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# Effective learning system techniques for human–robot interaction in service environment

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**Abstract**

HRI (Human–Robot Interaction) is often frequent and intense in assistive service environment and it is known that realizing human-friendly interaction is a very difficult task because of human presence as a subsystem of the interaction process. After briefly discussing typical HRI models and characteristics of human, we point out that learning aspect would play an important role for designing the interaction process of the human-in-the loop system. We then show that the soft computing toolbox approach, especially with fuzzy set-based learning techniques, can be effectively adopted for modeling human behavior patterns as well as for processing human bio-signals including facial expressions, hand/ body gestures, EMG and so forth. Two project works are briefly described to illustrate how the fuzzy logic-based learning techniques and the soft computing toolbox approach are successfully applied for human-friendly HRI systems. Next, we observe that probabilistic fuzzy rules can handle inconsistent data patterns originated from human, and show that combination of fuzzy logic, fuzzy clustering, and probabilistic reasoning in a single frame leads to an algorithm of iterative fuzzy clustering with supervision. Further, we discuss a possibility of using the algorithm for inductively constructing probabilistic fuzzy rule base in a learning system of a smart home. Finally, we propose a life-long learning system architecture for the HRI type of human-in-the-loop systems.


*Keywords:* Human–robot interaction (HRI); Fuzzy set and logic (FSL); Probabilistic fuzzy rule base (PFRB); Service robot; Soft-computing toolbox

## 1. Introduction

The existing robots are generally grouped into three types such as industrial robots, service robots and robots with special missions. The robots that we see in manufacturing sites belong to the first group while the robots built for special tasks such as Mars Rover and fire-fighting robots are of the last type. The robots that perform works and service activities directly for human beings are called service robots [1]. Recently, service robots are getting increased attention because of their potential applications for enhancing human well-being and quality of life. In particular, service robotic systems are often viewed as one of the primary alternative solutions for the arising caregiver-shortage problem in many advanced nations which are soon to confront with the demographic crisis of aged population.

Since a service robot interacts with human frequently during its operation, symbiotic coexistence, and safety are of great concern for the potential users, which is well reflected in a paper by Leifer [2] who proposed three rules of service robot design in the following context: (1) service robot design should be a social activity and service robots should be social agents: (2) service robots must tolerate ambiguity: (3) all applications should be reapplications. As a matter of fact, design of service robots should be carried out from the start in the form of multi-group activity involving not only the engineering team but also the potential user group. In case of assistive robotic systems, consultation with medical doctors and caregivers, as well as social workers and even policy makers, is further recommended.

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The objective of such design philosophy is to make a service robot to be a social agent that can interact with human in a friendly way. The 2nd proposition indicates that the robot should have proper human-like intelligence to figure out what to do, and where to go, etc., when it is not told precisely about the detailed actions to take to achieve a given task, not mentioning of handling many problems in an unstructured environment. Last, but not least, Leifer asserts that the system applications should be implemented with proven technologies and with assured confidence for success because human is involved and, as such, no trial-and-error is allowed. From these observations, we may derive a number of challenging R&D issues to study for faithful service robotic systems; some outstanding problems include: (1) effective integration in consideration of a number of requirements from various parties involved, (2) endowment of human-like intelligence, and (3) safe and friendly human–robot interaction design.

In this paper, we consider realization of service robotic systems from HRI (Human–Robot Interaction) perspective. Note that HRI is frequent and intensive in a service robotic environment. Recall that HRI can be considered a special form of HCI (Human–Computer Interaction) or a particular category of USI (User–System Interaction), which we briefly review in Section 2. When robot and human are interacting with each other, we may consider a human-in-the loop system that contains the two elements as subsystems. *Human-in-the-loop system* is a well-established notion and, traditionally, a major concern is to design the total system in such a way that the troublesome *human factors* are minimized. The complex airplane control system is a typical example, and we may call such design practice as machine-centered approach. When a robot is to assist a person with disability or an elderly, we find that the machine-centered design methodology is doomed to fail because training people with disability or old persons to learn about complicated robots is simply implausible. Rather, it seems better to take the other opposite approach of human-centered design for such an assistive service robotic environment. In this approach, it is proposed that *machine factors* should be minimized and, that the robot be designed to adapt to human by learning and understanding characteristics and behaviors of human, which is often called "human-friendly" system design approach.

The crux of the problem in the latter design approach, of course, is to let the robot know proper amount of human characteristics necessary for human-friendly interaction. We find that at least two kinds of difficulties, objective and subjective, are well-known and outstanding. The first one is that human is such a complex entity so that it is not easily modeled in the form to be understood by a machine robot. The second difficulty is that, even if some human characteristics are available, it is not trivial for the robot to act and interact in a way that human as a user feels socially comfortable in his/her own terms. In other words, it would be quite difficult for robot to have a proper human model and execute interactions in a human-friendly due to complexity and variability of the user's characteristics and behavior. Here, we may mention that uncertainty of the environment can be another source of difficulty as in the case of a residential space where the context undergoes continual change due to human's activities on the environment.

With advancement of effective bio-signal processing techniques, however, some of the difficulties mentioned above may be overcome for limited HRI applications. First, note that efficient acquisition and use of various human bio-signals are essential in human-friendly HRI to recognize human's behavior and physical status as well as understand human intention (see Fig. 1). Human bio-signals include body gestures such as hand gesture and some physiological bio-signals such as EMG, EEG, and ECG. Note that, as long as modeling is concerned, such signals show quite complicated characteristics such as high dimensionality, nonlinear-coupling of attributes, subjectivity, apparent inconsistency, susceptibility to environmental noise and disturbances, and time-variance as well as situation-dependency [3]. As such, building a human model from diverse and complex sources of information would be a very challenging task when it is to be used for human-friendly interaction in various situations for a long time.

Another observation to note is that, as a subsystem of the human-in-the-loop system, human seems to operate with perception-based input data and mostly employ an approximate reasoning inference mechanism, whereas robot is operating with measurement-based input data and under well-defined mathematical formalism. Imagine a home environment, for example, where the owner interacts socially with a service robot as a butler: one day, the master comes back home after work and finds that the house is somewhat hot. In this situation, the room temperature perceived by human and that sensed by robot are differently represented; e.g., "a little hot" and "26.5 °C", respectively. If the total human-in-the-loop system is constructed to be human-friendly, the owner may give an

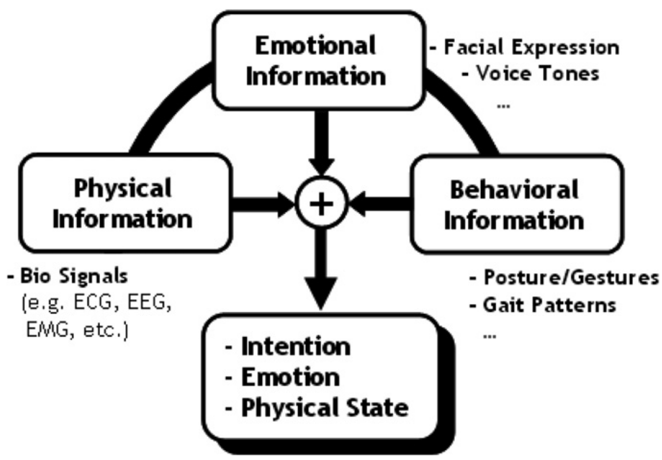



Fig. 1. Variety of information on human model for interaction.

instruction to the robot in his/her natural language such as "Lower the temperature a little," instead of reading the thermometer and telling the robot to reduce the temperature, say, by 5°. In this interaction, the robot should be aware of linguistic variables used by human such as "hot" and "a little". It would be also interesting to see how the concept "a little" would go through inference and be processed differently in case of a human butler and that of the robot. Human would employ approximate reasoning based on his experiences while the robot should find a proper action by means of some preprogrammed computation.

HRI has been under study in the robotics community for a long time [4], and numerous reports are available for successful interaction applications. Interaction itself can be treated from various view points such as social interaction, physical interaction, virtual reality interaction, and so on. The human-friendly HRI in assistive service environment involves social and physical interactions. Most of the known human-friendly interaction methodologies are far from practical use, especially when the human is either an old person or a disabled. Based on our experiences on this interaction problem, we find that, firstly, long-term learning can be an important aspect in handling complexity and time-variance of human characteristics and, secondly, as an effective and efficient engineering solution, the toolbox approach of combining intelligent learning techniques can be effectively utilized. The long-term learning concept is embryonic for the robotics community and some related studies have recently been initiated [3]. Regarding the second approach, we find that, with limited success, the so-called soft computing techniques such as FSL (Fuzzy Set and Logic) and ANN (Artificial Neural Network) can be used quite effectively for realizing human-friendly systems. We comment, in particular, that FSL-based technique is a very powerful tool for encoding human knowledge formed from perception-based data and for transforming it into machine knowledge for feedback and inference. In this paper, we demonstrate that, for human-friendly HRI, FSL method with other soft computing techniques can play an important role in establishing a learning system model for time-varying, inconsistent and user-dependent human bio-signals.

This paper is organized as follows. In Section 2, we briefly review some well-known approaches for HRI and then, the learning system issues are addressed in the context of HRI in assistive service environment. In Section 3, we describe the soft-computing toolbox approach for effective hybridization of existing intelligent techniques as a cost-effective powerful engineering solution to design a human-friendly system. Particular attention is given to a couple of learning system techniques based on fusion of FSL and other soft-computing techniques. In the section, use of the FSL-based learning techniques in the soft computing toolbox approach is illustrated as two examples. In Section 4, we observe that probabilistic fuzzy rules can handle inconsistent behavioral data patterns and show how such a PFRB (probabilistic fuzzy rule base) can be constructed from an algorithm of iterative fuzzy clustering with supervision [43]. We further discuss a possibility of establishing a PFRB-based learning system for a smart home. Then, we propose a life-long learning system architecture for the HRI process of human-in-the-loop systems. Finally, a brief concluding remark is given in Section 5.

