Assimilation and Accommodation for Self-organizational Learning of Autonomous Robots: Proposal of Dual-Schemata Model

Tadahiro Taniguchi
Dept. of Precision Engineering
Graduate School of Engineering, Kyoto University
Email tanichu@groove.mbox.media.kyoto-u.ac.jp

Tetsuo Sawaragi
Dept. of Precision Engineering
Graduate School of Engineering, Kyoto University
Email sawaragi@prec.kyoto-u.ac.jp

Abstract
In this paper, we propose a new self-organizational machine learning system, called Dual-Schemata model. This model is based on Piaget’s schema theory, which is well known theory in developmental psychology. In our model, we divide Piaget’s original schema into two parts; one is a perceptional schema and the other is an intentional schema. By this division, we can describe both adaptation and learning processes of a human and/or of an autonomous robot more simply and more effectively. Further, we show a series of experiments, in which a facial-robot with our Dual-Schemata model attempts to chase movements of a colored ball, and then we present that a robot gets to obtain some inner symbols concerning with those ball movements.

1. Introduction
Nowadays a consumer robot business is coming alive such as AIBO (sony), Wakamaru (mitsubishi), Roomba (iRobot), etc. So far many robots have worked in factories, but have never interacted with ordinary people for a long time. But the current advancement of information technology has made it possible for a human and a robot to interact with each other.

In order to realize a human-friendly interaction, a robot should be able to behave autonomously without supervision and teaching by a human. However, current technologies are not sufficient for a design of autonomous robots that are assumed to live together with humans. One of the main reasons of this is that there is no reliable technique of machine learning fitted to such a human-friendly robot.

There indeed exist many machine learning methods such as reinforcement learning, BP-algorithm of neural networks, genetic algorithms, and so on. However, most of those conventional methods are not effective for the design of autonomous robots, since all of these are based on the behaviorism.

From the viewpoint of behaviorism, learning is to associate something or some ideas with other things or ideas attempting to establish correct sensorimotor relational mappings. Wherein, the relational structure is usually given from outside, and there assumed to be some supervisors who teach the relations to the leaner. Thus, a main activity of learning in behaviorism is to modify and tune inner functions associating sensory inputs with correct responses so that a learner can get more rewards. This is a task of functional optimization.

Such an approach may indeed be effective for some tasks in which learners know well what kind of things to learn and the targets to be learned can be fixed, but in real world this approach is not effective at all.

Due to the existence of the intentional others (e.g., a human), a robot cannot completely predict nor control the results that are brought about through the interactions with the human. A robot can accumulate interactions with the external reality including a human, but cannot form any fixed models of such a reality inside, since there are so many things to learn and they are changing their properties from time to time. What a robot can do therein is just to reflect on those experiences and reconstruct a definition of the subjective reality, which causes it behave differently and changes its interaction patterns. By iterating this cycle, a robot comes to be embedded with the real world, and what are acquired within a robot becomes grounded to the world. We think that this is a general learning model of autonomous robots that is characterized as a continuous self-production process being driven by some internally-inspired motives.

Similar to the above, Harnad has insisted the "symbol grounding problem": how to extract intrinsic...
meanings out of the externally provided *encoded symbols*. Along this idea, we can say that any implemented knowledge designed by a human designer cannot be *grounding* for an artificial robot. Actually, cognitive scientists and artificial intelligence people used to be traditionally concerned solely with the cognitive representation which can be described as symbolic. It was concerned with the semantic relation between cognitive categories and their environment counterparts through some direct representational relation without taking into account any sort of internal organizational constraints.

