A Support Method with Changeable Training Strategies Based on Mutual Adaptation between a Ubiquitous Pet and a Learner

Xianzhi YE††, Lei JING††(a), Mizuo KANSEN††, Junbo WANG†, Kaoru OTA†, Nonmembers, and Zixue CHENG†††, Member

SUMMARY With the progress of ubiquitous technology, ubiquitous learning presents new opportunities to learners. Situations of a learner can be grasped through analyzing the learner’s actions collected by sensors, RF-IDs, or cameras in order to provide support at proper time, proper place, and proper situation. Training for acquiring skills and enhancing physical abilities through exercise and experience in the real world is an important domain in u-learning. A training program may last for several days and has one or more training units (exercises) for a day. A learner’s performance in a unit is considered as short term state. The performance in a series of units may change with patterns: progress, plateau, and decline. Long term state in a series of units is accumulatively computed based on short term states. In a learning/training program, it is necessary to apply different support strategies to adapt to different states of the learner. Adaptation in learning support is significant, because a learner loses his/her interests easily without adaptation. Systems with the adaptive support usually provide stimulators to a learner, and a learner can have a great motivation in learning at beginning. However, when the stimulators reach some levels, the learner may lose his/her motivation, because the long term state of the learner changes dynamically, which means a progress state may change to a plateau state or a decline state. In different long term learning states, different types of stimulators are needed. However, the stimulators and advice provided by the existing systems are monotonic without changeable support strategies. We propose a mutual adaptive support. The mutual adaptation means each of the system and the learner has their own states. On one hand, the system tries to change its state to adapt to the learner’s state for providing adaptive support. On the other hand, the learner can change its performance following the advice given based on the state of the system. We create a ubiquitous pet (u-pet) as a metaphor of our system. A u-pet is always with the learner and encourage the learner to start training at proper time and to do training smoothly. The u-pet can perform actions with the learner in training, change its own attributes based on the learner’s attributes, and adjust its own learning rate by a learning function. The u-pet grasps the state of the learner and adopts different training support strategies to the learner’s training based on the learner’s short and long term states.

**key words:** ubiquitous learning, training support, ubiquitous pet, mutually adaptation, changeable support strategies

1. Introduction

With the progress of ubiquitous devices and technologies, it is possible to embed tiny computing devices into homes, offices, and public spaces to grasp users’ interaction with the real world to provide services properly. Ubiquitous learning as one application field employing ubiquitous devices and technologies has great potential and becomes a hot topic. A learner can learn from the real world by observing, touching, or manipulating real objects, and learning support can be provided by smart objects, such as stationeries, schoolbags, desks, and chairs used in everyday life at proper time, place, and situation.

In a ubiquitous environment, requirements and possibilities for support of acquiring skills and enhancing physical abilities through exercise and experience in the real world are greatly increased. Training for acquiring skills and enhancing physical abilities is an important domain in ubiquitous learning. The most typical example is physical training, such as muscle exercise, rhythm controlling, etc. Other examples are training for dancing, snowboarding, cooking, manipulating a machine, etc. Our target domain of the study has the following features: the skills can be acquired by exercising repeatedly through body actions or movements; the performance of the learner in each exercise can be observed by sensors or other ways for evaluation. Not like the learning for acquisition of knowledge, training for acquisition of skills emphasizes the training process instead of the final goal.

Existing learning support systems provide educational functions to learners in various kinds of forms. Adaptation of support to learners is one of important research topics in learning support. Early e-learning systems provide only the contents with static hypertext pages, without adaptive support. A learner tends to lose his/her motivation and reduce his/her learning activities, because unchangeable instructions without adaptation to the learner easily make him/her unmotivated.

In contrast, many systems provide adaptive support. Systems with the adaptive support usually provide stimulators to a learner, and the stimulators are affected by not only the learner’s current learning state but also his/her past ones accumulated by the systems.

For example, G. Weber introduced a Web-based adaptive learning system, called ELM-ART (Episodic Learner Model, Adaptive Remote Tutor) [1]. Several adaptive techniques, based on a multi-layered overlay model and an episodic learner model, are used to give some kinds of adaptability. It is possible to make sophisticated link an-
notations and individual curriculum sequencing based on the multi-layered overlay model. The system can analyze and diagnose problem solutions and provide individualized examples to programming problems by using the episodic learner model.

With the progress of ubiquitous computing, ubiquitous learning becomes the next step in the field of e-learning. The ubiquitous learning provides opportunities for novel learning experiences. The feature of ubiquitous learning is the learning environments can be accessed in various contexts and situations. Some kinds of adaptive methods have been proposed for the ubiquitous learning.

B. Bomsdorf introduced a notion and a prototype system of plasticity of digital learning spaces, which can adapt learning materials (contents), functionalities, services, and tools to a given situation, i.e. surrounding learning environments [2].

Y. Rogers et al. developed a learning platform ambient wood for supporting learning outdoors [3]. Students can learn ecology through exploring a physical world by his/her observation with the support of related digital information. The support is triggered in an adaptive way to the students or environments.

H. Ogata proposed a computer supported ubiquitous learning environments for augmenting learning experiences in the real world [4]. Students can learn Japanese vocabularies, mimicry and onomatopoeia, polite expressions, and conversational expressions by using PDA, GPS, RFID tags, and sensor networks. The learning environment provides support adaptive to the learner’s context in learning Japanese language.

Though those ubiquitous learning support systems have adaptation to the surrounding learning environment, the activities of exploring, or situations of learning, they can not reflect a higher level of context of a learner such as dynamic changes of his/her learning states.

Ubiquitous support for training, simply called ubiquitous training as a special kind of the ubiquitous learning, has attracted a lot of attention from researchers in recent years. The ubiquitous training is for acquisition of skills, enhancing physical ability, and improving behaviors/habits, by providing stimulators to the learner based on the performance of his/her actions/behaviors.

D. Spelmezan and J. Borchers presented a wireless prototype system for real-time snowboard training [5]. The system can detect mistakes made by a learner during snowboarding. Sensors are attached to the learner’s body and inserted into his/her boots in order to give the learner immediate audible or tactile feedbacks on how to correct his/her mistakes on movements and body positions. The work shows the new possibility to support learners during sports training and to enhance their learning experience.

A computer game encouraging physical activities in [6] provides stimulators presented by a virtual fish linked with a learner’s exercise. The fish will grow bigger if the learner exercises more, and if the exercise quantity of the learner is lower than expected, then the fish will become sad to inspire the learner to exercise more.

In [7], [8], an alarm clock and a saving box are respectively bonded with some stimulators of virtual characters to help a learner form good habits. The virtual characters can act differently according to the learner’s activities. For example, a character will become big and happy if the learner often wakes up following the alarm set, while in the opposite, the character will become small and sad.

