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Atmosphere Understanding with Individual Difference and its Application to Distance Education

（個人差を含んだ雰囲気理解と
その遠隔教育への応用）

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Doctoral Thesis

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Abstract

Transform function from emotions represented in affinity arousal-pleasure space to atmosphere represented in Atmosfield is proposed for the extraction of atmosphere information in humans/robots communication. An experiment is done for the communication between two persons with emotions and atmosphere. By comparing output of the transform function with their emotions and directly given atmosphere information, it is shown that the proposed function expresses the atmosphere with accuracy rate 0.81, which is enough for casual communication between robots and humans. The transform function will be introduced to the ongoing human friendly household robot application project.

A method for understanding the atmosphere is proposed for humans-robot interactions in a multi-agent society, where the individual assessment of the atmosphere is estimated using a Support Vector Regression (SVR) method that represents the emotions of all agents and the atmosphere of the entire society is represented as a fuzzy set in a Fuzzy Atmosfield. This method provides the necessary information that allows each agent (human/robot) in the society to understand the differences between the objective characteristics of the atmosphere and the agent's individual assessment of the subjective atmosphere and to make appropriate behavioral decisions thereafter. In the experiments, 13 scenarios are tested by four humans. The characteristics of the atmosphere are calculated by applying the proposed method to the emotion data from the four humans. The results are compared with the subjective atmosphere information from the four humans and it is found that the average accuracy reaches 90%. This proposal is planned in order to realize customized services for the humans-robots interactions

in a “Multi-Agent Fuzzy Atmosfield”, which is the subject of the authors’ group’s ongoing research project.

A distance education system is designed based on fuzzy inference, where visualized atmosphere information is shared by all learners in a virtual classroom. It provides high aspirations, low isolated feeling, low stress, and high affinity to learners, and offers learner’s psychological information, individual difference information, and hints of system improvement to system manager. The effect of visualized atmosphere information to learner’s psychological states is confirmed by T score Anger-Hostility (A-H) of POMS test for 15 graduate students using CAI contents, and comparison experiment with traditional distance education in terms of paired t-test obtains p-value 0.011 of A-H. The proposal of atmosphere information presentation of virtual classroom provides a first step of establishing over face-to-face distance education system.

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Chapter 1

Introduction

Measurement of emotions and atmosphere in human robot communication is necessary for ongoing household robots project [1-9], where many robots and humans are supposed to communicate in natural way partly through internet. In the case of one to one communication between human and robot, there are many research works to study emotions from a cognitive science viewpoint [1-8]. In the casual communication among many robots and many humans, atmosphere becomes an important issue rather than emotions of humans/robots. The measurement of atmosphere becomes a central research topic in such problem setting but has not been studied enough.

A transform function from emotions represented in affinity arousal-pleasure space into atmosphere represented in atmosfield is proposed for the measurement of atmosphere in the communication field of robots and humans. It is applied experimentally to measure the atmosphere in the case of person to person communication.

In Chapter 2, Atmosphere in person to person communication is focused in 2.1 by introducing transform function, and it is extended to many persons case in 2.2. The availability is confirmed for the communication experiment between two persons in 2.3 toward the realization of casual communication between many robots and many humans.

Atmosphere understanding is a new paradigm for the authors' group's ongoing robot project[1-10], where it is expected that many robots and humans will communicate through the internet in a natural way that is referred to as casual communication. From a cognitive science perspective [11-4], most studies have focused on emotions, especially in the case of one-to-one communications between a human and a robot. For casual communications among many robots and many humans (e.g., during a virtual conference with twenty agents (humans/robots) or a home party with multiple humans and robots), the atmosphere is more important than the emotions of the individual human or robot. Several studies have focused on human-robot interactions [5-10][15][16], cognitive science [8][9], and representations of entire atmospheres [17-21][10] in which atmosphere-related factors were considered in order to define the attributes of the communication atmosphere. In this paper, the emotional information is represented in an affinity arousal-pleasure space [2] and the atmosphere is represented in a Fuzzy Atmosfield [21]. A transform function is proposed in [10] in order to determine the relationship between emotions and the overall atmosphere.

Given a specific atmosphere for humans-robots interactions, the agents (humans/robots) may interpret the atmosphere differently. For example, one agent may be feeling friendly, while another may not. In the proposed method for understanding the atmosphere, the information about the atmosphere is obtained by using Support Vector Regression (SVR) [22] to perform calculations based on information about the agents' emotions. The information for the entire atmosphere is aggregated into a fuzzy set in a Fuzzy Atmosfield. Questionnaires about emotions and atmosphere information are sent to each agent during the learning process for SVR and are adjusted to the individuality of each agent.