## 2. Human–robot interaction and learning issues

### 2.1. Typical models of human–robot interaction (HRI)

A simplistic model of HRI is shown in Fig. 2 [4]. This diagram is to illustrate that, when robot interacts with human as operator, robot is mostly the passive recipient of service from human, whereas when robot interacts with human as user, the robot becomes the active provider of service and therefore, in this service environment, definition of working space for the robot should be rigorously established in order to protect human from possible mishaps. This model can be considered as an extension of the case of an industrial robot for which the working space includes objects and other automation systems but no human. When the robot should perform more than simple tasks and the environment is broad and complex, as for a mobile robot in- and out-door environment, the roles of human partner may vary as shown in Fig. 3. Those multiple human roles in HRI along with their application domain examples can be summarized as follows [5]:

- Operator: Manus Arm-based Wheelchair, Master/Slave Robot
- Teammate: Carrying a Long Table
- Mechanic/Programmer: Industrial Robots
- Supervisor: Teaching Pendant Systems
- Bystander: Office Robots

For effective HRI, some people seek for hints from HHI (Human–Human Interaction) and many researchers look for solutions from techniques of HCI. In fact, Scholtz asserts that determining what is available in HCI research should be a first step of developing HRI framework [5]. Recently, the word "agent" is often used in referring to the human counterpart such as robot, computer or something else [6], in which a scheme of HAI (Human–Agent Interaction), called IDEA (Interaction Design for Adapta-

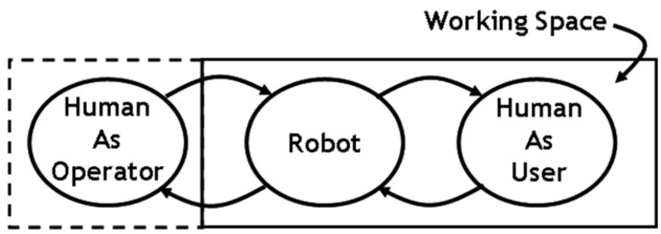



Fig. 2. 1:1 Human–robot interaction model by tanie.

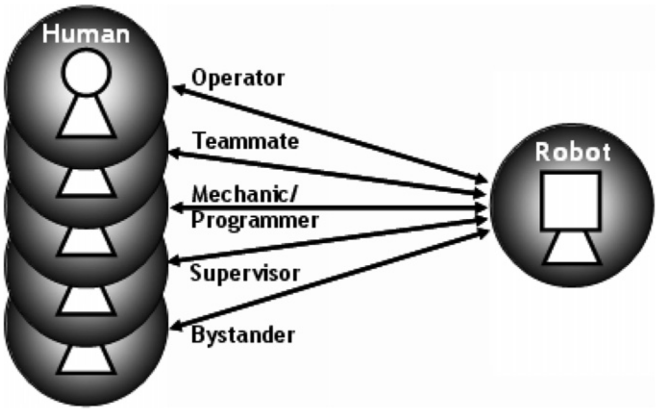



Fig. 3. Multiple human-role model of HRI [5].

tion), is proposed. Fig. 4 depicts a HAI model in which $B$ refers to behavior, $M(B)$ is for model of behavior, $L$ for learning and $I$ for interaction. According to the algorithm IDEA, human adaptation should be first exercised, then followed by agent adaptation. However, this kind of interaction may require heavy cognitive load on the part of human and is hard to adopt in case the human is physically weak.

When we study HRI, it is imperative to note that human and robot are two different entities having different descriptors of interaction. For robot, we use technical terms such as I/O devices, level of autonomy, model of user, morphology, composition, learning, and so forth, whereas, for human, we contrast utility notions such as end user, interaction role, level of shared interaction, physical proximity, task criticality, application area, ratio of people versus robot, etc. [7]. In case of service robotic systems, we may add intentionality, emotion and personality [6] as descriptors for human. From design and realization point of view, we also find a category of functionally driven engineering approaches in which safety, reliability, usability, task management, modeling, and evaluation are important items to check and encounter another category of biologically driven scientific methods for which cognition, ethos, interaction structure, mind and psychological aspects are paid serious attention. Recently, interaction is intensely being studied from "service" aspect. Thus, numerous forms of interaction seem possible, depending on application domains and or perspectives of viewing the interaction. However, it seems to be the state-of-the art that not many generic HRI models are available, especially for human-friendly interaction.

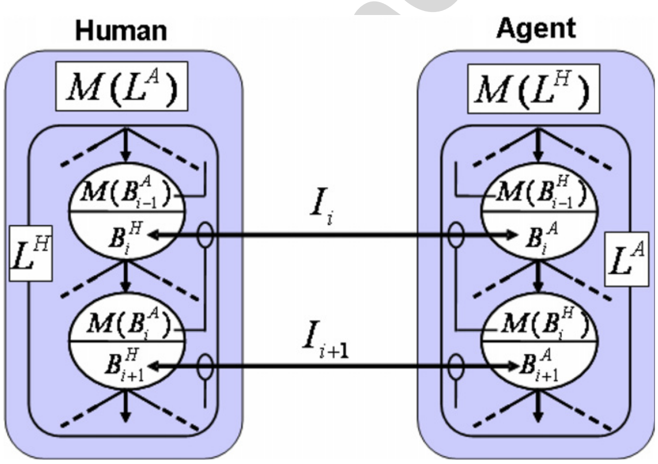



Fig. 4. Interaction design for adaptation scheme of HAI [6].

### 2.2. Learning issues for human-friendly robot in service environment

Consider a typical example of service in which a robot is to guide a very old person from one place to another. In this situation, interaction from the robot's part can include leading the human with soft grasp of hand, coordinated walking if the robot is of humanoid type, watching human's facial and body gestures with timely proper responses. Some of the robot's actions in this guide mission can be well defined in advance but many motion sequences of the robot may not be available for interaction in unknown environment or for detailed behaviors. That is, preprogramming for all possible robot motions is simply impossible, or if any, such packages may not work for many practical service environments. Even if not satisfactory initially, however, the guide mission would be gradually and successfully accomplished if, as in the case of human–human interaction, the robot is capable of *learning* in situ behaviors from human feedback and self adaptation for varying environment.

Various definitions on "*learning*" are available. And, approaches of analysis and design for learning systems are diverse, depending on application domains [8]. For example, *learning* in [9] is defined as changes in the system that are adaptive in the sense that they enable the system to do the same task or tasks drawn from the same population more efficiently and more effectively the next time. The notion of *learning* is addressed in [10] in view of machine learning, where a computer program is said to learn from experience E with respect to some (class of) tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E. In [11], *learning* is defined as automated system optimization based on sequential presentation of examples as a step-by-step process of improvement.

*Learning in robot* is also a broad concept, referring to actions of robot to adapt and change its (physical) behavior or its (non-physical) understanding based on input/output observations [12]. An attempt to categorize robotic learning methods is made and is illustrated in Fig. 5.

It should be pointed out that the notion of learning in robotics is expanding as applications are diversified. A robot, for example, can learn to dance, which is physical behavior as well as can know human intention, which is a non-physical entity, from facial expressions. As for physical behavior of a robot, we may further differentiate well-defined tasks from some pattern of behaviors for which

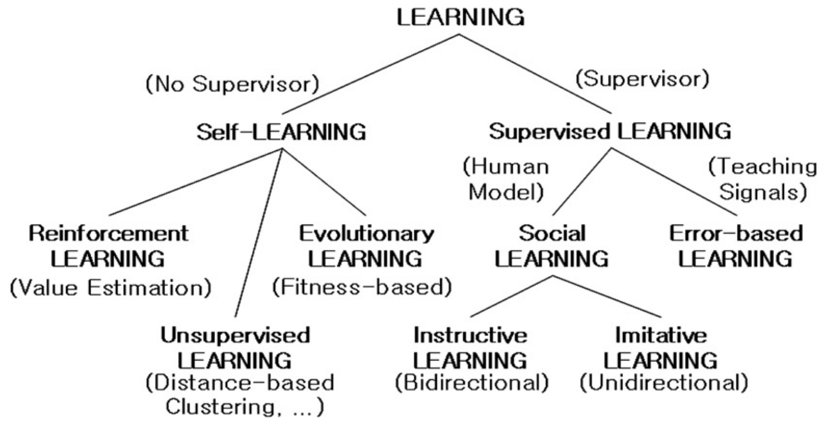



Fig. 5. A categorization for learning methods in robotics [12].

capturing some abstract level of features would be the goal of learning, rather than specific geometrical forms of actions. In the guide mission considered earlier, opening a door is a sequence of motions that robot can easily learn while some particular habit observed from human's gait pattern is a feature that would be helpful in coordinated walking. Typically, the learning unit plays a role of a bridge between knowledge and experience as shown in Fig. 6, where knowledge is obtained and modified by repetitive experiences through learning algorithms. Reinforcement learning updates its policy by action-reward pairs, for example, and an iterative learning control method generates the desired control input by repetitive trials of control action and observation of actual output [13]. In order to achieve required performance, the designer of a learning system has to decide a proper method of knowledge representation and learning mechanism depending on the target tasks and goals of learning.

It is further observed that the level of complexity and difficulty will be broad for a robot to learn various human behaviors. Let us consider an example of skill learning in archery. The objective is to hit the bull's eye against possible wind and other circumstances. The archer may accumulate his/her know-how on hitting the target from numerous trials-and-errors. This kind of learning can be called a basic level learning in consideration of the learning target being static. When we consider a moving target, however, the problem becomes more difficult. In a clay pigeon shooting, the player is trained to hit a moving target under all circumstances. We may say this kind of learning as a 2nd level of learning. A still more difficult type of skill learning can be compared with the situation of fishing using a fish-spear with fisherman on a boat in a river. In this case, the fisherman should spear a moving target fish even when the boat is in motion or is rolling in the river. We may say that this is a 3rd level skill learning which may be acquired gradually and in a long time to cope with continually changing target and environment. This last type of learning naturally leads us towards a notion of 'long-term learning'. It would be interesting to contrast the 3rd level learning with MRACS (Model-Reference Adaptive Control System) [14], where the system undergoes a structural change or there is severe change in the environment that considerably affects the control performance as shown in Fig. 7.

