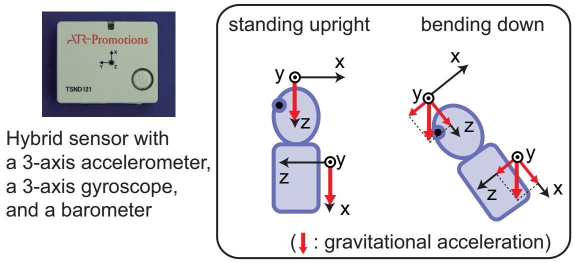

Fig. 7. Gravitational acceleration and learner's posture.

determination of what is being observed. On the other hand, it is known that head direction and gaze direction are closely related, so that head direction can be substituted for gaze direction [11]. For example, as shown in Figure 4 and Figure 6, to observe objects at ground level, learners need to crouch or bend their head down. A learner who is crouching down has a different head height to one who is standing upright (Figure 6). Thus, we classified a learner's posture (e.g., looking straight ahead, looking up, looking down, crouching down) based on head height and body tilt. Each learner was provided with wearable-type hybrid sensors shown in Figure 7 (head and body), in addition to a LPS (lower back) and a GPS (head) for sensing stable stay conditions. The hybrid sensor (22g, 37 x 46 x 12 mm) has a 3-axis accelerometer (50Hz), a 3-axis gyroscope (50Hz), and a barometer (25Hz) built in. The accelerometers are for obtaining 3D tilt information, and the barometers are for obtaining height information. The gyroscopes are for obtaining 3D information on the rotation of a learner's body and head.

B. Estimating posture

When designing a classifier for recognizing human behavior, it is first necessary to understand the typical characteristics of sensor data associated with each of the target behaviors. Thus, we investigated the sensor data obtained in our experiments. As shown in Figure 7, when a learner stands upright and is looking straight ahead, the output from the vertical axes of the accelerometers (i.e., the x-axis of the body sensor, the z-axis of the head sensor) should almost equal the gravitational acceleration (1000 mG). On the other hand, when the body and head of a learner tilts, the accelerometers also tilt. When the body and head rotate about the y-axis, the gravitational acceleration is split into two components along the x-axis and z-axis. For example, as shown in Figure 8, the sensor output exhibits different characteristics when a learner displays different target behaviors (e.g., looking up, standing upright, crouching down). Thus, acceleration data are useful for determining body posture. Data on air pressure and angular velocity are also useful for measuring head position and body rotation.

We are currently in the process of implementing such a body posture identification technique. The integration of multimodal sensor data is carried out using a machine learning method such as a support vector machine (SVM), which can achieve a high generalization performance. The non-linear discrimination function is defined by the below formula.

$$f(\phi(\boldsymbol{x})) = \sum_{i=1}^{n} \alpha_i y_i K(\boldsymbol{x}, \boldsymbol{x_i}) + b \tag{1}$$

$K(\boldsymbol{x}, \boldsymbol{x_i})$ is a kernel function, and we used the following Gaussian kernel:

$$K(\boldsymbol{x}, \boldsymbol{x_i}) = \exp\left(-\frac{||\boldsymbol{x} - \boldsymbol{x_i}||^2}{\sigma^2}\right) \tag{2}$$

C is the soft margin parameter, and α are Lagrange multipliers. Machine learning in a feature space is carried out by solving the following optimization problem under constraints:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(\boldsymbol{x_i}, \boldsymbol{x_j}) \tag{3}$$

$$Subject\ to \quad 0 \leq \alpha_i \leq C, \quad \sum_{i=1}^{n} \alpha_i y_i = 0 \tag{4}$$

V. Discussion

Our essential interest centers on understanding how knowledge is generated and develops in the real world. The aim of the present research is to make it possible to observe the process by which intellectual activities occur and progress in a real-world learning field, and to assess such activities using an objective standard. Although recognition of physical behavior can be approached using a machine learning method, it is conventionally difficult to estimate the corresponding intellectual state. This is because there is a wall between understanding superficial-level behavior and the internal-level learning situation. An essential difficulty is that the correlation between physical behavior and the intellectual state is not known.

In order to overcome this difficulty, we have proposed a new approach for sensing intellectual behavior by the complementary use of information on human activity and the spatial structure of the learning field. First, we noted the role of a learner's body as an interactive medium for obtaining knowledge from the surroundings. Thus, we investigated a characteristic stay behavior that can effectively identify situations during which a learner is engaged in important learning activity. We also showed a method for automatically recognizing the occurrence of such behavior using signal processing.