In [1-2], the entire atmosphere is represented by a vector in a Fuzzy Atmosfield. If an agent belonging to a society with multiple agents represents the entire atmosphere using a single vector and makes a decision based on that vector, the resulting decision may not be appropriate because the subjective assessments of the atmosphere usually vary from one agent to another. Because of several questionnaire-based experiments about the atmosphere, it has become clear that individual interpretations of the atmosphere can provide important information for making appropriate behavioral decisions in situations where the agents' perceptions about the atmosphere are spreading. The perception gaps that are caused by differing levels of personal sensitivity have not been studied enough in the small number of existing research studies about atmospheres in multi-agent societies. Therefore, a method for representing the differences between individual perceptions about the atmosphere for each agent is investigated in this paper through the introduction of a fuzzy set concept in a Fuzzy Atmosfield (i.e., an average vector with a standard deviation vector). When taking the differences between the individual assessments of the atmosphere into consideration, it may be appropriate to identify the entire atmosphere as a fuzzy set on a Fuzzy Atmosfield, rather than as a single vector. This representation allows individual agents to respond with appropriate behaviors toward other agents in the multi-agent society.

We performed a questionnaire-based experiment in order to confirm the accuracy of the proposed method for understanding of the entire atmosphere in terms of a fuzzy set. Four human-agents enacted 13 conversation scenarios, where each scenario continued for 100 s. A questionnaire about emotion and atmosphere was sent to each agent at 10 s intervals and a total of 520 (= 13 × 4 × 10) answers were obtained. The answers were used for SVR learning for each agent. The 13 scenarios were presented again to the same four human-agents at least one week later and the same questionnaires were sent to the subjects. The newly obtained data (i.e., 520 additional answers) were used for the testing data for the SVR. The accuracy of the proposed method was investigated by comparing the SVR output with data from observations of the four human-agents.

In Chapter 3, we discuss the results from a preliminary questionnaire-based experiment that showed that the assessment of the atmosphere can differ from one agent to the others. The motivation of the proposal is also mentioned in 3.1. In 3.2, we propose a method for understanding the atmosphere in a multi-agent society using SVR and fuzzy sets. The validity of the proposed method is confirmed by an experiment in 3.3.

Effects and satisfaction of distance education becomes important issue recently [23-55]. Several adoptive system based on learner's user model have been proposed for effective distance education [56-87], they show improvement of the learner's satisfaction. Learner's stress is focused to realize more effective distance education by analyses of learner's performance, where not only system's adaptation to learner but also learner's adaptation is necessary [88-95]. The best effective learning is not easy to realize under using only the unilateral system's adaptation because the learning process depends on learner's emotion. On the other hand, unilateral learner's adaptation to the system is also not simple to make enough efficiency for each learner because it requests high motivation of the learner. The motivation of learners becomes an important issue for learners' performance [95]. The learner's isolation and stress feelings in distance education are still open research topics [88-95]. The classroom lecture which has learners' sufficiency has many interactions among learners and lecturer, where the atmosphere of the lecture is shared by the learners and the lecturer. Therefore, educational environment which has interaction among learners and system such as virtual classroom lecture is necessary to realize effective distance education.

A distance education system is proposed to realize indirect interaction among learners and system, to decrease the learner's stress and isolated feelings, and to inspire learners, where visualized atmosphere information in a virtual classroom is shared by all learners based on fuzzy inference, where the fuzzy inference is suited to represent assessment of atmosphere because it includes humans' fuzzy expression. A multimodal interface such as Kinect® is introduced to each learner's learning environment in order to transfer the learner's state, i.e., facial expression, gesture/posture, and sound, to the system. The learner's state is mapped into a learner's emotion in affinity arousal-pleasure space [2]. Atmosphere information in the virtual classroom is obtained as an emotional vector on fuzzy atmosfield $[-1, 1]^3$ [21][96] by applying rule based fuzzy inference to learner's emotion information. A visualization program provides the atmosphere information of the virtual classroom to each learner.