A typical learning involves several steps; (1) target function specification, (2) selection of learning algorithm, (3) selection of data/data subsets, (4) preprocessing, (5) measure of performance, and (6) halt criteria [3]. In case of HRI, the target function specification and selection of learning algorithms are, in particular, not obvious in most cases. Let us consider, for example, human gesture and behavior pattern as the learning target. Recall that bio-signal acquisition and its use for pattern classification are

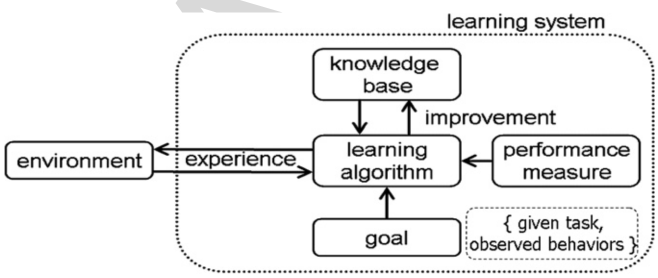



Fig. 6. Typical learning system structure*.

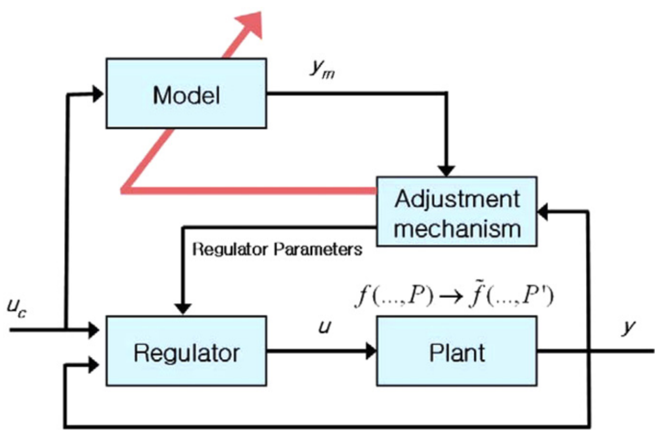



Fig. 7. MRACS with structure change in varying environment.

essential in human-friendly HRI in service environment [15]. It is well known that success rate of human bio-signal recognition is usually very low due to time-variance and user-dependence of bio-signal. Specifically, human bio-signals show complicated characteristics such as high dimensionality, nonlinear-coupling of attributes, subjectivity, apparent inconsistency, susceptibility to environments and disturbances, and time-variance as well as situation-dependency [3]. Among those characteristics of human bio-signals, we briefly discuss the following features in view of realizing a human-friendly HRI process in service environment:

(1) Complexity/high-dimensionality
(2) Subjectivity (User-dependency)
(3) Time-variance (Inconsistency)
(4) Difficulty of Real-time Learning and Control

First, it is noted that human bio-signals are usually high-dimensional complex data. For example, a human face is reported to have 44 muscles with 23 bones which can theoretically generate 55,000 expressions. If a pattern is required to be recognized from such high-dimensional data, the problem of selecting a set of attributes for classification is considered a foremost important issue to resolve. Also, one of the most difficult tasks in such a recognition problem may lie in performing classification with ambiguous/fuzzy boundaries, assuming that the features are properly selected and robustly extracted. At this point, we may pay attention to the human perception capability of extracting 'essential knowledge' from complex information/data by employing approximate reasoning, and expressing it in words. FSL-based techniques are known effective in transferring human knowledge to machines.

Secondly, differences of individual's characteristics in rendering bio-signals may hinder the system performance greatly. For example, a facial expression for the same emotional state can differ from person to person [16]. Also, it is reported that a directly measured bio-signal such as EMG shows user-dependent characteristics in amplitude, and frequency distribution of the signals and, in other extracted features [17]. In general, it is difficult to extract a set of user-independent features, therefore, personalization is often adopted as an engineering methodology to handle user-dependence problem.

Thirdly, even if the current service robotic system is designed and realized with high performance, meeting the requirements of the user at the time of design, it is obvious that the level of satisfaction would not be maintained for the user in a long time scale of operation. Some of the physical features or behavior patterns of human can vary in time and also some of the preferences of the user may change in a long time span. To cope with this kind of changes due to the long time factor, a gradual and incessant learning through interaction and feedback is required. For this, a life-long learning system framework is discussed.

Finally, we point out that it is technically challenging and important for the system to have a real-time learning and control capability for effective HRI. Most traditional pattern classifiers are designed to perform training/learning in off-line and then are applied to a real target system. However, when we consider an assistive service environment where HRI frequently occurs, it is important that human is the learning target as well as a real-time evaluator/teacher for the learning system. As such, on-line/incremental learning methods are preferred which include human in the system loop. We demonstrate some possibility of realization by presenting several illustrative examples in the paper.

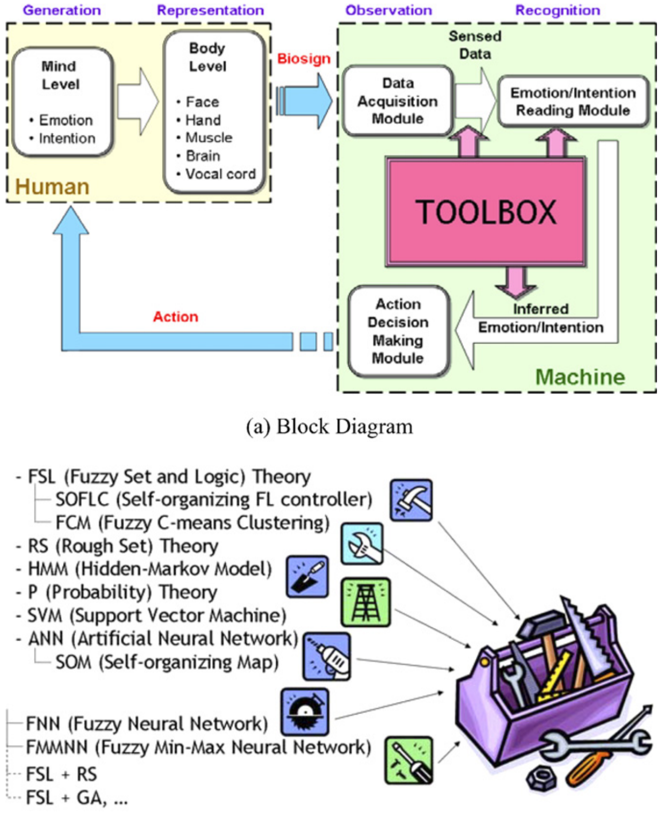
It is remarked that "learning system" may refer to an organized institution for human learning in some non-engineering communities, where e-learning is recently a hot subject of discourse and "learning system architecture" concerns with types of instruction and learning such as: (1) receptive learning, (2)directive learning, (3) guided discovery learning, and (4) exploratory learning [18].

## 3. Soft computing approach and fuzzy set and logic-based techniques for HRI

### 3.1. Soft-computing toolbox approach for HRI learning

It is usual that the designer selects a learning model and a learning algorithm in consideration of the functional requirements of the system to be designed. When the system under consideration has complex structure, one may utilize more than one learning model with multiple learning algorithms for building the overall learning system. This design methodology is often practiced in civil engineering and construction industry. In the case of building a house, for example, various kinds of tools can be used some of which may be employed here and there wherever such practice can facilitate the process of building the designed house. Similar approach can be utilized for designing a robot system to perform human-friendly HRI in service environment.

It is now well-known that there are available various soft-computing techniques, such as FSL [19], ANN [20], RST (Rough Set Theory) [21], ECT (Evolutionary Computation Technique) [22] or GA (Genetic Algorithm) [23], SVM (Support Vector Machines) [24], and probabilistic methods including HMM (Hidden Markov Model) [25]. These techniques can be 'tools in the soft-computing toolbox' to design a learning system as shown in Fig. 8. Known also as techniques of computational intelligence, these intelligent techniques have been developed mainly by mimicking physical and/or biological working mechanisms and behaviors of human or animal. Recall that FSL can be effectively adopted for human and robot interaction problems since many forms of human knowledge can be expressed by fuzzy sets and rules and it can make a machine reason in a similar way that human reasons about uncertain and ambiguous data. RST can be utilized in




(a) Block Diagram

(b) Toolbox

Fig. 8. Block diagram of soft computing-based human–machine interaction system.

reducing the number of rules, rendering a minimal set from the existing rule base, while ANN can be utilized for learning a general nonlinear function in many pattern classification areas using its layered structure of neurons with nonlinear activation function. In addition, some other methods, including Reinforcement Learning, SOM (Self-Organizing Map), Inductive Decision Tree, and Bayesian Learning, can also be used in constructing a learning system.

According to our extensive survey and experiences of developing real HRI systems, we have found that hybrid combination of soft computing techniques is quite effective in implementing functional blocks for the system's learning and adaptation. A combination of these soft computing techniques are chosen and utilized as tools wherever and whenever appropriate and relevant to the tasks and goals of the system as long as they play their inherent roles harmoniously with each other. As will be illustrated later in Section 3.3, the soft-computing toolbox approach can offer easy-to-implement and cost-effective engineering solutions for various problems of human behavior understanding in HRI. We remark that the performance of a system designed by the methodologies described in the paper can be further optimized by applying again some soft computing optimization techniques such as GA or SVM as long as the performance can be quantitatively expressed. Since human is involved in the HRI process, however, some practical measure of performance may include qualitative requirements such as safety, comfort, or human-friendliness for the user. In such cases, we may get performance evaluation in terms of satisfaction degrees in reference to some existing systems or by subjective judgment of the users, as we have done for evaluating KARES II, a wheel-chair based service robot system, developed at HWRS-ERC, KAIST [30].