With adaptive support, a learner can have a great motivation in learning at beginning. For beginners, the adaptive stimulators can greatly motivate them especially in progress learning state. However, when the stimulators reach some levels of adaptation, the learner may lose his/her motivation and interest, because the long term learning state of the learner changes dynamically, which means a progress state may change to a plateau state or a decline state. In different long term learning states, different types of stimulators are needed. However, the stimulators and advice provided by the existing systems are monotonic without changeable support strategies. In addition, adaptive support may also have some side effects, e.g. a learner sometimes may be excited too much due to acquisition of the stimulators and push himself beyond his physical limits, in order to acquire stronger stimulators, which may cause sudden and deep decline even accidents in training. For example in [6], some learners might overdo exercise to make their fish bigger and bigger. This also requires adopting different support strategies for different learning states.

To solve the above problems, we propose a mutual adaptive support based on the learning curve of a learner with changeable support strategies to enhance the training effect. Both the system and the learner have their own states. The system tries to change its state to adapt to the learner’s one in order to provide adaptive support. On the other hand, the learner can change his/her state to adapt to the state of the system by following the advice provided by the system.

In the mutual adaptive support, we create a virtual pet referred to as ubiquitous pet (u-pet) representing the system to interact with a learner. The reason we use a virtual pet is that we believe it can provide a flexible user interface which acts as a companion or a friend of the learner. In the mutual adaptive support, the u-pet looks as if it experiences the training process together with the learner, and the u-pet owns a different learning rate and values of attributes. After every training unit, the learning rate and the values of the u-pet are adjusted according to the difference between the values of the u-pet’s attributes and the learners’ attributes. Through the adjustment, the learning rate of the u-pet adapts to the learner’s long term learning state. In addition, the u-pet adopts different learning strategies to support the learner in order to adapt to the learner’s learning state. To support the mutual adaptive process, firstly we need to evaluate the short term learning state of a learner by collecting the actions of the learner in training. Secondly the long term learning state should be obtained by accumulating the short term learning states. Finally different learning strategies are necessary for different short states and long
term states of a learner in order to provide proper advice and to adjust the difficult degree of training contents.

In many intelligent tutoring systems (ITS), learning companion agents have been developed to provide adaptive support to learners.

In [9], an ITS based on the double test learning (DTL) strategy using two companions as co-students was introduced. In the DTL strategy, a co-student is created in the learning session and receives the same training as a human student, who can observe the test issued by a teacher to the co-student, and learn from the co-student’s mistakes. However, there is no direct communication/interaction between the co-student and the human student. Moreover, this method is based on predefined rules and students’ profile. Therefore, the evaluation methods or content’s levels cannot be flexibly adapted to a student’s real learning state.

In [10], R. A. Faraco et al. introduced a learning companion system for the distance education, referred as LeCo-EAD, which uses the information about a particular student in order to adapt diverse aspects of its functionalities to the student’s individual needs. A learning companion may interact with the student in different ways, such as guiding, learning, or provoking the student. Learning contents are organized as conceptual maps presented to the student on the Web pages. New concepts are presented based on the student’s scores of doing exercises and according to a prerequisites hierarchy. However, the adaptation is based on static state transition and the learner’s profile, and the support strategies such as the ways of changing content’s levels etc. can not tuned based on the learner’s long term state deeply and properly.

In [11], companion agents which share the learning space and study collaboratively with a real learner were proposed. One type of the companion agent is called novice agent, which has poorer problem-solving knowledge than the real learner. In contrast, another type of companion agent is called advance agent, which has more problem-solving knowledge than the u-pet. One of innovative features of our system is that not only the short term state but also the long term learning state are grasped and used for adaptive support. Another is that a set of the learning strategies are prepared and applied to provide different stimulators and the difficult degree of learning contents for a learner in different learning states and phases in the learner’s learning curve. Our system can also prevent a learner from some overdoing situations in training.

Therefore, the u-pet is more suitable for the training domain than a peer-agent such as the companion agents, though companion agents are more suitable for support of learning knowledge than the u-pet.

The rest of the paper is organized as follows. The model and the mutual adaptive learning process are discussed in Sect. 2. Our proposed method is presented in Sect. 3. Evaluation of the method is given in Sect. 4. Finally the conclusions are given in Sect. 5.

2. Model

Knowledge and skills can be acquired through learning and training. From long term view, the learning/training process of a learner has progress, plateau, and decline phases. The length of the long term is dependent on different training programs and different phases in training. By our experience, the length is around 1/4 units of the total units to have change of support strategies. In the example shown in Sect. 4, the length is about 6–7 training units (2nd day of the 5 days training program). The performance in a series of units may change and has different phases: progress, plateau, and decline in a training process. The long term state is dependent on short term states accumulatively. It is necessary to adopt different support strategies for flexible support adaptive to the learner’s different states of short and long term states.

One of innovative features of our system is that not only the short term state but also the long term learning state are grasped and used for adaptive support. Another is that a set of the learning strategies are prepared and applied to provide different stimulators and the difficult degree of learning contents for a learner in different learning states and phases in the learner’s learning curve. Our system can also prevent a learner from some overdoing situations in training.

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Mutual Adaptive Learning Process

To this end, we propose our method with the following principles to support the learning.

(a) Preventing the progress from moving too fast when a learner is in the progress state, because too fast progression usually results in deep decline or long plateau. Especially it may cause accidents in physical training.

(b) Focusing on rebuilding confidence and motivation to recover from the decline state and the plateau state as fast as possible.

Based on the two principles, we propose a mutual adaptation process, which can provide adaptive learning strategies based on the long term state of a learner.

Ubiquitous learning is not only in a classroom but also outside the classroom for sports, experiencing the life, working, and entertainment. The learning contents are not only text books or Web based contents, but also game-based contents, physical training, or experiencing in a workshop or factory, etc. The learner’s learning activities can be detected by various sensors including RF-IDs, and wireless technologies. A u-pet is created as a metaphor of the system for convenience, reasonableness, and efficiency. For each learner, a u-pet is created and the u-pet is a companion of a learner. The u-pet is always with the learner and encourages the learner to do the training. When the learner is not performing the training, the u-pet will remind the learner to start training at proper time and proper place based on a pre-decided schedule.

Figure 2 shows the basic model of our support system. In this model, we consider only one learner and his/her u-pet. A learner is denoted with $U$, and a u-pet is denoted with $P$. Each learner has some attributes, such as the strength of leg stamina, skills for controlling rhythmic actions, experiences of machine operations, etc. An attribute of the learner $U$ is denoted with $u_i$ $(1 \leq i \leq n)$. Similarly, the u-pet $P$ has the same attribute as the learner’s attribute, and the attribute of the u-pet $P$ corresponding to $u_i$ is denoted with $p_i$. The values of $U$’s attributes and $P$’s attributes are used for representing the states of the learner and the u-pet. Those values are changing with the time. As shown in Fig. 1, we use $V_t(u_i)$ and $V_t(p_i)$ to denote the values, where the subscription $t$ means the values are function of time $t$.