Each learner studies by communicating with the system and is able to recognize the atmosphere of all other leaners that are supposed to stay in the same virtual classroom at the same time. Each learner gets much more motivation, decreases isolated feelings, reduces stress, and increases the feeling of acceptance by the system via visualized virtual classroom atmosphere. System manager gets each learner's psychological status, obtains individual difference of atmosphere recognition by learners, and makes use of educational contents improvement or business strategy.

In chapter 4, the availability of the atmosphere information is confirmed through a comparison experiment of the proposed distance education with an ordinal distance education using CAI contents on computational intelligence [97] enforced to 15 leaners. The evaluation is based on learners' mood obtained via Profile of Mood State (POMS) test [8].

A distance education system with atmosphere information is proposed in 4.1. The definition of customized knowledge, visualization of atmosphere information, and their application to distance education are introduced in 4.2. The efficiency of the atmosphere information is confirmed by using POMS test and CAI contents in 4.3.

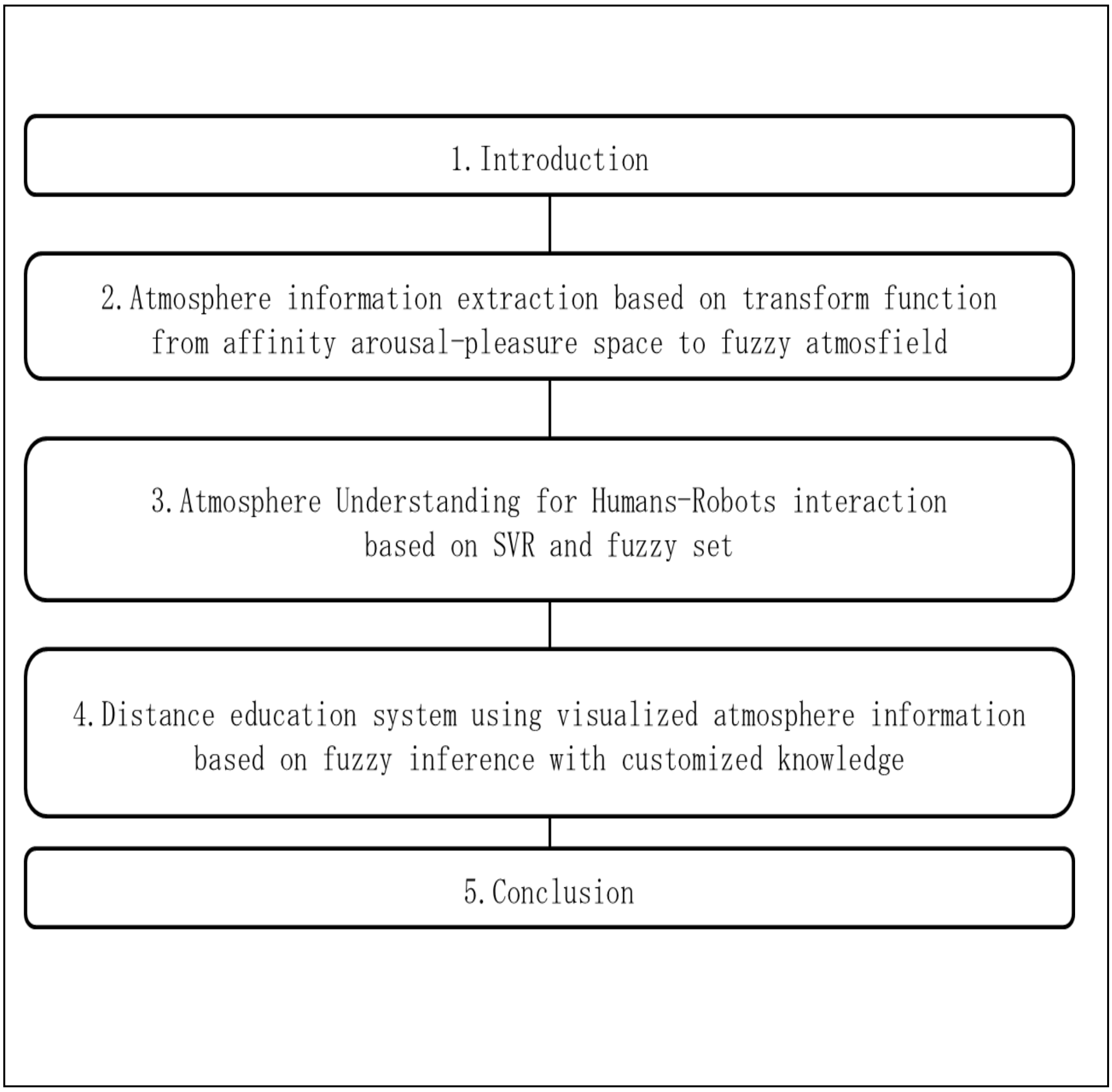


Fig. 1.1 Thesis Road Map

of “Atmosphere Understanding and its Application to Distance Education”