### 3.2. Fuzzy set and logic-based learning techniques

There are many possible ways of hybridizing different techniques from the soft-computing toolbox in designing a learning system. In this paper, we restrict our attention to FSL-based hybrid approaches since they are most relevant to HRI in assistive service environment. Later, we present a couple of case study examples for illustration.

FLC (Fuzzy Logic Controller) has been very successfully adopted for various industrial and home appliance systems. In the system, the fuzzy set and logic theory is utilized in substituting a human expert by FLC by using its knowledge representation/description capability in a human-in-the-loop system. However, one drawback of the conventional FLC is that re-tuning of the fuzzy controller is necessary when the system parameters undergo some significant changes. To design a control system in consideration of both uncertainty of plant parameters and robustness against external disturbances, Procyk and Mamdani proposed an adaptive control technique called SOFLC (Self-Organizing Fuzzy Logic Controller) [26]. It has a basic form of fusing FLC and a performance error-based rule-learning technique. The original SOFLC is, however, valid for a very limited class of systems and shows unstable characteristics when the stable state is slightly disturbed by external signals as noted in an inverted pendulum system in [27]. An improved version of self-learning controller is presented in [27] with a new design principle that the learning law should not modify the fuzzy control rules if the system moves satisfactorily along the zero error hyper plane [27].

Another popular version of a fuzzy system with learning capability is obtained by fusing FSL and ANN with an advantage that FSL system emphasizes interpretability while ANN accomplishes nonlinear mappings [28]. Typical fusion forms of FL and NN include: (1) Neuro-Fuzzy System (parallel form/series form), (2) NFS (Neural-Fuzzy System) and (3) FNN (Fuzzy-Neural Network) [3]. The parallel/series form of a neuro-fuzzy system has low degree of fusion and usually used for representation of expert knowledge. On the other hand, a NFS has a fuzzy inference architecture with ANN learning for tuning of membership: this is sometimes called as a neuralized fuzzy system. A FNN is an improved form of NN and it is said to be a 'fuzzified neural network'. *Lin's* FNN has a special form of FNN with 5-layered structure [29]. Lin's FNN has been used for a number of applications in our projects, including a personalized facial expression recognition system [16] and an intention reading unit for a rehabilitation robots [15][30]. FMMNN (Fuzzy Min-Max Neural Network) [31] is also one form of FNN, which we is very effectively used for recognizing hand postures [32] and bio-signal features [33]. FMMNN is a simple hyper box-based learning system with fast incremental learning and on-line adaptation capability. Hyper boxes, which are correspondent to fuzzy rules of the classes, are easily constructed from input data and are simply modified to minimize a classification error by constructing non-overlapped hyper boxes between different classes. Recently, we find that GWFNN (Gabor-wavelet Fuzzy Neural Network) can play an effective learning role in user adaptation stage for our PDA-based facial expression recognition system [34].

### *3.3. Applications of soft computing toolbox approach with FSL-based techniques*

In this section, we briefly describe two project examples for which the soft-computing toolbox approach is adopted and Fuzzy Set and Logic-based techniques are successfully used.

#### *3.3.1. Case study (1) sign language recognition system [35]*

Sign language is a special form of human gesture for communication among persons with hearing impairment. Recognition and graphical generation of sign language have been an important subject of research for communication between a hearing-impaired person and an ordinary person as well as among people with hearing impairment. In KAIST, we have been developing two versions of KSL (Korean Sign Language) recognition system as an automated sign language interpreter. Earlier version was a Data Glove-based system, and the recent version is a camera vision-based system. It is remarked that Korean Sign Language is composed of sign words and manual alphabets, which are expressed by both dynamic hand motions and static hand postures. To achieve fast and accurate recognition, we have used fuzzy set and automata representation for gesture segmentation while we have adopted HMM method for dynamic gesture word matching to deal with scalable and spatio-temporal data pattern. And also, FMMNN has been utilized for classification of the static hand postures.

The overall system structure is shown in Fig. 9, where the learning methods mentioned above are used from the soft-computing toolbox, and, as reported in [35], we have obtained quite successful performance with 95.8% as recognition rate of hand posture and 94.9% as recognition rate of sign words among 414 manual alphabets and compound words.

#### *3.3.2. Case study (2) personalized facial expression recognition [16][34]*

In HHI, the facial emotional expression is known to play very crucial role as much as various body gestures. For human-friendly interaction between human and robot, therefore, it is desirable for the robot to have a capability of recognizing human facial emotional expressions, in addition to the face detection and tracking function. In fact, the human facial expression recognition has become an integral part in many advanced service robotic systems. As mentioned earlier, the problem of recognizing emotion from face is known to be very complex and difficult due to high dimensionality of facial structure. In addition, subjectivity and individuality in facial expressions are quite troublesome and may not be ignored in understanding emotions [36]. After some years of work, we have successfully developed a first version of FEERS (Facial Emotional Expression Recognition System) in which Ekman's linguistic rules of six universal emotion expressions are transformed into fuzzy rules, and the RST is applied for rule reduction while a ANN-based fuzzy observer is introduced for recognition. This first version has shown limited success in terms of success rate. To enhance performance, we have further used Lin's FNN-based classifier. This FNN is capable of modeling human's expertise-based decision making process and easy-to-train structure by well-known techniques (such as error back propagation). Furthermore,

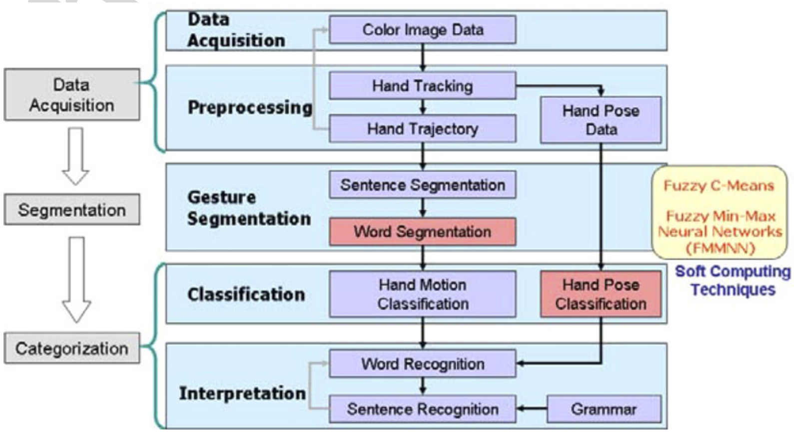



Fig. 9. Block diagram of KSL recognition system.

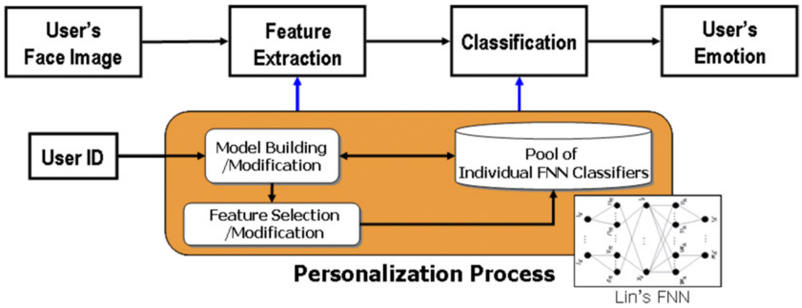



Fig. 10. Learning structure for personalized facial expression recognition.

due to its connection structure, FNN provide an easy way to locate causes of errors using input/output relationship. For personalized recognition, we have proposed a systematic way of performing personal model selection and structural modification [16] as shown in Fig. 10. The proposed method in [16] enables a selection of specific model among many individualized models via fuzzy similarity measure and modification of old model. We have also suggested a novel feature selection method using FNN's structure-based connection degree and histogram of connection degrees to find a set of user-dependent features. As a result, we have obtained 90.4% classification rate for 7 facial expressions by using 1764 images which are acquired from 22 persons. For modification of the old model, GWFNN is also used to build a long-term adaptive learning scheme with Q-learning and unsupervised FNN [34]. In our preliminary experiment with 3 facial expressions, GWFNN-based adaptive facial expression recognition gives 93.35% classification rate where only 234 images are used containing 3 facial expressions among 1764 images.

## 4. Architecture of probabilistic fuzzy rule-based learning system

For a system, a fuzzy IF-Then rule can be made from a pair of input and output data. We say that two IF-THEN rules are inconsistent if, for the same antecedent values, the two rules have different consequent values. If a system produces different output data for the same input, the information about the system may well be said to be inconsistent, which is, grossly speaking, one of the characteristics of human bio-signals and human-behavior. Consider, for example, the case in which TV watching pattern of an inhabitant in home environment is to be modeled and the learned knowledge is to be applied for constructing an automatic channel recommendation system. To describe these kinds of human's behavioral pattern, we may need a lot of accumulated data related to the behavior. Wang and Mendel's method [37] is often used to extract fuzzy rules from numerical data patterns for a given fuzzy partition space. This approach shows difficulty in dealing with inconsistent data pattern as shown in Fig. 11 where improperly divided fuzzy partition by incomplete prior-knowledge may cause extraction of meaningless rules and

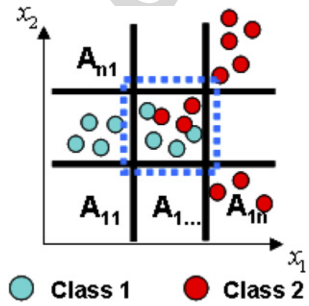



Fig. 11. Example of inconsistent data pattern.

loss of meaningful information. In general, we find that human I/O data can be sparse due to limitations of appropriate sensors for human behaviors and measurement difficulty, and also, can be mostly inconsistent in the sense that when transformed into rules, there are many inconsistent rules. We remark that a conventional supervised classifier usually minimizes classification error by rejecting inconsistent data and may show low satisfactory performance due to loss of information during the learning process.