The value of $U$’s attribute $V_t(u_i)$ is decided based on the data collected by the sensors from the learner. We define one evaluation function for an attribute $u_i$ of the learner. The evaluation function defines a method, dependent on a specified application, for evaluation of the data collected by the sensors, and it decides the value of $V_t(u_i)$. The value of $P$’s attribute $V_t(p_i)$ is dependent on its own state and the value of $U$’s value of the corresponding attribute. We define one learning function for an attribute $p_i$ of the u-pet. A learning function defines a learning method in specified contents, and it decides the value of $V_t(p_i)$.

The core of the mutual adaptive process in training is that the u-pet and the learner try to adapt to each other. The relation of the u-pet and the learner in the adaptation process includes two situations: learning and teaching.

(1) The u-pet learns from a learner

From the view of learning curve, the mutual adaptive process can be divided into many phases. There are two types in these phases. The first type is that $V_t(u_i)$ is higher than $V_t(p_i)$. The second is that $V_t(u_i)$ is lower than $V_t(p_i)$. Figure 1 shows the phases of the process in different types, the real-line curve represents $V_t(u_i)$ and the dotted-line curve represents $V_t(p_i)$. Depending on whether $V_t(u_i)$ is lower than or higher than $V_t(p_i)$, the learning method in the learning function of $p_i$ will be adjusted differently. And the learning function finally results in affecting the value of $V_t(p_i)$. In the situation, the u-pet adapts to the long term learning state of the learner and we consider this adaptation as “the u-pet learns from the learner”.

(2) The u-pet teaches a learner

The u-pet can progress in learning with a learner’s progress through changing its own attributes, and the progress results in an adjustment of the learning method in a learning function of an attribute of the u-pet. From this long term adaptation, the u-pet grasps the long term state of the learner. According to the long term state and short term state based on comparison of the current values of $V_t(p_i)$ and $V_t(u_i)$, different training support strategies are decided. Training support strategies are designed based on the two principles (a) and (b) mentioned above. The u-pet changes the level of the contents, and gives different advice and facial expressions to
the learner according to different support strategies. Those supports affect the learner’s training.

To specify those traits of the adaptation process, the following problems must be solved.
(1) How to design a concrete algorithm for the u-pet to adapt to a learner’s state and to give advice to the learner.
(2) How to design the learning strategies to adapt to learning states of the learner.
(3) How to apply the learning strategies to different learning states.

In the next section, we will explain our methods to solve the above problems.

3. Our Method

In this section, we present an algorithm for the mutual adaptation process. At first, the formal definition of some concepts in the u-pet model is given as follows.

**Definition 1** the attributes of a learner

In a traditional training, there are many physical or skill training programs. Even though in a single program, several abilities of a learner may be developed. So let U be the set of attributes of a learner for training. \( U = \{u_1, u_2, \ldots, u_n\} \). The size of U is n. Every attribute in the set U represents a specific ability needed to be trained, for example the strength of legs or stamina of arms. And we use \( V_i(u_t) \) to denote the value of \( u_t \) at the time t.

The values of U represent the state of the learner. Correspondingly we need to have a set of attributes of the u-pet to guide the training of the learner.

**Definition 2** the attributes of a u-pet

Let P be the set of attributes of the u-pet, \( P = \{p_1, p_2, \ldots, p_l\} \). And the size of P is m. Any \( p_i \) in the set P corresponds to \( u_i \) in the set U. We use \( p_i \) to represent an attribute of the u-pet. And we use \( V_i(p_t) \) to denote the value of \( p_t \) at the time t. The values of P represent the state of P. We assume that the variation of any pair of \( u_t \) and \( u_j \) from the set U and P follows learning curves in Fig. 1 and the initial value/competence of the two elements in a pair is the same. That is \( V_{0i}(u_t) = V_{0j}(p_t) \), where \( t_0 \) denotes the initial time.

In the mutual adaptation process, a learner and its u-pet own different functions each other. The learning functions compute the values of U and P, respectively. To evaluate the true learning state of a learner, we need an evaluation function for an attribute of the learner.

**Definition 3** the evaluation functions for the attributes of a learner

Let the Fu be the set of evaluation functions. \( Fu = \{f_{u1}, f_{u2}, \ldots, f_{u_l}\} \). The size of Fu is n. Any \( f_{ui} \) in the set U owns an evaluation function \( f_{ui} \) in the set Fu. This is because different types of attributes need to be evaluated in different ways. The data of the evaluation functions come from the external devices, such as sensors or RF-IDs, or we can say from the contexts of the specific training environment. Parameters \( ev_1, ev_2 \) of \( f_{ui}(ev_1, ev_2, \ldots) \) denote the events from the external devices. The number of the parameters depends on the dimension of the context of the specific training program and they are application-dependent.

**Definition 4** the learning function for the attributes of a u-pet

Any attribute of the u-pet needs to have a corresponding learning function to simulate the learning state for the u-pet. Let the FP be the set of learning functions. \( FP = \{fp_1, fp_2, \ldots, fp_n\} \). The size of FP is n. Attribute \( p_i \) in the set P owns a learning function \( fp_i \) in set FP. The learning functions vary according to types of the attributes. Every learning function owns a learning rate \( \lambda \). Adjusting the learning rate guarantees the adaptation of the u-pet to behaviors of a learner.

**Definition 5** feedback parameters of a u-pet

A feedback parameter is used for selecting support strategies and is based on the difference between an attribute of the u-pet and the same attribute of a learner. The feedback is used as a parameter to decide the learning support related to a short term learning state of a learner. We use \( fb_i \) to denote a feedback parameter of an attribute \( u_i \). And we use FB to denote the set of \( fb_1 \), i.e. \( FB = \{fb_1, fb_2, \ldots, fb_n\} \). The size of FB is n. We use \( V_i(fb_i) \) to denote the value of \( fb_i \) at the time t.

**Definition 6** a training course

A training course is a composition of different training items, e.g. enhancing muscles of legs and muscles of arms etc. For each item, we use \( d_i \) to denote a group of corresponding attributes from the set of U and P, evaluation function set Fu and learning function FP, and feedback parameter set FB, i.e. \( d_i = \{u_i, p_i, f_{ui}, fp_i, fb_i\} \). And let \( D \) be the set of \( d_i \), \( D = \{d_1, d_2, \ldots, d_n\} \). Then the definition of a training course \( C_k \) is the group of different elements in D, i.e. \( C_k = \{d_{i1}, d_{i2}, \ldots, d_{im}\} \), and \( \lambda_{im} \in D \). We suppose the size of \( C_k \) is q and \( q_{im} \) represents the m-th element in the learning course \( C_k \).

**The Adaptive Algorithm**

The purpose of this algorithm is to adapt the u-pet to a learner based on the learning actions of the learner in training. This algorithm uses a learning function to obtain a learning rate \( \lambda \) and a feedback parameter, which are used to decide the long term learning state and the short term learning state of the learner. Moreover, they are also used to decide the learning strategies applied to the learner.