Chapter 2

Atmosphere information extraction based on transform function from affinity-arousal pleasure space to fuzzy atmosfield

2.1 Atmosphere between 2 persons

2.1.1 Transformation from person's emotion to fuzzy atmosfield

Measurement of atmosphere and emotion is necessary for many robots/humans communication. To express atmosphere mathematically, concept of atmosphere field is proposed and it is named as Atmosfield in [1], where Friendly-Hostile, Lively-Calm, and Casual-Formal, three dimensional fuzzy cube is used to represent the Atmosfield. Person's emotion depends on the situation, and is changing time by time. By considering such a time-varying emotion, Affinity Arousal-Pleasure space, abbreviated as AAP space, is proposed to express the emotion in [2]. Atmosphere in communication among many people depends on each person's emotion and the situation. This paper focuses on transformation from emotions into the Atmosfield by using Affinity Arousal-Pleasure space.

2.1.2 Transformation into Friendly-Hostile axis

The Friendly-Hostile axis expresses the relation between two persons in their face to face communication. If two person's emotions are different, the position on Friendly-Hostile axis, denoted by Friendly value in short, must be in Hostile direction, and the length of difference vector between two person's emotional vectors in AAP space must be longer. Therefore, it may be concluded that the Friendly value indicates the length of difference vector between two person's emotional vectors. If two persons have, however, displeasure emotion each other even in the case of the shorter length of difference vector, the Friendly value should be lower and the situation can be said hostile. So, the Friendly value should depend on the value of pleasure axis in AAP space.

By considering what kind of influence affects the pleasure axis value to the Friendly atmosphere, the Friendly value should be assigned near to zero if a person has displeasure emotion although the other has a pleased emotion. So, the function translating the emotions to Friendly axis is influenced by sign of average with two person's pleasure value. But, in this case, the Friendly value has no information of the relation between the two persons. So, transform function must have the term about Affinity because the Affinity value is very important element to measure the atmosphere. To make the friendly mood, there should be no person who has low affinity. So the transform function should have the minimum affinity value of the two persons. The lower affinity emotion, however, has a large influence to the atmosphere after the time measured. So the Affinity value must be added as integral term to express the atmosphere in the time. By considering all of these issues, the transform function into Friendly axis is given by

$$Fr = \frac{1}{2}\left\{ sign(\overline{P})\frac{L}{2\sqrt{3}} + \frac{\sum \min(Af_1(t), Af_2(t))}{T} \right\}, \qquad (2.1)$$

where

L: Length of difference vector of vectors in AAP,

$sign(\overline{P})$: Sign of Average pleasure value,

T: Number of sampling data,

$\min(Af_1(t), Af_2(t))$: The minimum affinity value of two persons on the time.

The length of difference vector L is calculated by

$$L = \sqrt{(Af_1 - Af_2)^2 + (Ar_1 - Ar_2)^2 + (Pl_1 - Pl_2)^2}\ , \qquad (2.2)$$

where

Af_1 : Sign of Average pleasure value,

Af_2 : Sign of Average pleasure value,

Ar_1 : Sign of Average pleasure value,

Ar_2 : Sign of Average pleasure value,

Pl_1 : Sign of Average pleasure value,

Pl_2 : Sign of Average pleasure value.

2.1.3 Transformation to Lively-Calm axis

The position on Lively-Calm axis, called Lively value in short, depends on Arousal value directly. Lively mood may not be occurred without Arousal person. So the Lively value must be linear with average of Arousal value. The Lively value, however, may not be expressed completely by only arousal. For example, if two persons are displeasure although they are arousal, they may have some stress without affinity. The case can be considered as serious and hostile. In such a case, the mood may not be lively. But, if the two persons have high affinity, the situation may be changed to quarrel. Then, the atmosphere becomes lively though the relation between two persons is hostile. In other case, if the two persons are in highly pleasure and affinity, it is easy to think that the atmosphere of conversation becomes lively. If they are not affinity but pleasure, they may be thought as in the situation of first meeting. In such a case, they may usually start conversation. And, the atmosphere becomes livelier.