Based on the above considerations and requirements, we invent a new machine-learning paradigm that is not originated from behaviorism, but is based on some other philosophies and can explain all the processes commonly found in mankind’s developmental and cognitive systems in general. Main idea of our proposing Dual-Schemata model is summarized as follows:

1. encoding of the sensations (sets of signals from transducers interpretable as states of reality) by using elementary signs
2. associating encoded sensation with codes of actions
3. constructing strings of codes for "states actions-..." stored in the memory
4. assigning to these strings of signs values of goodness interpretable under specific goals, which allow interpretation and/or reflection of "experiences"
5. discovering classes of experiences (generation of the concepts)
6. forming hypotheses of new behavioral rules using previously stored results of prior processes.

Our proposal in this paper is one of the first steps of the new machine-learning paradigm.

2. **Schema Dynamics**

J. Piaget insisted that human development of cognitive system is based on a Schema System. Schema is a module of human cognitive system. Our cognitive system has many schemata, and they can be active in parallel during we interact with the environment. Schemata are dynamical entities that can adapt to our environment in order that we can perform in a more natural way. He believes that our cognitive system is not designed a priori, but it becomes functional through interacting with many things around us after the birth. With respect to the human developmental process, Piaget explicated the stages of psychological maturation. Distinguished characteristics here is that although the each stage forming the development engages different brain areas to a varying degree, each stage has a common developmental curve (i.e., starting at a rapid pace, followed by deceleration, and ending in a plateau). He insisted that this dynamics of development is governed by growing organization of schemata, and dynamical schema reconstruction can reduce the number of degrees of freedom, while the variety and frequency of interactions with the environment do increase accordingly.

During the above developmental process, the fundamental mechanism underlying therein consists of the two successive phases of *assimilation* and *accommodation*; each developmental cycle *assimilates* a new segment into the preexisting structure, and *accommodates* the structure to the segment. In terms of schemata, assimilation is a phase in which a schema gets the outside world into the inner world and comes to describe outside world. This assimilation process does not always work well, but may encounter some unexpected things, when a schema *accommodates* itself as well; accommodation is a phase in which a schema changes its own structure dynamically in order to adapt to the unknown to encounter.

Summarily, two factors must be accounted for in a model of memory dynamics within an autonomous robot: when a new experience that partially coincides with an earlier one and partially contradicts it, an autonomous agent must be able to destabilize its memory creating a conflict or tension. As the experiences accumulate and the tension reaches a threshold, the system snaps into a new organization that restores the stability temporarily, until the experience base is further expanded. The process can continue indefinitely, adding new experiences and integrating them into the base. We think this model is capturing an essence of self-organization, and can be extended as a very modern system philosophy, i.e., *constructivism* instead of conventional behaviorism. In the next section, we propose a Dual-Schemata model, which is modified from Piaget’s original schema model.

3. **Dual-Schemata model**

In this section, we propose a Dual-Schemata model, which consists of two kinds of schemata; *perceptual schema* and *intentional schema*. Both of these do work
together, thus play a role equivalent to Piaget’s original schema. Especially, we put an emphasis on dynamical aspects of those schemata, in which a machine-learning method for autonomous robots is embedded.

Perceptional Schema (PS) describes an external reality as a function. The function (F) is a mapping from a sensory input at time t (S_t) and time t+1 (S_{t+1}) to a motor output at time t (A_t). If PS works well, F (S_t, S_{t+1}) is nearly equal to A_t. Therefore, if an autonomous robot intends to reach a state S_{t+1} at time t+1, it chooses F (S_t, S_{t+1}) as A_t at time t.

Intentional Schema (IS) is a schema, which makes a decision on where the robot wants to be at the next time. An IS has a function (G) mapping from S_t to S_{t+1}. This stands for robot’s action or behavior chosen by the robot as its will.

When these schemata work together, they will come to be a program of the robot’s behavior (H).

\[
A_t = F(S_t, S_{t+1}) \quad S_{t+1} = G(S_t) \quad A_t = H(S_t) = F(S_t, G(S_t))
\]

In this paper, we regard that an IS is given, but PS is not given. Robots must get some PSs through interacting with their environment without any teaching signals. Piaget took a schema as a primitive type of symbol or language. In the same way, we take PS as a primitive symbol.