**Begin**

for any \( C_k \) start course (provide learning content)

for each \( d_i \in C_k \) //**For each group of training object do the same procedure below.***/

\[ V_i(u_t) := f_{ui} \]

//**update the \( u_t \) according to the current result of the evaluation function***/

\[ V_i(p_t) := fp(V_{i-1}(p_t), \lambda(t-1)) \]

//**update the value of \( p_t \) according to the learning function which is based on the performance of U and learning rate of P in last
In the above algorithm, the learning functions of long term learning, and Δλ unit. We use logical factors and physical factors of the learner. For example, the real life is much complex, which should include psychological factors and physical factors of the learner. The learning in knowledge, skills, and experience. Moreover, they have been used in a variety of learning systems. However, these models usually only represent the behavior of simple learning or learning in a context-free situation. The learning in the real life is much complex, which should include psychological factors and physical factors of the learner. For example, the learner’s motivation and physical limit decide how much he/she can learn in terms of both quality and quantity. Therefore, we give our general form of a learning function based on this view.

\[
fp_i(V_{t-1}(p_i), \lambda(t-1)) = c \lambda(t-1) \Delta f + (1-c)V_{t-1}(p_i)
\]  

(1)

In Eq. (1), \(c\) is a coefficient for adjusting the weight of the result in the last training unit and current training unit. We use \(\lambda\) to represent the psychological state of the long term learning, and \(\Delta f = f(t) - f(t-1)\) to represent the growth of competence/value related to physical limit by time. The function \(f\) is chosen from traditional learning function such as \(y(t) = a + kt^b\) (DeJong model), or \(y(t) = a + k(t + c)^b\) (S-Curve model), according to different learning contents.

The Evaluation Functions

Evaluation functions \(f_{ui}\) are for evaluation of training progress dependent on specific training programs. By grasping the actions and movements of the learner in training using sensor networks and other ubiquitous techniques, performance of the learner e.g. how many times the learner has lifted weights can be detected. Those kinds of data can be considered as input parameters of the evaluation functions. There can be a variety of evaluation functions for different training programs. An example of an evaluation function will be given in Sect. 4.

Training Support Strategies

Training support strategies are strategies to adjust feedback methods and evaluation methods to a learner according to different states of the learner for enhancing and enlarging training effect.

There can be several factors affecting learner’s progress, decline, and plateau in the learner’s state: psychological factors, physiological factors, physical factors, and social factors. The most important factors are psychological factors including:

1. Learning motive
2. Developing more complex habits based on simpler ones
3. The conflicts of new habits with the old ones.

The learning state here includes two types in detail, the long term learning state and the short term learning state. The support strategy should adapt to the long term state and the short term state of a learner with adjusting feedback methods and evaluation methods, with consideration of the three factors mentioned above. The key to solve the problem of mapping different states to support strategies lies on how to map a learning rate \(\lambda\) and a feedback parameter to the long term state and the short term state.

1. Mapping method for the long term learning state

By adjusting the learning rate \(\lambda\), a u-pet’s attribute is adapted to the corresponding attribute of the learner. Therefore, the learning rate \(\lambda\) represents trend of the changes of the learner’s attribute with time. From long term view of learning, the learning rate reflects the trend of the learner’s behavior. Since \(\lambda\) represents the learner’s long term learning state of one attribute, we use \(\bar{\lambda}\) to denote the average of the long term learning state of more than one attributes. We assume that a learner performs several kinds of training in a unit \(C^k\), \(C^k = \{d_{k1}, \ldots, d_{km}, \ldots, d_{kn}\}\), where each \(d_{km}\) is one kind of training. Then we get \(\bar{\lambda}\) from the following equation.

\[
\bar{\lambda} = \frac{\sum_{m=1}^n \lambda_{km}}{q}
\]

(2)

The long term learning state of the learner includes
progress learning state, plateau learning state, and decline learning state. They represent the progress, plateau, and decline of learning trends. Correspondingly, given a \( \lambda_e \) (\( \lambda_e > 0 \)) as a threshold, we can decide different long term learning states of the learner when \( \bar{\lambda} \) is bigger than \( \lambda_e \), \( \bar{\lambda} \) is smaller than \( -\lambda_e \), or \( \bar{\lambda} \) is between \( \lambda_e \) and \( -\lambda_e \).

(2) Mapping method for the short term learning state
The short term learning state is related with the difference of a learner’s current training result and the u-pet’s current result. Feedback parameter \( fb \) is decided based on the difference. For simplicity, we use \( \bar{Fb} \) to stand for the average of \( fb \) of all attributes. However, although the average value \( \bar{Fb} \) is the same for different situations, the distribution of \( fb \) may be different, which means that the learning balance in different situations of training is very different. A well balanced state is that the value of each attribute of \( U \) is almost the same, which means the attributes/abilities are well trained in a balanced way. Moreover, we use \( bl \) to stand for the balance of the short term learning state. We assume that a learner performs several kinds of training in a learning unit \( C_k \). \( C_k = \{d_{k1}, \ldots, d_{km}, \ldots, d_{kb}\} \), where each \( d_{km} \) is a kind of training. Then we have the following procedure to compute the balance of the short term learning state.

- Step 1: We get the average of the learner’s short term learning state.
  \[
  \bar{Fb} = \frac{\sum_{1 \leq l \leq q} V_l(fb_{km})}{q}
  \]
- Step 2: We get distribution of each \( fb \) according to the average of the learner’s short term learning state.

**IF** \( \bar{Fb} \geq fb_{km} \)
\[
l_m = (\bar{Fb} - V_l(fb_{km}))^{1/2}
\]
**ELSE**
\[
l_m = -(V_l(fb_{km}) - \bar{Fb})^{1/2}
\]
- Step 3: To prevent the disturbance of orderless data, we use \( L \) to denote the list of \( l_m \) in an ascending order, \( L = \{l'_1, \ldots, l'_m, \ldots, l'_q\} \).
- Step 4: We get the balance degree of the short term learning state.
  \[
  b_l = \frac{\sum_{m=1}^{q} (m \times l'_m) - \sum_{m=1}^{q} m \times \sum_{m=1}^{q} l'_m}{\sum_{m=1}^{q} m^2 - \left(\sum_{m=1}^{q} m\right)^2}
  \]

Partition of \( b_l \) and \( \bar{Fb} \) leads to a more detailed description of the short term learning state of the learner. Without loosing generality, we give the basic grouping of different values of \( b_l \) and \( \bar{Fb} \), which represents the basic classification of short term learning state in Fig. 3.

In Fig. 3, the two horizontal dotted lines divide the whole area into three parts: one adjacent to the x axis, which represents the average of the short term learning state is close to that of the u-pet’s, while other two parts represents that the short term learning state is much higher or lower than that of the u-pet’s respectively. In addition, the single vertical dotted line divides the whole area into two parts: the left one, adjacent to the y axis, means the short learning state is balanced, while the other represents unbalanced area. The sub-area II, for instance, represents that the short term learning state is balanced and higher than that of the u-pet’s in average, while the sub-area VI means totally opposite. Under different long term learning states of the learner, even the same area leads to different learning strategies for the learner. We give an example of learning strategies based on different combinations of the long term learning state and the short term learning state as follows.