These cases may be summarized in the tabular form as in Table 2.1. The interlinear space should be 13 points.

Table 2.1 The relation between lively atmosphere and average emotion

Condition			Result
Arousal	Pleasure	Arousal	Pleasure
Arousal	Pleasure	Arousal	Pleasure
Arousal	Displeasure	Arousal	Displeasure
Arousal	Displeasure	Arousal	Displeasure
Sleep	Pleasure	Sleep	Pleasure
Sleep	Pleasure	Sleep	Pleasure
Sleep	Displeasure	Sleep	Displeasure
Sleep	Displeasure	Sleep	Displeasure

In the table 2.1, the function will be given by

$$Lively = \frac{1}{2}\overline{Ar}\,\overline{Pl}(1-\overline{Af}) \quad , \tag{2.3}$$

where

$\overline{Af}$: Average of Affinity value,

$\overline{Ar}$: Average of Arousal value,

$\overline{Pl}$: Average of Pleasure value.

It should be noted that the Lively value has no integral term because of the easiness to change as time passes.

2.1.4 Transformation to Casual-Formal axis

Casual-Formal atmosphere is formed by personal relations. When casual atmosphere appear, the two persons may have high affinity. Casual atmosphere is influenced by Friendly-Hostile atmosphere and Lively-Calm atmosphere, because both of Casual atmosphere and Formal atmosphere exist in the same emotion condition.

Then, all situations are summarized as in the Table 2.2.

Table 2.2 The relation of Casual-Formal atmosphere with other Parameters for 2 persons

Condition				Result
Friendly	Lively	Pleasure	Arousal	Casual
Friendly	Lively	Pleasure	Sleep	Casual
Friendly	Lively	Displeasure	Arousal	Casual $\left(\overline{Af} > 0.5\right)$ Formal $\left(\overline{Af} < 0.5\right)$
Friendly	Lively	Displeasure	Sleep	No exist
Friendly	Calm	Pleasure	Arousal	*
Friendly	Calm	Pleasure	Sleep	Casual
Friendly	Calm	Displeasure	Arousal	Formal
Friendly	Calm	Displeasure	Sleep	Casual
Hostile	Lively	Pleasure	Arousal	No exist
Hostile	Lively	Pleasure	Sleep	No exist
Hostile	Lively	Displeasure	Arousal	Formal
Hostile	Lively	Displeasure	Sleep	No exist
Hostile	Calm	Pleasure	Arousal	No exist
Hostile	Calm	Pleasure	Sleep	No exist
Hostile	Calm	Displeasure	Arousal	Formal
Hostile	Calm	Displeasure	Sleep	0

* : eq. 2.7

In the definition of translation Function about Friendly axis, some conditions do not hold true, e.g., Friendly, Lively, Displeasure and Sleep. Considering all issues in Table 2.2, the translation function for Casual is given by

$$Casual_{temp} = \frac{1}{2} FrLv\left\{\overline{Pl} + \overline{Ar}\left(\overline{Af} + 1\right)\left(1 - \overline{Pl}\right)\right\} \times 100, \tag{2.4}$$

where

Fr : Friendly-Hostile value,

Lv : Lively-Calm value,

$\overline{Af}$: average of affinity-no affinity,

$\overline{Ar}$: average of arousal-sleep, and

$\overline{Pl}$: average of pleasure-displeasure.

But, if a person has a big sleep emotion, the atmosphere can be said neither Casual nor Formal. Therefore it is necessary to make a scale function that is given by

$$\theta\left(\overline{Ar}\right) = \left\{ \begin{array}{c} 1(Casual_{temp} > 0) \\ 1(Casual_{temp} < 0, |Ar| < 0.5) \\ 2 - 2\left|\overline{Ar}\right|(Casual_{temp} < 0, |Ar| > 0.5) \end{array} \right\} . \tag{2.5}$$

Casual atmosphere, however, has special case like the situation Friendly, Calm, Pleasure and Arousal as '*' in Table 2.2.

In this case, both of Casual atmosphere and Formal atmosphere exist and are easily changing to each other. To express such a sensitive atmosphere, some specified function may be necessary and is given by

$$Casual_{temp} = 2\frac{\left|\overline{e_m(t) - e_m(t-1)}\right| \exp\{-(t - t_0)\}}{\max\left|e_m(t)\right|}, \tag{2.6}$$

where e_m means vector length in AAP and is given by

$$e_m = \sqrt{Af^2 + Ar^2 + Pl^2}\ , \tag{2.7}$$

Af : value of one's affinity-no affinity,

Ar : value of one's arousal-sleep, and

Pl : value of one's pleasure-displeasure.