In this way, an autonomous robot powered by Dual-Schemata learning model can create some PSs for itself. It means the autonomous robot obtains symbols by its own will. A PS comes to describe the external reality correctly through two phases. They are assimilation and accommodation.

In a Dual-Schemata model, robots interact with its environment and record the interaction history in their memory. The basic unit (u_t) used in this memorization consists of S_t, S_{t+1}, and A_t. There is a particular storage (Str) in the memory corresponding to each combination of (PS, IS). We call this Str(PS, IS), which is a collection of u_t’s. Assimilation is a process of modifying an existing F to a new F so that this modified function can minimize an average of F’s errors.

\[
E(PS) = \frac{1}{\#Str(PS, IS)} \sum_{IS} \sum_{at \sim (S_t, S_{t+1}, A_t)} (F(S_t, S_{t+1}) - A_t)^2
\]

In this minimization process, any kind of optimization method may be adopted. In this process a PS is assimilated to its environment. In other word this is a process of establishing a relationship between the robot and its environment.

In this process, autonomous robots can control their sensory input S_t meaning that it can go wherever it wants in its state space intentionally. This is an assimilation process in Dual-Schemata model.

During the interaction an autonomous robot sometimes encounters an unexpected situation, in which the F’s error \((F(S_t, S_{t+1}) - A_t)^2\) suddenly becomes very large. In such a situation, we can assume that one of the following three possibilities is occurring:

- PS has not been assimilated to the environment sufficiently. The schema is immature. The error is due to the robot.
- Noises and/or some discontinuous inputs are provided. It must be ignored.
- Environment is changed into another new state, but the autonomous robot doesn’t know that, then an error occurred. It is due to an environment’s change. The robot has to recognize this change.

In case of the third possibility in the above, the robots continue to attempt to assimilate an encountering new environment into the existing one, assuming that a new environment equals to some prior environment. This may cause an increase of F’s errors, since the robot remains to be bound by its past ideas and cannot make adaptation to a new idea. An autonomous robot can get only one idea without someone else who teach it that the two are different.

In fact, we human beings can get many different ideas by ourselves from our surrounding contexts. Wherein, we often make a subjective judgment like “That may seem to be another thing, but these may be actually the same things from another perspectives”. Similar to this, an autonomous robot must be able to make this kind of flexible judgment. That is, instead of attempting to interpret things in terms of what is familiar to it, a robot must be able to shift its view from a pre-existing
structure of schemata, thus it can get to re-interpret it as a new idea. This process is accommodation.

In Dual-Schemata model, accommodation is to divide an existing PS into two new parts and to store an experience of a new environment into a new PS. An autonomous robot can get a new idea not by forgetting it, but by accommodating. We have to clarify when this accommodation occurs. As stated above, there are three kinds of errors. Accommodation must be triggered only when the third type of errors is identified. On the other hand, in cases the first and the second types of the error occur, accommodation may harm the ongoing order-organizing process. Therefore, it would be a key design issue in our Dual-Schemata model how to distinguish this third type of the error from the other types.

To resolve this issue, we introduce two parameters concerning with a reliability of the currently formed schemata. One is PS’s self-confidence parameter \( R(t, u_i, PS) \), and the other is \( AL(t, PS) \) which acts as a buffer for noises. \( R(t, u_i, PS) \) stands for the confidence with which its environment at time \( t \) is described by PS. This parameter is derived according to the below.

\[
R(t, u_i, PS) = \frac{E(u_i)}{E(PS, IS(t))}
\]

\[
E(PS, IS) = \frac{1}{\#Str(PS, IS)} \sum_{u_j \in IS} \left( F(S_j, S_{j+1}) - A_j \right)^2
\]

\[
E(u_i) = (S_i, S_{i+1}, A_i) = (F(S_i, S_{i+1}) - A_i)^2
\]