By fusing FSL and probabilistic reasoning, however, we may effectively handle inconsistent data in forming IF-THEN rules. Note that some of the merits of an if-then fuzzy rule-based system are its capability of easy accumulation and modification of interpretable knowledge which can be also combined with human expert's knowledge in a seamless fashion. Also note that one of the effective ways to express knowledge without loss of much information caused by inconsistent data patterns is to utilize probabilistic reasoning. Thus, fuzzy logic and probabilistic reasoning can be combined in the form of so-called *PFR (Probabilistic Fuzzy Rule)*. In the probabilistic fuzzy rule, fuzzy set deals with linguistic uncertainty in describing the antecedent part of a rule and probability theory handles probabilistic uncertainty of the consequent part of the rule. In a fuzzy classifier system, the antecedent part of the rules partitions the input space into a number of regions by fuzzy sets, while the consequent part describes the class labels as the output for the partitioned regions. In a probabilistic fuzzy classifier, probabilities for all the class labels are described in the consequent part of the rules [38–42].

While acquisition of fuzzy rules usually requires expert's knowledge and/or prior analysis on the case-specific data pattern, construction of an interpretable PFRB can be carried out with low human intervention and without much prior knowledge. In this section, we show a learning system with capability of representing given data patterns automatically with a minimal number of meaningful probabilistic fuzzy rules using a small number of heuristic design parameters.

### 4.1. Representation of probabilistic fuzzy rule base

We briefly describe probabilistic representation of a fuzzy rule base to familiarize notational conventions to be used in the section. In a classical fuzzy rule-based classifier, the antecedent part of a rule defines the operating region of the rule in the $M$-dimensional input feature space while the consequent part of the rule describes one of the $K$ classes, indicating a crisp class label from the label set $\{c^1, c^2, \ldots, c^K\}$. Compared with the classical fuzzy rule-based knowledge, the probabilistic fuzzy rule has the probability information in the consequent part as shown in Eq. (1):

$$\begin{aligned} R_i : &\text{If } x^1 = \tilde{A}_i^1 \text{ and } x^2 = \tilde{A}_i^2 \text{ and}, \ldots, \text{and } x^M = \tilde{A}_i^M \\ &\text{then } \Pr(y = c^1 | x = \tilde{A}_i) = P_i^1,\ \Pr(y = c^2 | x = \tilde{A}_i) \\ &= P_i^2, \ldots, \Pr(y = c^K | x = \tilde{A}_i) = P_i^K,\ i = 1, \ldots, N \end{aligned} \tag{1}$$

where $x = (x^1, x^2, \ldots, x^M)$, $\tilde{A}_i = (\tilde{A}_i^1, \tilde{A}_i^2, \ldots, \tilde{A}_i^M)$ and $R_i$ denotes the $i$th rule. Note that the vector fuzzy set $\tilde{A}_i$ is assumed to have its membership function with shape of multivariate Gaussian function described by Eq. (2):

$$\mu_{\tilde{A}_i}(x) = \exp\left\{ -\tfrac{1}{2}(x - m_{\tilde{A}_i})^T \left( \sum_{\tilde{A}_i} \right)^{-1} (x - m_{\tilde{A}_i}) \right\} \tag{2}$$

Here, $m_{\tilde{A}_i}$ and $\sum_{\tilde{A}_i}$ are, respectively, the mean vector and the covariance matrix of the data that form the fuzzy set $\tilde{A}_i$. It is remarked that an ordinary fuzzy rule can be considered a special case of a rule expressed in Eq. (1). The totality of rules, $R_i, i = 1, \ldots, N$ is called the PFRB.

### 4.2. Algorithm for iterative fuzzy clustering with supervision [43]

In order to endow a service robot with capability of learning some user's behavior, we consider a classifier learning system equipped with a PFRB that can handle inconsistent data pattern such as shown in Fig. 11. To construct PFRB, we present a learning scheme, called IFCS (iterative fuzzy clustering with supervision)-Algorithm. The learning system starts with a fully unsupervised learning process with FCM (Fuzzy C-Means) clustering algorithm [44] and with some cluster validity criterion [45][46], but it gradually constructs meaningful fuzzy partitions over the input space and obtains corresponding rules with probabilities through an iterative learning process of selective clustering with supervising guidance based on cluster-pureness and class-separability. We show that effective combination of an unsupervised learning process with a proper supervising scheme can be effective for searching regularities in data patterns, and in particular, in finding more separable and/or analyzable groups of geometrical shapes.

To describe IFCS algorithm in more detail, we define the notions of cluster-pureness index and class-separability index as follows. Let $x_j \in R^M$ be the $j$th training input vector and $\{c^1, c^2, \ldots, c^K\}$ be a given label set for $K$ classes. Let $d_j \in \{c^1, c^2, \ldots, c^K\}$ be the class label of $x_j$. Given a labeled data set $X = \{(x_1, d_2), (x_2, d_2), \ldots, (x_n, d_n)\}$, we sort $X$ by the class labels and obtain $X_s = \{(x_{11}, c^1), (x_{12}, c^1), \ldots, (x_{1n_1}, c^1), \ldots, (x_{Kn_K}, c^K)\}$, where $x_{jk}$ denotes the $k$th data with the class label $j$ and $n_j$ denotes the number of data with the class label so that $\sum_{j=1}^{K} n_j = n$. We also get an unlabeled form $X_{su}$ of $X_s$ as $X_{su} = (x_{11}, x_{12}, \ldots, x_{1n_1}, \ldots, x_{jn_j}, \ldots, x_{Kn_K})$.

**Definition 1.** (Cluster-pureness Index)

Let $\mu_{ijk}$ be the membership value of $x_{jk}$ for the cluster $i$ and $f(\cdot)$ be a function satisfying

$$f(z) = \begin{cases} 1, & z \geqslant 0 \\ 0, & z < 0 \end{cases} \tag{3}$$

The cluster-pureness index $P_i^\alpha$ of the cluster $i$ is defined by

$$P_i^\alpha = \frac{\max_{j \in \{1,2,\ldots,K\}} \sum_{k=1}^{n_j} \mu_{ijk} f(\mu_{ijk} - \alpha)}{\sum_{j=1}^{K} \sum_{k=1}^{n_j} \mu_{ijk} f(\mu_{ijk} - \alpha)} \tag{4}$$

**Definition 2.** (Class-separability Index)

Let $m_i^\alpha(j)$ and $\Sigma_i^\alpha(j)$ be the mean vector and the covariance matrix, respectively, of data satisfying $\mu_{ijk} \geqslant \alpha$, $k = 1, 2, \ldots, n_j$ where $\mu_{ijk}$ denotes the membership value of $x_{jk}$ for the cluster $i$, and let $f(\cdot)$ be a function satisfying Eq. (3). The class-separability $S_i^\alpha$ of the cluster $i$ is defined by,

$$S_i^\alpha = \max_{a \neq b} Sep_i^\alpha(a,b) N_i^\alpha(a) N_i^\alpha(b) \tag{5}$$

where

$$N_i^\alpha(j) = f\left( \sum_{k=1}^{n_j} f(\mu_{ijk} - \alpha) - 2 \right) \tag{6}$$

$$Sep_i^\alpha(a,b) = 1/(1 + \mathrm{e}^{-4.4(\lambda_i^\alpha(a,b) - 0.5)}) \tag{7}$$

$$\begin{aligned} \lambda_i^\alpha(a,b) = {} & \frac{1}{8} (m_i^\alpha(a) - m_i^\alpha(b))^T \left[ \frac{\Sigma_i^\alpha(a) + \Sigma_i^\alpha(b)}{2} \right]^{-1} \\ & \times (m_i^\alpha(a) - m_i^\alpha(b)) + \frac{1}{2} \ln \frac{\left| \frac{\Sigma_i^\alpha(a) + \Sigma_i^\alpha(b)}{2} \right|^2}{\sqrt{|\Sigma_i^\alpha(a)| |\Sigma_i^\alpha(b)|}} \end{aligned} \tag{8}$$

The overall structure of the learning algorithm of IFCS is shown in Fig. 12.

We describe the detailed steps of IFCS-algorithm with its flow chart given in Fig. 13 in the following.

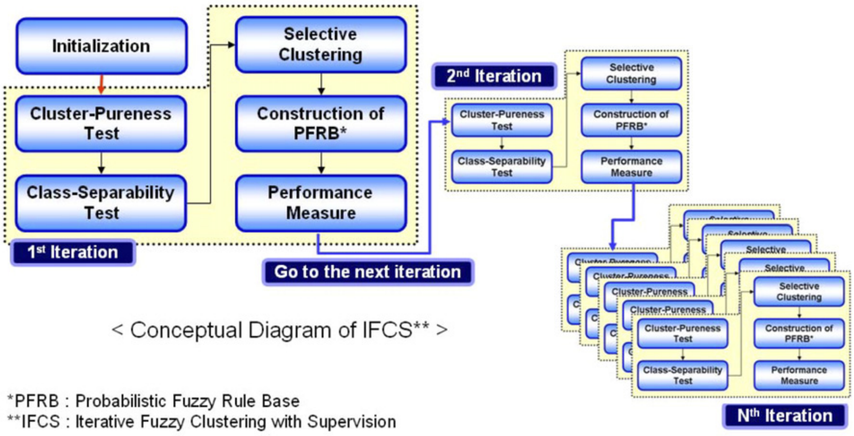



Fig. 12. Overall structure of IFCS algorithm.