This function is given by the assumption that Casual atmosphere makes easier to change emotions. In a conversation of two persons with such an atmosphere, stopping the talk makes formal atmosphere.

Finally, the transform function into Casual-Formal axis is given by

$$Casual = \theta(\overline{Ar})Casual_{temp}\ . \tag{2.8}$$

2.2 Atmosphere among n-persons

2.2.1 Emotions and atmosphere of n-persons

Communication by many persons will be discussed, where the issue focuses on transform function from emotions of n-persons into atmosphere. The transform function to Friendly-Hostile axis is proposed in 2.2.2. Then, the transform function into Lively-Calm axis is proposed in 2.2.3. Finally, the transform function into Casual-Formal axis is proposed in 2.2.4.

2.2.2 Transformation to Friendly-Hostile axis

In n-persons case, the definition of length of difference vector between vectors in AAP to express Friendly value is too subjective for observers. The atmosphere should be observed objectively. If one's emotion is generated independently and the distribution of emotion as an element of AAP is normal, then the length of difference vector between vectors in AAP must be varied according to the standard deviation. To include 95% of emotions, transform function has 2σ, where σ is the standard deviation. And about affinity term, the influence of affinity may depend on the number of persons and is expressed by using the influence coefficient in inverse proportion to number of persons. By considering all of these issues, the transform function to Friendly axis is given by

$$Friendly = sign(\bar{P})\frac{2\sigma}{2\sqrt{3}} + \frac{\sum \min(Af\ (t))}{T}, \tag{2.9}$$

where

σ: standard deviation,

$sign(\bar{P})$: sign of average pleasure value,

T: number of sampling data,

$\min(Af\,(t))$: the minimum affinity value of n-persons on the time,

N (> 2): number of persons.

The standard deviation σ is calculated by

$$\sigma = \sqrt{\frac{1}{n-1}\sum_i \left\{ \left(\overline{Af} - Af_i\right)^2 + \left(\overline{Ar} - Ar_i\right)^2 + \left(\overline{Pl} - Pl_i\right)^2 \right\}}\ , \tag{2.10}$$

where

$\overline{Af}$: average value of n-persons on affinity-no affinity,

Af_i : affinity-no affinity value of i-th person,

$\overline{Ar}$: average value of n-persons on arousal-sleep,

Ar_i : arousal-sleep value of *i*-th person,

$\overline{Pl}$: average value of n-persons on pleasure-displeasure, and

Pl_i : pleasure-displeasure value of *i*-th person.

2.2.3 Transformation to Lively-Calm axis

In the communication of two persons, the lively mood can be expressed by average value of each parameter. But, in the n-persons case, the average value can't be expressed correctly. For example, if the summation of each emotion is 0 though two persons have lively mood, the mood may be lively. By the assumption that the calm mood has no influence to lively one, $Liveliness_{personal}$ is given by

$$Liveliness_{personal} = \max\{ArPl(1-Af), 0\}, \tag{2.11}$$

where

Af : one's value on affinity-no affinity axis,

Ar : one's value on arousal-sleep axis,

Pl : one's value on pleasure-displeasure axis.

Finally, the transform function is given by

$$Lively = \frac{\sum_i Liveliness_{personal}}{\#(Liveliness_{personal} > 0)}, \tag{2.12}$$

where N (> 2) is number of persons.

2.2.4 Transformation to Casual-Formal axis

About the relation of Casual-Formal axis, other axis and emotions are already given in table 2.2. But, it needs to reconsider the function in the special case that is Friendly, Calm, Pleasure and Arousal. In many persons communication, the sensitive mood is not easy to change. Almost all cases continue the state from the time before. So, the table should be modified as shown in the Table 2.3.