If PS is still immature, \( E(PS, IS) \) reveals so large, then \( R \) becomes small. But if PS becomes matured, \( E(PS, IS) \) gets smaller, then \( R \) comes to be very sensitive to \( E(u_i) \), unexpected input. Thus, by monitoring \( R(t, u_i, PS) \), PS can distinguish the first type of error from the third one. Further, \( AL(t, PS) \) stands for a doubt that the environment at time \( t \) is not what PS assumes. If \( R \) takes a larger value and exceeds over a certain threshold, \( AL \) increases, while \( R \) becomes less, \( AL \) decreases accordingly. \( AL \) is an integer satisfying \( AL \in [0, AL_{max}] \). When \( AL \) reaches to \( AL_{max} \), PS starts accommodating itself. In other words, PS comes to believe that its environment has already changed from what it assumed so far. Then, PS divides itself into two parts, and attempts to assimilate a new environment to those revised ones. If \( F \)'s error reveals discontinuous like a noise, a value of \( AL \) increases instantly, but soon it decreases to zero. In this mechanism PS can distinguish the second type of error from the third type.

In this way an autonomous robot embedding a Dual-Schemata learning system can become aware of differences existing in its surrounding environment. Actually, a real environment may often go back to the original state. In such a case, a robot must be aware of that it is a prior environment, and should not confuse it with another by creating a new PS through accommodation. Our model can also overcome this difficulty. When the environment turns out to be the original state, \( R \) of \( PS_{original} \) corresponding to the original environment will decrease, and \( AL(t, PS_{original}) \) comes down to \( AL_{turn} \). If \( AL \) climbs down below \( AL_{turn} \), \( PS \) shifts back to \( PS_{original} \). In this way, a robot can distinguish the current state environment correctly. In this way our Dual-Schema model can recognize the differences of the external world. In the next section, we show an example of the performance of an autonomous robot embedding the above Dual-Schemata learning system.

4. Experiments

To demonstrate the validity and effectiveness of our model, we designed a facial robot with two USB cameras onboard and 2-degrees of freedoms (i.e., pan and tilt). We use this as a testbed of an autonomous robot.

As a demonstration task, we make this facial robot learn to chase (i.e., to gaze) a blue colored ball moving along some regular orbit by actuating the USB cameras through pan and tilt control commands. Then, after the robot’s learning the movements of the ball, we intentionally change the blue ball’s moving orbit from the prior one. Wherein, the focus of our concern exists in how the robot gets to be aware of the difference of the orbits in terms of the robot’s own embodied experiences accumulated so far. Be sure that we are not focused on dealing with a task of classifying the movements provided as objects to be classified into one of the predefined classes. Rather,
we are interested in how the motion concepts observed in the external reality can be grounded to the actor (i.e., a robot) in relations with its own bodily movements of chasing without any predefined motion concepts.

For this purpose, we at first design an optical sensory system. It can get BMP-data 10 frame/sec, and we designed an encoder that can convert each pixel of the BMP-data into fuzzy values showing the degrees of “blueness” of the pixel. From this converted fuzzy image, the encoder calculates the center of gravity of the blue area, which is stored as a 2D vector as a sensory input \( V_t \). This sensory input is sent to Dual-Schemata system. Getting these inputs in succession, Dual-Schemata system makes an entity of \( S_t = (V_t, V_{t-dt}, V_{t-0.1}, A_{t-dt}) \) as explained in section 3. Based on the definitions of \( G \) and \( F \), \( S_t \) is used to derive a motor output vector \( A_t \), which is a 2D vector with the first dimension of pan’s displacement and the second of tilt’s.

As for another construct of Dual-Schemata model, we define the following three kinds of intentional schemata.

1. Intentional Schema for Chasing:
   This IS always keeps a blue ball at the center of the robot’s visible sight.

2. Intentional Schema for Searching:
   This IS issues a command for random target chasing, but attempts to keep the blue ball within a robot’s visible field, rather than chasing the ball in a pinpoint way.