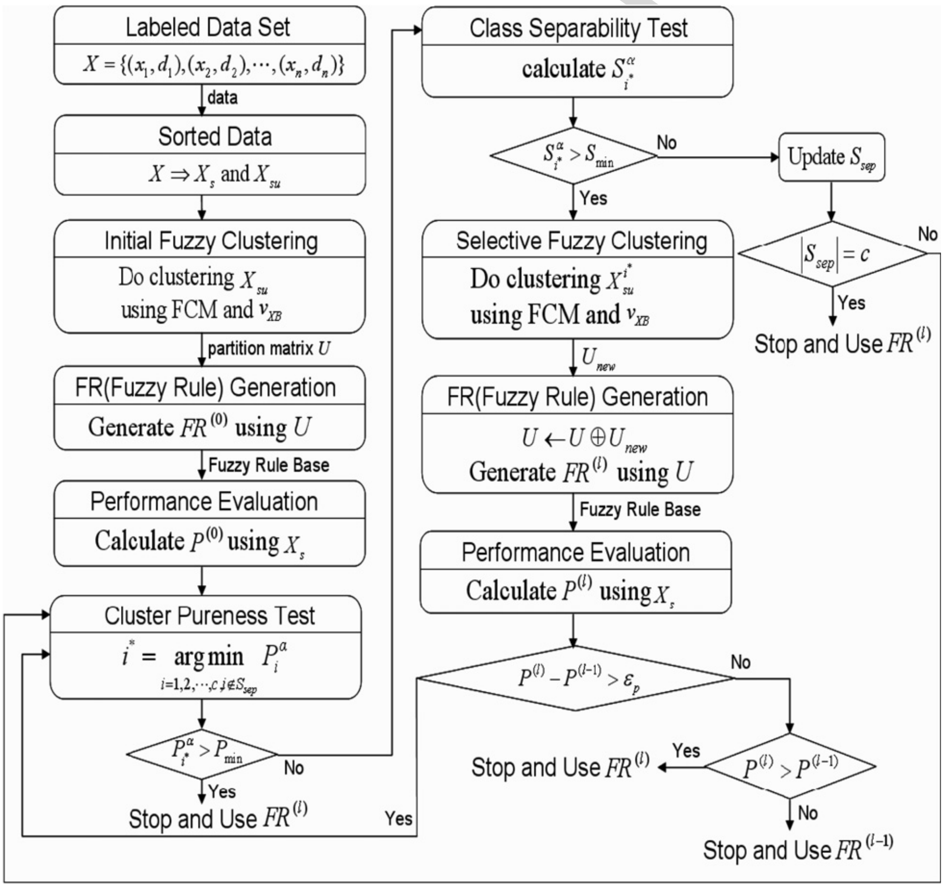



Fig. 13. Flowchart of the IFCS algorithm[43].

#### 4.2.1. Initialization

At fitst, initial clustering using FCM algorithm is performed with the cluster validity $v_{XB}$ from the $X_{su}$. We find the first local minimum to get the number of clusters $c$ with high reliability and high calculation speed from the cluster validity values. Then, after obtaining the initial partition matrix $U$, a fuzzy rule base of the form in Eq. (1) is generated along with the recognition rate as a performance measure. Let $S_{sep}$ be a set of the cluster indices which have passed the class-separability test, and suppose $S_{sep}$ is initially an empty set.

#### 4.2.2. Cluster-pureness test

We calculate the cluster-pureness index $P_i^{\alpha}$ for each cluster $i$. Then, we find $i^*$ wich corresponds to the smallest value of $P_i^{\alpha}$, i.e., $i^* = \arg\min_{i=1,2,\ldots,c} P_i^{\alpha}$. If the selected $i^*$ is already in $S_{sep}$, the cluster with the next smallest value of $P_i^{\alpha}$ is selected as $i^*$.

*4.2.3. Class-separability test*

For the selected cluster $i^*$ in the cluster-pureness test, we conduct the class-separability test using Eq. (5). That $S_{i^*}^{\alpha}$ is larger than $S_{\min}$ implies that data in the cluster $i^*$ is separable with different class labels while that $S_i^{\alpha}$ is smaller than $S_{\min}$ implies that each of the class in the cluster $i^*$ is no more separable. Then, $S_{sep}$ is updated by including the element $i^*$. If $|S_{sep}| = c$, all the clusters are not separable and the procedure is terminated.

*4.2.4. Selective fuzzy clustering*

Again, FCM clustering with the cluster validity $v_{XB}$ is performed for the unlabeled data set $X_{su}^{i^*}$ that contains only the data $x_{jk} \in X_{su}$ satisfying $\mu_{i^*jk} \geqslant \alpha$. Find the first local minimum to get the number of clusters $c'$ in $X_{su}^{i^*}$ and conduct re-clustering. Then, labeling newly generated clusters, obtain a partition matrix $U_{new} = [U_{c+1}^T \ldots U_{c+c\prime}^T]^T$ from $X_{su}^{i^*}$, where $U_i = [\mu_{i11}\mu_{i12}\ldots\mu_{ijk}\ldots\mu_{iKn_K}]$. We obtain the partition matrix $U$ by omitting the $i*$-*th* row of $U$ and by adding $U_{new}$ to $U$, i.e., $U = [U_1^T U_2^T \ldots U_{i^*-1}^T U_{i^*+1}^T \ldots U_c^T U_{new}^T]^T$. The total number of clusters increases by $c'$-1.

*4.2.5. Performance evaluation*

Using the newly updated $U$, a new fuzzy rule base of the form Eq. (1) is generated. Then, we obtain the recognition rate as a performance measure. The procedure is terminated if the recognition rate is not increased by a pre-specified number $\varepsilon_P$. Otherwise, the procedure is repeated from the cluster-pureness test until one of the terminating conditions is satisfied.

Based on the algorithm on the IFCS presented above, we are developing a learning system in which three layered memory subsystem is adopted in the inductive learning process for a HRI system as explained in the following case study.

*4.3. Usage of probabilistic fuzzy rule base*

As an application example, we show construction of a PFRB-based behavior learning system and discuss its usage for HRI in a smart home environment.

*4.3.1. Case study (3): PFRB-based behavior pattern learning system*

A smart house, called ISH (Intelligent Sweet Home), has been under development at KAIST since the year 1999. By this project, we focus our efforts on human-friendly technical solutions for motion/mobility assistance and advanced human–machine interfaces to provide people with physical disability with easy control of both home-installed appliances and assistive robotic systems including an intelligent bed, intelligent wheelchair and transferring system [47,48]. Since the smart house consists of a number of subsystems and tasks, and each task requires usually more than one subsystem for cooperative execution, we have noticed that an inhabitant with some cognitive difficulty often expresses difficulty to handle dexterously all the subsystems with various human–machine interfaces. To resolve this difficulty, we have been developing a human-look service robot as shown in Fig. 14 so that the user can operate the whole system [49] with ease. The robot should possess high level of intelligence for their control and management of the semi-structured environment, and be able to perform human-friendly actions and interactions with the user, offering high level of comfort and functionality. For this, the stewardess robot generates a sequence of subtasks, distributes subtasks to subsystems, and supervises actions of each subsystem to synchronize subtasks, thus, reduces the cognitive load of the user.

The robot is to be equipped with various recognition subsystems for human-friendly interaction such as facial emotional expressions, hand and body gestures and human gait patterns, not mentioning other typical functional subsystems including navigation subsystem and face detection/tracking subsystem, all of which are integrated for a large-scale robot. One of the key features of the stewardess robot is its learning capability including intention reading of the user so that some awkward or difficult situations can be avoided for the user with some physical disability. The system is also supposed to provide a personalized service depending on the inhabitant's preference and life style. All of these functions of the robot will enable the home system to perform appropriate tasks autonomously instead of cumbersome manual operations by observing the inhabitants' behavior. As mentioned earlier, we have observed that a desired human-friendly interaction system in the ISH would be possible only when the management system would be equipped with a powerful learning capability.

As an initial stage attempt to design a life-long learning system, we have constructed a probabilistic fuzzy rule base by observing the user's behavior pattern in daily life using IFCS algorithm. More specifically, we first separate a knowledge base for temporal storage and a knowledge base for control. Then, we adopt a reliability measure of probabilistic fuzzy rule for improvement of the rule base. Among possibly numerous probabilistic fuzzy rules, only those rules that are considered reliable by the reliability measure are accumulated in the knowledge base for control, and then, the learning system provides classification results using the knowledge base. Fig. 15 shows a structure for an inductive learning process for extraction of probabilistic

Fig. 14. Stewardess robot, "*Joy*" in Intelligent Sweet Home, KAIST.

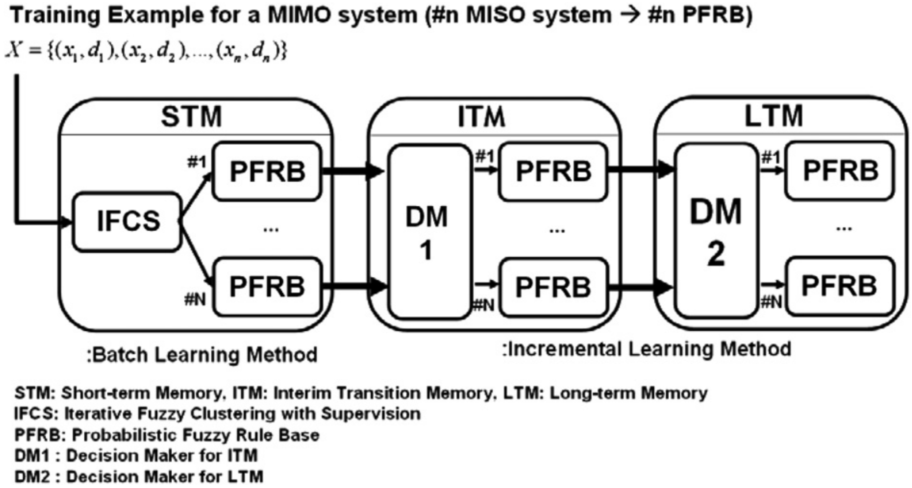



Fig. 15. A structure for inductive learning phase for probabilistic fuzzy rule base extraction.

fuzzy rule base using IFCS algorithm. Overall learning takes place in three processes called STM (short-term memory), ITM (interim transition memory) and LTM (long-term memory). In the STM, the IFCS learning algorithm generates a PFRB (probabilistic fuzzy rule base) from a set of training examples which are observed during each time period. PFRB in STM is considered to be a temporal rule base, while ITM is a pool of possibly reliable probabilistic fuzzy rules for control. By a fuzzy membership-similarity measure between rules, DM1 (decision maker 1) adds or merges each rules from STM into ITM. If the DM1 decides to merge the incoming rule into existing rule base in the ITM, a probabilistic similarity-measure between rules is calculated. And it is reflected in updating the reliability measure value of the merged probabilistic fuzzy rule. Reliability measure of a probabilistic fuzzy rule is recursively calculated along the curve $y = 1 - e^{-\gamma x}$, where $x$ is an accumulated value of the probabilistic similarity-measure and $\gamma$ is a design parameter. DM2 selects probabilistic fuzzy rules from ITM to be transferred to LTM according to the reliability measure. LTM is the storage of a PFRB for control as shown in Fig. 16.