Second, this research confirmed the 2D regional dependence of learning topics in a real-world learning field, and showed that each region offers only a small number of topics. The research also focused on the 3D spatial structure of the field, i.e., the vertical distribution of an ecosystem in a multi-layered hierarchy. The results indicated that each layer contains different knowledge, and height is an important factor influencing the knowledge that a learner can obtain. Even if more than one topic occurs in the same region, we found that height information can be used to uniquely distinguish the topic being learned. We also consider the possibility of classifying human

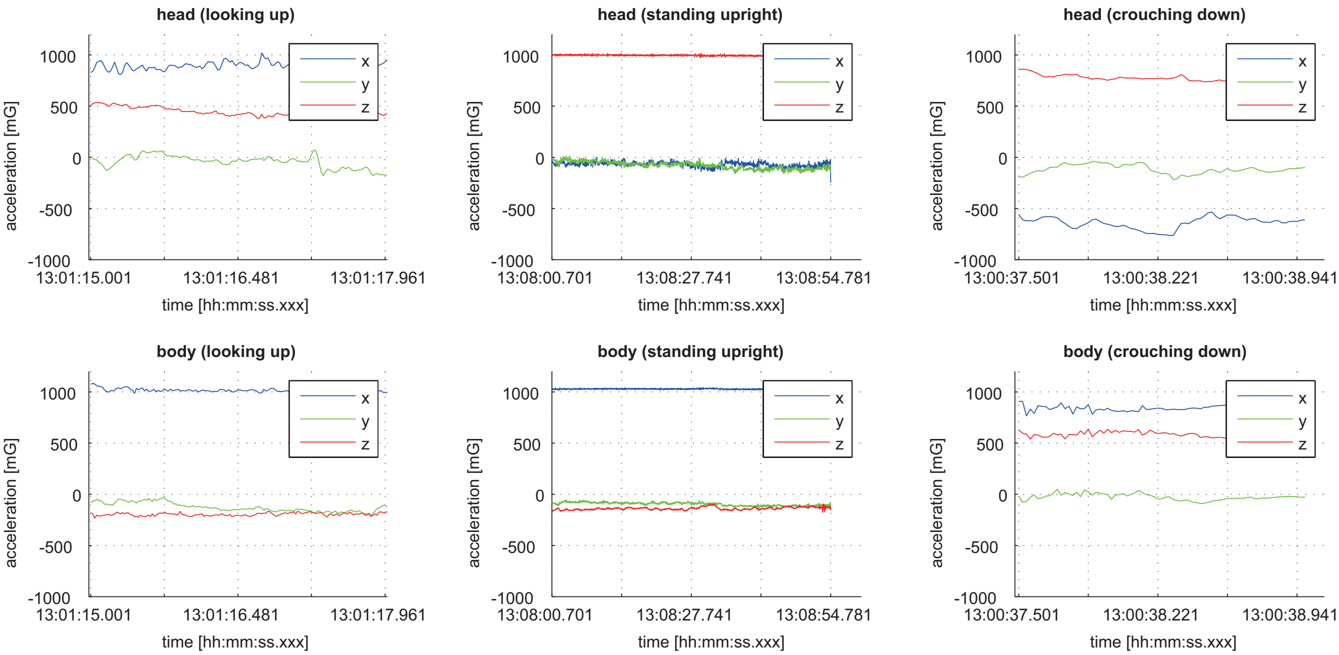

Fig. 8. Learner acceleration data for different target behaviors.

posture with respect to the vertical direction using a machine learning technique to three-dimensionally identify the learner's topic of interest.

This paper examined relationship among the human body, intelligence, and the environment by investigating real-world learning as a model case. Although many studies have been carried out on groupware, learning support, and ubiquitous computing, it is an unsolved and important problem to estimate intellectual situations at a high level of abstraction by integrating the results of low-level signal recognition.

It is hoped that our approach will act as a core for realizing an advanced service for context-aware learning support. For example, it could identify learning objects whose existence is overlooked or whose value is not discovered. This technique could identify 3D locations where knowledge has not yet been found, and could selectively encourage a learner to be aware of potential information. Moreover, numerical indices could be generated of how diversely and actively a learner studied, which are useful for assessing intellectual activity in real-world learning fields.

VI. Conclusion and Future work

To enhance human intellectual activity, it is important to understand how humans acquire and process knowledge. This paper focused on people who interact with their surroundings and learn from them, and a method was proposed for understanding how they access knowledge that exists in the real world. It involves automatically sensing particular stay behavior that occurs during important learning activities. In addition to the regional dependence of learning topics, it also takes into account the spatial structure of the learning field, i.e., the vertical distribution of an ecosystem in a multi-layered hierarchy. We found that each layer of an ecosystem contains different knowledge, and height is an important factor influencing the knowledge that a learner can obtain. We found that height information can be used to uniquely distinguish the topic being learned. We also discussed the possibility of identifying the learning topic of interest based on the body posture of the learner. Our challenge is to develop a method of estimating the intellectual state of the learner at a high level of abstraction using low-level signal data, and integrating the recognition results.

The rapid progress being made in engineering technologies has led to new ways of innovating learning support. Our intention is not to select engineering technologies that fit conventional methodologies, nor to replace old educational tools with new ones. Our challenge is instead to create an effective method of learning support that can be embodied only using the innovation of computational power. Our research is fundamental for achieving a practical understanding of the dynamics of human knowledge processing and promoting new intellectual activity in a next-generation ubiquitous society.

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