3. Intentional Schema for Random Movements:
   This IS issues the actuation commands determining the next displacement of a robot’s gazing destination randomly. This schema plays a role of exploration.

Activating these schemata in turn, the facial robot keeps learning to chase the blue ball. In this experiment, we let the robot change the activation of schemata in an order of from 3 through 1 to 2, and made it iterate this cycle. Each schema is kept activated as long as three minutes.

In this experiment, we at first kept the blue ball stay at the same position (i.e., still). At this time, the facial robot could not chase (i.e., gaze at) the ball at all, since the robot had no idea about its encountering environment (i.e., having no belief that the ball is not moving). However, as the above learning cycle iterates for about 20 minutes, the robot starts to form motion concepts and attempts to assimilate those encountering experiences into what it has formed temporally so far. Finally, the robot comes to keep gazing at the blue ball.

Next, we changed the movements of the blue ball from the stilled into the horizontal movements. The robot cannot chase the balls since it is not familiar with these new moving patterns. Recognizing this, the robot turns into accommodation, and creates a new PS, and then it resumes assimilation under this accommodated PS. At this time, this autonomous robot had already got two symbols (one is “still”, and another is “moving”), each of which corresponds to two different PS. After attempting to chase the ball as long as 20 minutes again, the robot comes to chase the horizontally moving ball. Following this, we showed other different moving patterns of vertical movements of the ball, which is followed by circular moving in succession. After all, the robot got to chase all of those orbits with moderate accuracy.

Fig.3 Chasing for stopped, horizontally moving, vertically moving, and circle drawing ball.
We iterated the above alternative provision of movements of the ball during a experimental session (i.e., we repeated showing the stilled ball, horizontal, vertical and circular movements in turn. We monitored the evolution of the values of $AL(t,PS)$ along the time horizon as shown in Fig.6. Looking at this graph, we can see occurrences of the accommodation of PS. Every time the robot encounters a novel environment (i.e., movement), it creates a new schema that is grasped by the robot as a corresponding symbol standing for that novel environment. These symbols are kept internally during the lifetime of the robot.

5. Discussions and Future Perspectives

We proposed our new learning system called Dual-Schemata model, and showed the performances of a robot embedding this model. This autonomous robot could acquire many different concepts on visible motions without any teachers. In this approach, robots used the interaction contexts and formed criterion by itself for differentiating what is familiar with from what is novel. This criterion is not provided by the external teacher, but is formed by itself in an unsupervised way.

This fact that the robot by itself forms the criterion for recognizing the external environment may seem not to be fitted nor valid for universal applications of industrial robots. However, we would like to stress that a learning activity of social robots should be able to reflect both an actor’s own subjectivity and context-dependence with respect to its interactions with some external entities including human users.

Due to the existence of the intentional others, a social robot cannot completely control the results that are brought about through the interactions with the external, but it attempts to mimic the behavior of the others by looking into others. By interacting with the others and reflecting on this experience, a social robot must be able to reconstruct a definition of the reality, which causes them behave differently and changes the subsequent interaction patterns. This is a general learning model of observing systems, rather than observed systems. Note that this activity is not controlled by the external designer but is driven internally.

In the conventional cybernetics views, an environment has been regarded as sources of perturbations, and the main goal of the desired system has been thought as keeping a system's stability by protecting themselves by avoiding and isolating these externally provided perturbations. On the other hand, in our social robots such eternal random perturbations will lead to a robot’s internal chaotic state changes and are used as sources of creativity; a robot proactively forms significant relations with those through iterative and cyclic self-organizing processes and by absorbing them within them.

Our model is not still sufficient for realizing the above-mentioned social robots, especially with respect to interactions with some living people, and modification their way to interact with us. But we think we can deal with this problem by extending and revising the definitions of our Schemata Model.

Reference