- **Case 1.** \( \bar{\lambda} > \lambda_e \)
  Here \( \lambda_e \) is a threshold decided depending on specific learning contents.

  In this case, a learner is in a progress learning state, which means proper and sufficient motives are presented. The learner has seldom difficulty in forming new behaviors from existed behaviors or changing simple behaviors into complex behaviors, which means he/she can acquire a skill smoothly. However, during this period, the learner may confront problems of progressing too fast to hurt him/her or lose confidence when suddenly confront some big obstacles.

  The support strategies are mainly represented by the advice to the learner, facial and body expression of the u-pet, and the level of learner (LoL). We assume that LoL varies in the range from \( LoL + 3 \) to \( LoL - 3 \) after each training unit, which affects the upgrade or downgrade of the level of contents (LoC). Table 1 shows the details for the case 1.

- **Case 2.** \( -\lambda_e \leq \bar{\lambda} \leq \lambda_e \)

  In this case, a learner is in a plateau learning state, which means the learner faces the physical limit and sufficient motives are required. The learner may have some difficulties in forming new behaviors from existed behaviors or changing simple behaviors into complex behaviors for overcoming temporary physical limitation, which means skill acquisition will last for very long time. The learning strategy in this situation focuses on helping the learner to
Table 1  Training support strategies for progress learning state.

| Area   | Situations                              | LoL (Level of learner) | U-pet's expression | U-pet's advice |
|--------|-----------------------------------------|------------------------|--------------------|---------------|
| I (p1) | The learning result of a learner is consistent | LoL:= LoL +3            | Happy              | Keep on       |
| II (p2) | This situation indicates that a learner may progress too fast and hurt himself/herself | LoL:= LoL +2            | A little tired     | Take rest a little |
| III (p3) | This situation indicates that a learner may confront some obstacles in learning. | LoL:= LoL +0            | A little worried   | Pay attention  |
| IV (p4) | This situation indicates that the learning result of a learner is unbalanced | LoL:= LoL +2            | Unbalanced smile   | Be concentration |
| V (p5) | The learning result of a learner is unbalanced and a little inconsistent, and some attributes of training are progressed too fast. | LoL:= LoL -1 Slow down the too fast parts | Tired and abnormal/unbalanced smile | Be concentration, Rest a little on some part |
| VI (p6) | The result is unbalanced and inconsistent, also the learner may face some obstacles | LoL:= LoL -1 Change to easier level | Abnormal, worried | Be more careful, pay more concentration |

Table 2  Training support strategies for plateau learning state.

| Area   | Situations                              | LoL (Level of learner) | U-pet's expression | U-pet's advice |
|--------|-----------------------------------------|------------------------|--------------------|---------------|
| I (p1) | This situation indicates the learning result is consistent. | LoL:= LoL +0          | Dull               | More work     |
| II (p2) | This situation indicates that a learner may begin to break out from the state of plateau. | LoL:= LoL +1          | Surprised          | You can do better |
| III (p3) | This situation indicates that a learner may confront some obstacles in learning, or a learner may begin to lose confidence. | LoL:= LoL -1          | Sick               | Be careful    |
| IV (p4) | The learning result of a learner is unbalanced. | LoL:= LoL -1          | Abnormal and dull | More work, pay concentration |
| V (p5) | This situation indicates that the learning result of a learner is a little inconsistent and progress is unbalanced. | LoL:= LoL -1          | Surprised and abnormal | Be concentration, You can do better |
| VI (p6) | This situation indicates that the learning result is unbalanced and inconsistent and also a learner may lose confidence. | LoL:= LoL -2          | Abnormal and sick | Be careful, pay concentration |

Table 3  Training support strategies for decline learning state.

| Area   | Situations                              | LoL (Level of learner) | U-pet's expression | U-pet's advice |
|--------|-----------------------------------------|------------------------|--------------------|---------------|
| I (d1) | This situation indicates the learning result is consistent but did not turn good. | LoL:= LoL -1          | Weak               | Summon up     |
| II (d2) | This situation indicates that a learner may begin to break out from the state of decline. | LoL:= LoL -0          | Refreshed          | Good sign     |
| III (d3) | This situation indicates that a learner is losing his/her motive. | LoL:= LoL -2          | Very weak          | Don't give up |
| IV (d4) | This situation indicates that the learning result of a learner is unbalanced and did not turn good. | LoL:= LoL -2          | Abnormal and weak  | Summon up, pay concentration |
| V (d5) | This situation indicates that the learning result of a learner is a little inconsistent and progress is unbalanced. | LoL:= LoL -0          | Refreshed but abnormal | Good sign but pay concentration |
| VI (d6) | This situation indicates that the learning result is unbalanced and inconsistent and also a learner is losing confidence. | LoL:= LoL -3          | Abnormal, very weak | Don't give up, pay concentration |

break out from the plateau learning state. To break out from this state and to move into a progress learning state, the learner may need to repeat content of same level for many times. In addition, the learner needs sufficient motives for preventing the learner from losing confidence in repeated learning. The support strategies are shown in Table 2 for case 2.

- Case 3. \( \lambda < -\lambda_e \)

In this case, a learner is in a decline learning state, which means the learner is losing confidence and alternative or proper motives are required. The learner may have some difficulties or obstacles in forming new behaviors from the existing behaviors or changing simple behaviors into complex behaviors, and is losing motivation or confidence, which means they cannot acquire a skill well. The learning strategy in this situation focuses on helping the learner to break out from the decline learning state and to rebuild the confidence and interest in learning. To break out from this state and move into progress learning state, the learner may need to repeat learning contents at an easy level. In addition, the learner needs sufficient and proper motives to rebuild the confidence and interest in learning. The support strategies are shown in Table 3 for case 3.

Content Adjustment Method

The adjustment of content is very important in helping a learner. Especially, the difficulty of content is vital to the training effect of the learner. An appropriate difficulty of content increases the motivation of the learner greatly and improves the confidence of the learner, because these two psychological states have an important relation with the training effect of the learner.

In this paper, to describe the adjustment of content, two concepts are defined: LoL (the level of a learner) and LoC (the level of content). LoC presents the level of the contents.
The higher the more difficult. The LoL describes the level of a learner, which is a parameter to decide LoC.

By applying the LoL, the support strategies can control the changing speed of LoC (mainly content’s difficulty). Therefore, when a learner in a progress state learns fast, the content’s difficulty will accordingly be upgraded fast. When a learner faces some difficulties in training, the content’s difficulty will be upgraded slowly or even downgraded to restore the learner’s confidence. The detailed method is below.

After the LoL is updated according to the support strategies shown in Tables 1, 2, and 3, the content’s difficult level (LoC) is updated as follows: \( \text{LoC} := \text{INT}(\text{LoL}/M) + 1 \). Function \( \text{INT} \) is to take the integer part of \( \text{LoL}/M \). Here, \( M \) is an integer. In other words, wherever the LoL increases by \( M \), then LoC is increased by 1. The concrete values are decided and tuned for specific contents and applications.