To show effectiveness of the proposed learning system, we have tested air-conditioner control data as well as TV watching pattern data. We have obtained a performance of high classification rate with small number of acquired rule base for each data pattern, and, the learning system can provide probable outputs in sequence from probability of each class in the learned PFRB. Regarding TV watching pattern data, the success rate goes up to success rate of around 95% if we include the second probable class for classification even though the data pattern shows inconsistent characteristic. The learning system can recommend a favorite TV channel for the inhabitant with high satisfaction degree within 2 trials, which can be very useful to apply in a practical system.

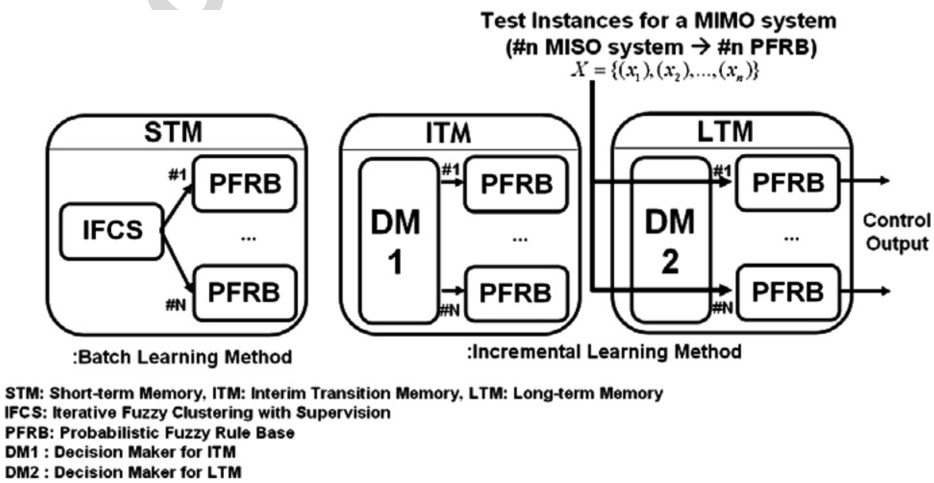



Fig. 16. A structure control phase for probabilistic fuzzy rule base extraction.

### 4.4. Architecture of life-long learning system for HRI

A typical pattern classifier is first trained for regularities in I/O relationship from given data pattern in off-line, and then, the learned system is used for recognition and/or control. When the system recognizes human behavior in short term with an assumption that selected features of the behavior remain stationary, such a classifier is quite successful in performance, especially with various soft-computing techniques employed in the process of perception and recognition [50]. If the system is supposed to operate in a service environment of residential space for a long period of time, however, such an approach may not work because we must deal with time-varying and non-stationary learning targets such as human bio-signals, body gestures and other behavioral patterns in parallel for a long time span. One obvious implication is that the learning system needs a huge memory capacity with capability of efficient management in view of long term learning and adaptation for human-friendly interaction.

There have been several attempts to design a learning system from a view of memory structure in reference to a human cognitive learning model. The learning system of ''Cognitive Robot'' has been designed inspired by the *central executive* from *Baddeley*'s working memory model [51] with a combination of STM and LTM [52]. Note that an early conceptual approach of introducing memories in the learning system started from studies on cognitive models of human memory in the field of psychology and cognitive informatics. *William James* identified three components in human memory [53], known as the after-image, the primary, and the secondary memory. Since then, contemporary theories on memory classification [54] [55] commonly described it as the sensory memory, short-term memory and long-term memory. Based on this model, *Wang* suggested that the logical architecture of memories in the brain can be classified into the following four categories: (1) the SBM (Sensory Buffer Memory), (2) the STM (Short-Term Memory), (3) the LTM (Long-Term Memory), and (4) the ABM (Action Buffer Memory) [56]. Also, *Pelayo* described storage process in the memorization process with four kinds of above explained memories incorporated with timed arc Petri Net [57]. It is instructive to refer to Hawkins [58] who asserts that, if an intelligent machine is ever to behave like a human, it should have a memory structure and functionality similar to the neo-cortex of human brain. Specifically, the neo-cortex stores sequences of patterns in a hierarchical invariant form, and recalls patterns auto-associatively and predictably in the 6 multilayered memory structure. It performs as basic learning components the bottom-up classifications of patterns and the top-down construction of sequences.

Referring to learning through the entire lifespan of a system [59], we may use a new terminology ''life-long learning'' or continuous learning. *Grossberg* asserts that, in contrast to a paradigm adapting only to a changing environment, the notion of life-long learning suggests preservation of previously learned knowledge if it does not contradict the current task [60]. To build a learning system that is capable of frequent and intense interaction between human and robot for a long time, we adopt the concept of life-long learning for building a system that is capable of performing human-friendly interaction with the user with physical disability in assistive service environment. Here, assistive service includes fetching and delivering articles and foods in the home as well as rendering entertainment services, such as turning on/off TV, in response to gesture commands for the user's independent living.

We propose a life-long learning system architecture whose brief schematic block diagram is shown in Fig. 17(a). The overall system under consideration functions as a pattern classifier, a controller or a multiple combination of them and its information flow process has a structure consisting of IE (Inference Engine), PFRB, and CDS (Context Descriptor Set). The inference engine performs logical operations and numerical computations with input data and the rules. The rule base, PFRB, corresponds to the model of the learning target which contains a given number of rules and parameters in each rule. The CDS is introduced to reflex the fact that context awareness is essential for rendering proper services in a continuously changing service environment. The context descriptor set corresponds to a set of models of the environment which concerns the outside of the system boundary. These context models can be qualitative as well as quantitative. In the system theory, the context is often expressed as a set of fixed assumptions some of which may look artificial to make the theory mathematically tractable. As mentioned earlier, however, HRI takes place in a service environment (of a residential space in our study) for which the context may change in time and in space so such fixed assumptions on the environment and the system would have very limited applications.

The context dependence of the system is concisely illustrated by a metaphorical diagram called ''Context as a box'' [61]: inside the box are sentences as the content and outside of the box carries a collection of parameters and their values. The representation of context dependency may vary in terms of partiality, approximation and perspective [61] and proper reasoning should be applied along these dimensions for successful text understanding that corresponds to a satisfactory system operation. We shall adopt a notational convention similar to that in [61] to represent the context of the system in terms of parameters, $P_i (i = 1,\ldots,N)$ *and a value* $V_{ij}, j = 1,\ldots,M$, *for each parameter* $P_i$, which we call the context descriptors. These descriptors and their values may initially be determined by some a priori knowledge about the system and also by initial information of the environment. During the operation of the system, these parameters may change or may be deleted/newly introduced to reflect accumulated monitored information on environment and the user or the operator feedback.