4. Implementation and Evaluation

We have developed a prototype system consisting of a mutual adaptation module based on the adaptive algorithm, a support module based on the support strategies, a data collection module, and a u-pet interface. We implement the mutual adaptation module in the form of DLL (Dynamic Link Library). Therefore, a training application can easily link with it and provide mutual adaptation process support to learners, and developers of training application do not need to know the detail of the module. We use C++ in VC6.0 for building the DLL and to implement other modules. The data collection module is for dealing with the data collected by using RF-ID readers and/or sensors. Data collection and sensors are dependent on different applications.

In the implementation of our system, available contents are registered in an XML file. What attributes can be trained by using each of the contents is also registered in the file. If a learner wants to train plural attributes, he/she can select one of the contents that can cover the attributes. If there is no content which can cover the necessary attributes, the learner can select several contents to cover the attributes.

In this section, we use an application example (case study) to show how our system works and the effect of the support provided by our system.

Outline of the Application

In this experiment, a rhythm training application is used for improving skills of controlling rhythms in physical exercise.

The application gives scripts of rhythms with visual and/or auditory way, and each rhythm is related to a series of actions. A learner is required to do the actions by using a gymnastic apparatus according to the given rhythm as correct timing as possible, not early or late.

The learner’s performance attribute considered in the application is the rhythm accuracy, which means how accurate the learner can perform actions following a given script, in the sense of timing.

The data is collected from a gymnastic apparatus using sensors, and the evaluation function compares the given rhythms (the timing of actions) to the rhythms that the learner performed, and counts the percentage of correct actions to the total actions in the script.

The Overview of the Experiment System

Figure 4 (a) shows the experiment system, which includes a gymnastic apparatus, sensing devices, and a monitor as user interface. A learner uses the gymnastic apparatus to perform certain actions, by stepping down on the right and left pedals alternately. The monitor displays contents, advice, and evaluation results to the learner. The contents include scripts of rhythmical actions, methods for following the rhythm, and music accompanied with the given rhythm to increase the learner’s interest.

The sensing devices include an RF-ID reader and tags attached to pedals of the gymnastic apparatus. We use RF-ID, since the tags can be flexibly attached to different objects in order to detect and identify the real actions on the objects, which is vital to the real life learning. The RF-ID reader reads the tags in order to detect the movement of pedals of the gymnastic apparatus to grasp the actions of the learner. Though there is a delay of 200 ms due to reading tags by the reader, the movement can be detected and taken as the input of the algorithm of the u-pet.

Figure 4 (b) shows a subject is using the experiment system by stepping on the pedals, while watching the message from the monitor (the interface of the u-pet), and Fig. 4 (c) shows an RF-ID reader and tags attached on the gymnastic apparatus.

Figure 5 is a screenshot of the monitor. The left part of the screenshot shows a script of the actions with rhythms represented by two kinds of colored rectangles, which move down (animation). There are two horizontal lines at the bottoms, upper line and lower line. The subject is required to step down when a rectangle is moving between the upper
line and the lower line, which means the subject does the action on the correct timing. The levels of difficulties of the rhythms are set based on adjusting the speed of the moving rectangles and the distance between the upper and the lower lines. The left and right leg/foot should follow the two kinds of moving rectangles, respectively. The right side of the screenshot shows a list of actions received from sensors (data from the reader). In the middle part of the screenshot, a moving u-pet is shown. It acts together with the learner as an interface of the u-pet. The speed of its moving is adaptive to the learner based on the attribute of the u-pet.

The core of the application is our algorithm proposed in the last section. It compares timing of the actions in the given rhythmic script with the actions from sensors. The evaluation function in this application is to count the percentage of actions performed at correct timing to the total actions in the given script. After each training unit, the u-pet gives different advice and expression to the learner shown in Fig. 6.

In addition, we developed a PDA based interface of the system as shown in Fig. 7, so that the training can be performed in a specific place such as a private or small place. The PDA based interface is implemented in Embedded C++ in EVC4. The basic functions of the PDA are the same as the PC based interface shown in Fig. 5. Some differences have been made according the low resolution and battery problem of the PDA. As shown in Fig. 7, the lower portion shows the u-pet and its advice. The upper portion shows the script of the rhythm. Rectangles to represent rhythms move from right to left.

Objectives of the Experiment

(a) To confirm whether the system/algorithm can adapt to a learner smoothly.
(b) To see whether the provided contents levels and advice are suitable for the learner’s learning states.
(c) To investigate if the system is effective as a support system.

Methods of the Experiment

(a) Comparing the learning curves of subjects (learners) with ones of the u-pet based on the collected data.
(b) Observing and recording the behaviors of subjects by human observers and comparing the recorded behaviors with the learning states of subjects. Interviewing the subjects in the break time between two training units about their feelings on their performance, the difficulty of the rhythmic script of the unit, and the advice of the u-pet, etc.
(c) Taking a questionnaire on learning effects of the subjects, when finishing training of all units.

Description of the Experiment

In this experiment, training scripts of five different difficulty levels of contents (LoC) are prepared by setting interval time between two actions and the maximum difference from correct timing.

The whole training lasted for five days and a subject was required to do 5 training units per day. The time period of each training unit was 5 minutes and the break time between two units in a day was around 2 minutes. Totally five subjects attended the experiment.

Observing and recording the behaviors of learners by human observers, and comparing the recorded behaviors with the learning statuses of subjects were performed in each training unit. View points of the observation are real performance of a subject, expression and words of the subject to the u-pet’s advice and expression, and expression and words of the subject about the current level of contents.
During the observation, we mainly record a subject’s expression, words, and performance. For example, did the learner smile or speak pleasantly to the feedback from the u-pet? Did the learner say anything hard about the training? And those recording are based on the three view points of observation.

Also, interviewing the subjects in the break time between two training units about their feelings on their performance, any difficulty of the scripts provided by the system, and the advice and expression of the u-pet, etc. were performed.

After all the training units, a questionnaire on learning effects was filled out by each subject.

Experiment Results

Comparison of the Subject’s and the U-Pet’s Curves
To confirm whether the system/algorithm can adapt to a learner smoothly, we collected data about the subjects’ training performance and computed the state of the u-pet.

Figure 8 shows the historic values of the attribute of subjects and the attribute of their u-pets. The X-axis stands for ordinal numbers of the training units and the Y-axis stands for the value of the attribute in each unit.

From the comparison of the learner’s attribute and the u-pet’s attribute, we can figure that the change of the u-pet’s learning curve follows the learner’s learning curve, but the variation of the u-pet’s learning curve is smoother than the learner’s. From this, it is confirmed that the u-pet’s learning curve is adapted to the learner’s gradually, and the u-pet’s learning curve remains some independences from the learner’s. The independences give the chances for the u-pet to advise the learner to slow down for rest or to do more effort for training.

To See Whether the Provided Contents Levels and Advice are Suitable for a Learner’s Learning States.
The support strategies are decided based on the difference between a learner’s attribute and the u-pet’s attribute as well as the learning rate $\lambda$. Figure 9 shows the support strategies in every training unit, and each point shows the type of support strategies referring to the Table 1, Table 2, and Table 3. In Fig. 9, p1–p3, d1–d3, and f1–f3 refer the labels of strategies in Table 1, Table 2, and Table 3 respectively. Here, “p” is short for progress, “f” is short for flat which means plateau, and “d” is short for decline.

We prepare 5 difficult levels of scripts ($1 \leq \text{LoC} \leq 5$) by changing the interval times between two actions (the shorter the more difficult), and the allowable difference from the correct timing of an action (the smaller the more difficult). In each of the 5 levels, we set 8 levels of a learner (LoL) for the learner to go up from one LoC to a more difficult LoC. In other words, the system increases the level of the learner (LoL) based on the performances of the learner. When the level of the learner is increased over some threshold, the system will provide the next difficult level of a rhythmic script. Here the level of content (LoC) is set to $\text{INT}((\text{LoL}/8) + 1$ in this case study, so that the learner will not easily upgrade to the next level. The growth of LoL is according to the learning state of the learner, and the support strategies shown in Table 1, Table 2, and Table 3. Figure 10 shows that the growth of the level of learner (LoL).
From Fig. 10(a), we can see at 7th training unit and 11th training unit of subject A, LoC is changed to level 2 and level 3, respectively, since the LoL is increased up to 9 at 6th unit, and up to 16 at 10th unit. The performance of the subject declined at 7th training unit and 11th training unit as shown in Fig. 8(a), because the subject is unfamiliar with harder levels of rhythms. After 11th unit, LoL remained almost unchanged for some training units (plateau state) as shown in Fig. 10(a), since level 3 is harder than level 2. Those changes can be confirmed through observation and interview.

More specifically, let us see the situations of subject A. From the observation of subject A, the movement of her feet in 7th and 11th training units could not follow the rhythm apparently. Subject A in the interview after 7th and 11th training units said that her performance was not good. The observation of subject A after 7th unit shows that the movement is obviously improved in 8th, 9th and 10th training unit. Moreover, in 10th training unit, subject A said that she did very well. However, after 11th training unit, the observation shows performance improvement is very slowly. In some training units the subject’s movement seemed to be improved a little, however in the next training unit, the performance turned bad again. After several training units, the performance became consistent and improved gradually. The interview also shows the same situation. In 15th and 16th training units, the subject thought that she did well and also would do well in the next training unit, but in 17th training unit, the subject admitted that her performance was not good. After 17th training unit the subject thought her performance became good.

In the same way, for each of the five subjects, we confirmed the data collected by the system with the observation and interview. Due to the page limitation, we only show data of subject B and C in Fig. 8(b), Fig. 9(b), and Fig. 10(b). Regarding the difficulty of content, from answers to the interview, the subjects think that content’s difficulty level of about 60% units is appropriate. For about 30% units, the subjects think that the current level is difficult. For about 10% units, the subjects said it was too easy. However, for most situations, the subjects think that the current level is more interesting and challengeable even though it is a bit harder than his/her current skill.

The observation and interview of subjects’ performance show that most subjects could do well for LoC = 1 quickly, and most subjects’ performance fell at the first few training units in the new level of contents. All subjects progressed at first and then fell into a plateau state. That is, the real learning curve does not proceed smoothly: the plateaus and sometimes declines are also possible phases of the learning curve.

From the result of interview, around 80% units, the subjects think that the u-pet’s expression and advice fit for their learning situations, and is helpful for them to restore confidence or increase motivation. This indicates that the support strategies fit for learner’s learning states and are helpful. Therefore, our method can detect a learner’s learning state and give appropriate support to the learner. For not more than 20% units, the subjects’ answers are negative, because they think that the u-pet expression and advice are a little simple.

More concretely, let us see the Subject A’s situation. The distribution of $\lambda$ for subject A is shown in Fig. 11 (suppose $\lambda_e = 0.5$, $\lambda$’s initial value = 0.1). For example, at 10th training unit, the long term learning state is progress (due to $\lambda = 0.7$), and the subject’s value is a bit higher than the u-pet’s shown in Fig. 8(a). Therefore, the support strategy $p1$ is provided to the subject at 10th training unit as shown in Fig. 9(a), which means the learning result of the subject is progressing, and the subject’s state is good, and the u-pet also praises the subject. In the 10th training unit, the observation shows that subject A paid attention to the u-pet’s expression, and smiled to the advice of the u-pet. The subject mentioned the current level was easy. In the interview, subject A thought her performance was good, the advice was appropriate, and the current level is easy. The subject also
said that she could feel rhythms and her feet’s movement could follow her control precisely.

In 11th training unit, the observation shows that subject A paid attention to the u-pet’s expression, and smiled to the advice of the u-pet. However, the subject did not mention ease or difficulty about the current level. In the interview after the unit, the subject thought her performance was good and the advice was appropriate, but the level was difficult. The subject also said it became difficult, but she liked to do the difficult level.

As another example, let us see 20th training unit of subject A. The long term learning state is decline state ($\lambda = -0.65$), and the subject’s attribute is almost the same as the u-pet’s at 20th training unit as shown in Fig. 8 (a). Therefore, the support strategy $d_1$ is provided to the subject at 20th training unit as shown in Fig. 9 (a). Therefore the u-pet encourages the subject and tells the subject to try more. In 20th and 21st training units, the observation shows that subject A only paid attention to the u-pet’s expression, but did not have any response to the advice of the u-pet. However, after 20th and 21st in the interview, the subject thought her performance was good, the advice was appropriate, and the current level was easy.

By checking Fig. 10 (a), we can see the LoL decreased to 15, thus LoC is changed accordingly from level 3 to level 2 at 20th and 21st, based on the content adjustment method proposed in Sect. 3. This can explain why the subject felt easy. In other words, our system adapted to the level of a state of the subject, by changing the difficult level of training contents.

For further discussion, some common traits in support strategies of different subjects can also be found in Fig. 9 (a) and (b). For first few training units, the support strategies are varied from $p_1$–$p_3$ or $f_1$–$f_3$, in which some positive stimulators including praise are provided. The support strategies are varied from $f_2$, $d_1$, $d_2$, which means the comfort based advice is provided and then the support strategies change back again. This is also consistent with learning habit of general learners and fit for the theory of a learning curve.

From the above discussion, we can conclude that the providing of support strategies is according to the learner’s short term learning state and long term learning state.

**Investigation of Effectiveness of the System**

To investigate if the system is effective as a support system, we take a questionnaire after all training units are finished.

**Questionnaire**

1. Is the system more interesting than a normal physical training?
2. Do you think the u-pet is a learning partner of you in the training program?
3. Is the u-pet based interaction acceptable and friendly?
4. Could the system provide proper rhythms which can fit to your level?
5. Is the advice from the u-pet helpful to you?
6. Does the exercise difficulty’s adjustment maintain your motivation or restores your confidence?
7. Would you like to use such training systems in your real life?
8. Besides above questions, write down freely your comments.