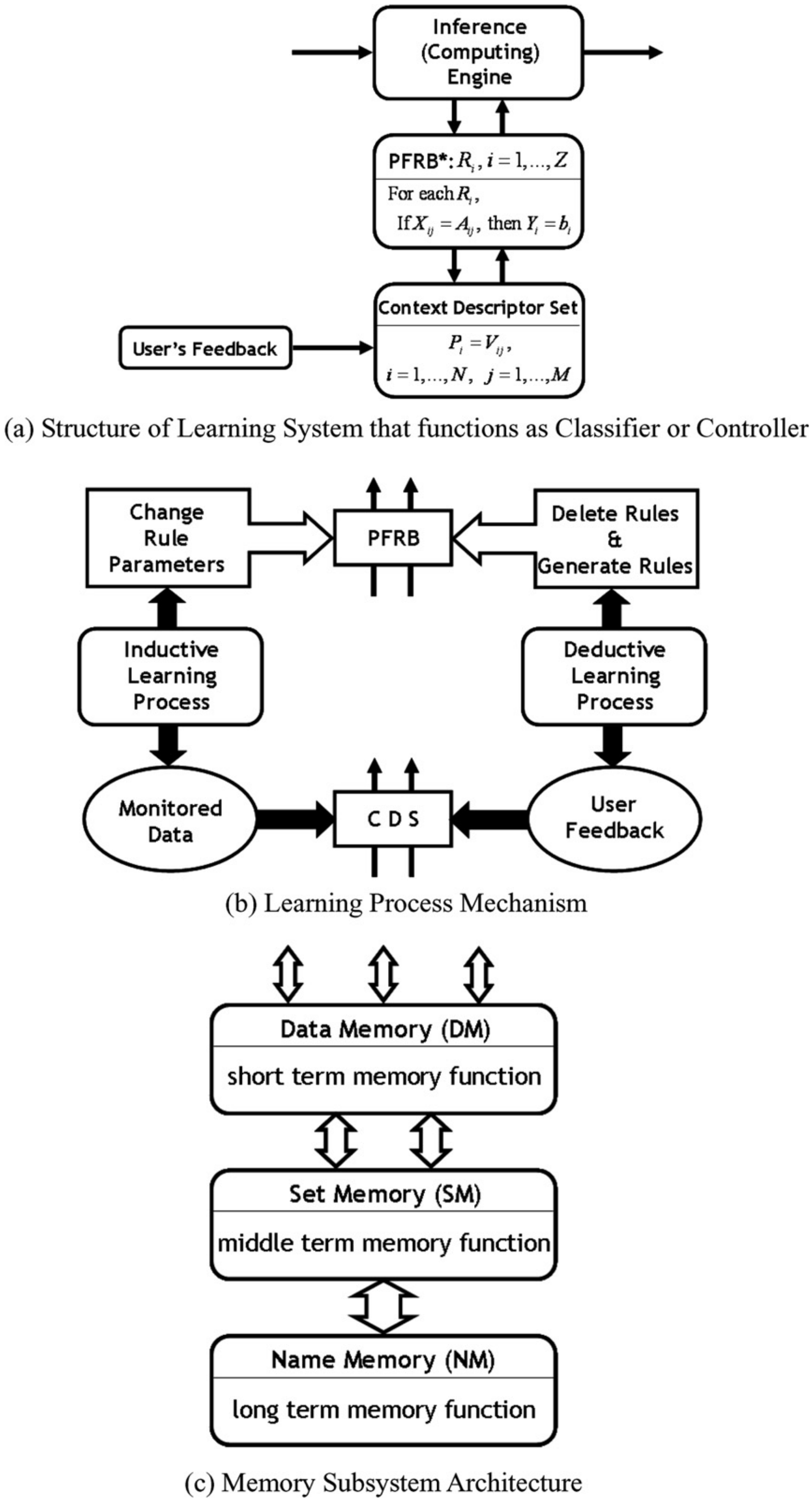



Fig. 17. Proposed life-long learning system architecture for HRI.

In the system, it is to be designed that learning takes place in two forms of inductive learning and deductive learning whose conceptual block diagram is shown in Fig. 17(b). The inductive learning process works for both the rule base PFRB block and the context descriptor set block CDS in a way that the parameters of the blocks are updated inductively by pairs of system input /output data and by accumulated monitored data of the environment. The deductive learning process operates also for both PFRB and CDS. First, some of the rules that are judged as bad or unnecessary can be deleted from the rule base or newly instituted into the base PFRB in the given context. This kind of action corresponds to structure change of the rule base and can be configured deductively, meaning that the structural change is carried out in a top-down fashion in consideration of context constraints. Secondly, the user feedback that may be obtained during or after interaction in the form of unconscious reactions, or conscious demands should be taken care of deductively unless the feedback has an immediate resolution. Personal habits and preferences should be understood along with limitations of the system at hand and in view of partial, approximate and/or perspective representations. For proper contextual reasoning, one may adopt those methodologies of localized reasoning, push and pop or shifting in [61].

In order to facilitate information flow for data processing and learning mentioned above, some effective memory subsystem should be incorporated so that all the relevant knowledge and data such as rules and parameter values are stored and retrieved efficiently. It is proposed that the memory subsystem consists of three units hierarchically as shown in Fig. 17(c): (1) DM (Data Memory) with a STM function, (2) FM (Feature Memory) with a middle term memory function and (3) RM (Relation Memory) with a LTM function. On the one hand, DM unit handles information/data as in an ordinary memory and can include a buffering function for sensory input and action output as well. On the other hand, with a finite capacity of memory size, this unit should be capable of handling huge data contained in sequences of temporal-spatial patterns that come into the system incessantly. One approach is to introduce an autonomous down-sizing-filter function to DM by which some bad/less reliable information or un-fired/less privileged rules, etc., are gradually deleted. In this approach, rules and information may be tagged with some form of weights denoting measure values such as aging, reliability or importance degree. More effectively, the memory data can be grouped into a number of clusters or regions and the content of each region is continually summarized and expressed as some invariant features. This extracted feature values are stored in the next level of memory unit, called FM. DM is a kind of STM since most of the data in the memory would go through some modifications. Next, the features are to be again grouped and related in FM and the relation names are passed to the deeper layer called RM. Functionally, FM would work as a form of associative memory and retention of information or data in FM is affected by DM, thus the content of the memory may change. RM is the most abstract level in the hierarchy and the content would be least dynamic as in a LTM unit. For example, consider a dweller's habit of having snack while watching TV in the living room: a sequential monthly data of TV channels selected by the user and information about snacks that the user has are continuously stored and updated in DM while data of most watched TV channel and most favored snack are statistically obtained from DM and are stored in FM. Finally, the two pieces of information are related and the relation is stored in RM. This mechanism is partly similar to the memory structure of the neo-cortex of human brain which efficiently handles huge sequential patterns [58]. The information in RM and FM, when retrieved, helps the total system to locate the necessary information in DM and also can be used for prediction of the system behavior in sequential actions [58].

It is remarked that the framework of a learning system architecture proposed above is to be developed and evaluated in terms of actual hardware and, as discussed in the previous section, the project is still in embryonic stage and that this memory structure may be extended to a more complex, hierarchical memory system having 4 or more layered units.

## 5. Concluding remarks

The human–robot interaction process in service environment has been considered as a human-friendly human-in-the-loop system where interaction occurs frequently and intensely. As an effective engineering approach of achieving human-friendly HRI process, we have attempted to use soft computing techniques of various types for recognition of human gestures, human bio-signals and human intention as well as human's physical status and behavior, as summarized in Fig. 18.

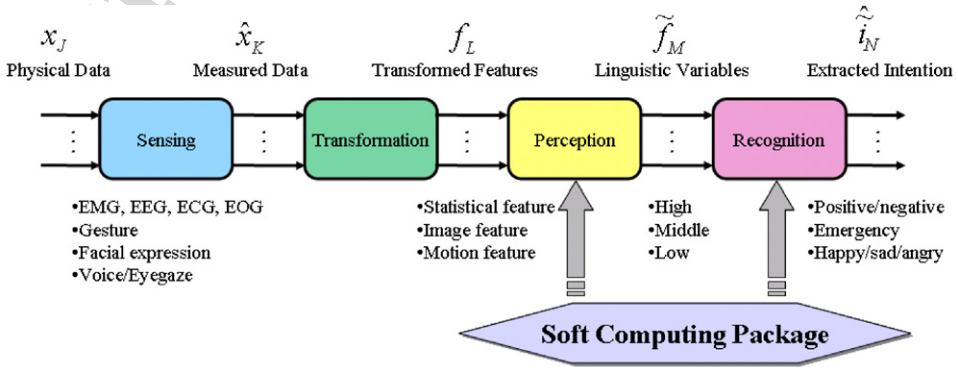



Fig. 18. Typical human behavior recognition procedure.

To cope with formidably complicated characteristics of human such as high dimensionality, nonlinear-coupling of attributes, subjectivity, apparent inconsistency, susceptibility to environments and disturbances, and time-variance as well as situation-dependency, we have proposed a long-term learning system to be used in assistive service robotic environment such as an intelligent residential space where old/disabled people live independently. It is noted that life-long learning capability is essential for robot to coexist with human as well as serve well for human in the long run in continually changing environment.

In this paper, we have shown that FSL-based hybrid learning techniques can play an important role in modeling time-varying, inconsistent and user-dependent characteristics of human bio-signals. These intelligent techniques have been shown to work for some recognition systems in HRI process. Finally, we have proposed a framework of life-long learning architecture with probabilistic fuzzy rule base to be utilized for long-term human-friendly HRI process. We remark that the proposed life-long learning system architecture is in its early stage of development and would need a great deal of efforts for actual realization and practical utilization.

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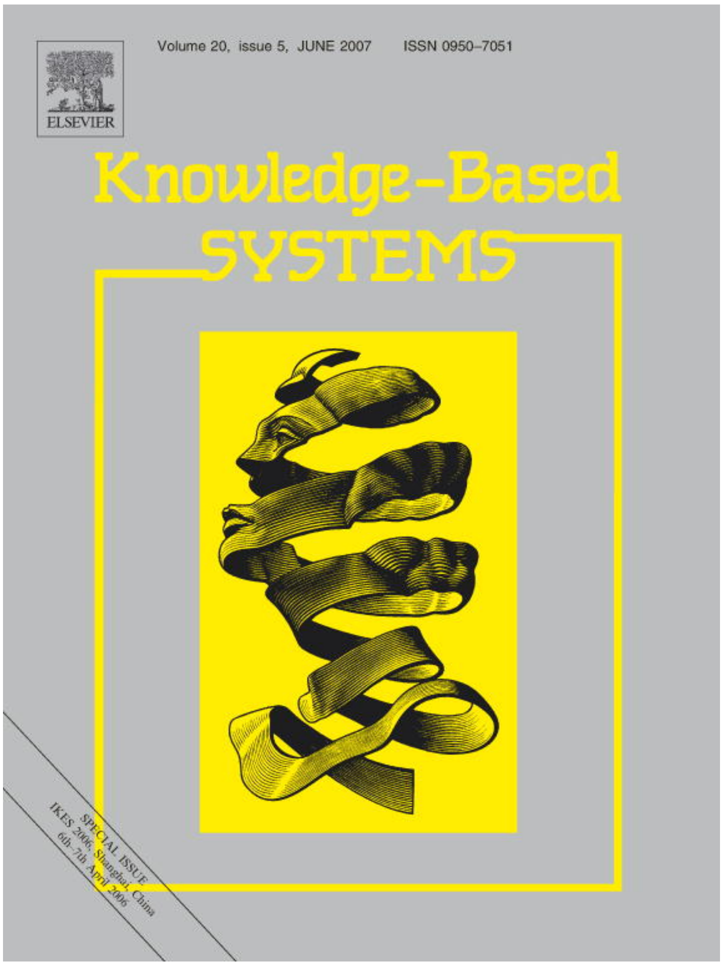
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