The subjects were asked to answer each question with 5 scales, such that 5: Strongly agree, 4: Agree, 3: No Strong feeling, 2: Disagree, 1: Strongly disagree. The statistics of the answers is shown in Fig. 12.

**Interpretation of the Questionnaire Results**

From Fig. 12 and comments written freely by the subjects, we can get some hints for evaluation and improvement of the system.

**Need for Training Support Applications Based on Mutual Adaptation between the U-Pet and a Learner**

From Q1 and Q4, all subjects answer either 4 or 5. Most subjects like to use such an application. Some subjects report that he/she likes to train together with the u-pet and the u-pet motivates him/her in exercise. Other subjects after using the system hope the system can link more objects in the real life, for example the bed, desk, bicycle, and so on. From those, we can see that such training support applications can raise learner’s motivation and interest. However, some subjects think that the system should provide more advice to a learner. From this point of view, we think that the support strategies should be given in more detailed ways, to obtain better results.

**The Features of the Training Support Application**

From Q2, Q3, most subjects think such a training application based on mutual adaptation is easily understandable and acceptable. Most of the subjects think the u-pet can adapt to a learner’s behavior and reflect the effect from the learner’s interaction. Some subjects think the expression of the u-pet is lively and rhythm of movement is very distinctive. A subject said that she was very happy and wanted to do more training when the u-pet praised her. Thus, we can indicate...
that a training support application based on mutual adaptation between the u-pet and a learner can affect the training of the learner especially when the u-pet’s progress and growth reflect the learner’s performance. However, some subjects think that it will be more interesting if the learner can choose the character of the u-pet and it will be better if the u-pet has more expressions. From this point of view, we think the support messages and advice should be improved and enriched.

The Effectiveness and Possibility of Such Training Support Application

From the result of Q6, most of the subjects think exercise difficulty’s adjustment maintains a learner’s motivation or restores confidence. However the answers of Q5 are not so satisfied. Some subjects think that the advice should be more detailed ones, and give more hints. For solving the problem, our current support strategies should be extended to give more detailed and professional advice. From the result Q7, it shows that most subjects like to have such a training support application in the real life, and a subject said that she really loved such an application and wished to continue to use such an application after the experiment. From this, we can say the effectiveness and possibility of the application are positive.

5. Conclusions

In this paper, we proposed a mutual adaptation process with changeable support strategies for enhancing physical abilities and acquisition of skills. Traditional non-adaptive learning support systems have problems for a learner to grasp a picture of his/her learning states and for the systems to provide a support adaptive to his/her states, so that the learner cannot learn efficiently and may lose his/her interests in learning easily. Existing adaptive learning support systems have problems to provide changeable learning strategies. Therefore, the systems may provide efficient support adapted to the learner in some learning phase, but cannot deal with other phases, so that the learner may either push himself beyond his limits or lose his/her interests easily.

One of the aims of this research is to propose a mutual adaptive support to enhance the training effect. Both the system and the learner have their own states. The system tries to change its state to adapt to the learner’s in order to provide adaptive support. On the other hand, the learner can change his/her state to adapt to the state of system, following the advice of the system. The mutual adaptation is not only the adaptation of the short term learning state but also the adaptation of the long term learning state of the learner.

The second aim is to design changeable support strategies and to adopt different support strategies for different learning states in order to enhance the learning effect of a learner.

By our methods, learning effects can be greatly improved. More specifically, the performance/state of a learner can be grasped. The learner can get support adapted to his/her learning performance/state. Especially, when the learner is in a decline phase which means the performance of the learner gradually becomes bad, our system can support the learner by encouraging the learner with positive messages, and/or changing the difficult level of the learning contents to easier one. When the learner is in a progress phase which means the performance of the learner is greatly improved, our system can support the learner by awarding the learner, and/or warning the learner of the possible danger in pushing him/her beyond the limits, which may cause sudden and deep decline even accidents in training.

In addition, we use a u-pet as an interface of the support system to interact with a learner as a companion in a ubiquitous environment. In the mutual adaptive process, the u-pet looks like to experience the training process with the learner together, and the u-pet owns a different learning rate and attributes of competence/performance, which give the chances to provide the mutual adaptive support.

Besides the rhythm training system described in Sect. 4, our methods can be applied to many physical exercise/training, such as weight training, aerobics, and dancing. The data collection part, e.g. the types and deployment of sensors, may be changed for different applications, but the algorithm and supports strategies proposed in this paper can be used for those applications.

A limitation of our method is that it cannot be applied to knowledge-based training which needs knowledge and reasoning, such as playing chess, because applying knowledge and logic thinking are difficult to be observed and evaluated quantitatively by the sensors.

In the future, we will apply the proposed algorithms and strategies to different training programs and we will also research on how to remove the limitation of the proposed method.

In this paper, the average performance of all attributes is used for reducing the complexity of designing support strategies, though performance of every attribute has been computed. Development of new methods and elegant support strategies which can support every individual attribute separately will be one of our future works.

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Xianzhi Ye received his B.E. degree in computer science and engineering from the Zhejiang University, China in 2005. He received M.S degree in computer science at the University of Aizu, Japan in 2009. Since 2009, he has been a software engineer in the Department of Information Technology, Bank of WenZhou, China. His research interests include ubiquitous learning and natural intelligence.

Lei Jing received his B.E. degree in Electrical and Mechanical Engineering from the Dalian University of Technology, China in 2000, M.E. degree in Computer Science from the Yanshan University, China in 2003, and Ph.D degree in computer science and engineering University of Aizu, Japan in 2008 respectively. He is currently an assistant professor with special duty in Asia Career Development Program at University-Business Innovation Center, the University of Aizu. His research interests include sensor networks, context-aware computing, and ubiquitous learning.

Mizuo Kansen received his LL. B. from Sophia University in 1987, and his M.S in Computer Science and Engineering from Aizu University in 2003. He is a member of IPSJ and JSAI. His research interests are e-learning systems and case-based reasoning systems.

Junbo Wang received his B.S. and M.S. in Electrical Engineering from YanShan University, China in 2004 and 2007 respectively. He is now pursuing a Ph.D. degree in the graduate school of Computer Science and Engineering at the University of AIZU, Japan. His current research interests are ubiquitous situation awareness platform, ubiquitous learning, and sensor networks.

Kaoru Ota received the B.S. degree in computer science and engineering from the University of Aizu, Japan, in 2006, and M.S degree in computer science from Oklahoma State University, USA in 2008. She is working toward Ph.D degree in computer science at the University of Aizu. Her current interests of research are mobile agents in wireless sensor networks and ubiquitous learning.

Zixue Cheng received B.Eng. degree from Northeast Institute of Heavy Machinery in 1982; his Ph.D from Tohoku University, Japan in 1993. He was an assistant professor from 1993 to1999, an associate professor from 1999 to 2002, and has been a full professor, since 2002, in the School of Computer Science and Engineering, the University of Aizu, Japan. His current interests include Distributed Algorithms, Distance Education, Ubiquitous Learning, Context-aware Services, and Functional Safety for Embedded Systems.