Table 2.3 The relation of Casual-Formal atmosphere with other Parameters

Condition				Result
Friendly	Lively	Pleasure	Arousal	Casual
Friendly	Lively	Pleasure	Sleep	Casual
Friendly	Lively	Displeasure	Arousal	Casual (ave(Af) > 0.5) Formal (ave(Af) < 0.5)
Friendly	Lively	Displeasure	Sleep	No exist
Friendly	Calm	Pleasure	Arousal	Casual(t) = Casual(t-1) Casual(0) = 0
Friendly	Calm	Pleasure	Sleep	Casual
Friendly	Calm	Displeasure	Arousal	Formal
Friendly	Calm	Displeasure	Sleep	Casual
Hostile	Lively	Pleasure	Arousal	No exist
Hostile	Lively	Pleasure	Sleep	No exist
Hostile	Lively	Displeasure	Arousal	Formal
Hostile	Lively	Displeasure	Sleep	No exist
Hostile	Calm	Pleasure	Arousal	No exist
Hostile	Calm	Pleasure	Sleep	No exist
Hostile	Calm	Displeasure	Arousal	Formal
Hostile	Calm	Displeasure	Sleep	0

So, the transform function into Casual-Formal axis is given by

$$Casual_{temp} = \frac{1}{2} FrLv\left\{\overline{Pl} + \overline{Ar}\left(\overline{Af} + 1\right)\left(1 - \overline{Pl}\right)\right\} \times 100 \,, \tag{2.13}$$

where

Fr : Friendly value,

Lv : Lively value,

$\overline{Af}$: average of affinity-no affinity,

$\overline{Ar}$: average of arousal-sleep,

$\overline{Pl}$: average of pleasure-displeasure.

As in the way as the case of two persons' communication, it is necessary to introduce a scale function $\theta\left(\overline{Ar}\right)$ given by

$$\theta = \left\{ \begin{array}{c} 1\left(Casual_{temp} > 0\right) \\ 1\left(Casual_{temp} > 0, \left|\overline{Ar}\right| < 0.5\right) \\ 2 - 2\left|\overline{Ar}\right|\left(Casual_{temp} < 0, \left|\overline{Ar}\right| > 0.5\right) \end{array} \right\}. \tag{2.14}$$

Finally, the transform function into Casual-Formal axis is given by

$$Casual = \theta\left(\overline{Ar}\right) Casual_{temp} \quad . \tag{2.15}$$

2.3 Experiment on two persons' conversation

In the experiment of two persons talk, the emotion and feeling atmosphere are observed in every 3 minutes. The data are summarized in Table 2.4 and 2.5

Table 2.4 Emotion and feeling of a person

emotion			atmosphere		
Affinity	Arousal	Pleasure	Friendly	Lively	Casual
0	0	0	0	0	0
0.3	-0.4	0.6	0.5	-0.2	0.3
0.5	-0.2	0.6	0.5	0.1	0.5
0.5	-0.3	0.2	0	-0.6	0.2
0.7	0.2	0.7	0.5	0.3	0.5
0.6	0.2	0.5	0.4	0.2	0.6
0.4	0	0.2	0.3	-0.6	0.2

Table 2.5 Emotion and feeling of another person

emotion			atmosphere		
Affinity	Arousal	Pleasure	Friendly	Lively	Casual
0	0	0	0	0	0
0	-0.5	0	0.1	-0.7	-0.6
0.2	-0.3	-0.2	0.2	-0.7	-0.7
0.4	0.1	0.2	0.4	-0.2	-0.3
0.3	0.2	0.1	0.3	-0.4	-0.1
0.4	0.2	0.1	0.4	-0.3	0.2
0.2	-0.2	0	0.2	-0.8	-0.3

The atmosphere is calculated as shown in Table 2.6.

Table 2.6 Calculated Atmosfield value

Atmosphere		
Friendly	Lively	Casual
0.0	0.0	0.0
0.2	-0.2	0.0
0.3	-0.1	0.0
0.2	0.0	0.0
0.3	0.1	0.1
0.2	0.1	0.0
0.1	0.0	0.0

And, the Relative distance between average of observed data and calculated data is shown in Table 2.7 to 2.9.

Table 2.7 Evaluation of Friendly value

Observed	Calculated	Relative distance
0	0	1.00
0.3	0.2	0.90
0.4	0.3	0.96
0.2	0.2	0.96
0.4	0.3	0.89
0.4	0.2	0.81
0.3	0.1	0.89

Table 2.8 Evaluation of Lively value

Observed	Calculated	Relative distance
0	0	1.0
-0.5	-0.2	0.71
-0.3	-0.1	0.77
-0.4	0	0.63
-0.1	0.1	0.83
-0.1	0.1	0.86
-0.7	0.0	0.31

Table 2.9 Evaluation of Casual value

Observed	Calculated	Relative distance
0.0	0.0	1.00
-0.2	0.0	0.84
-0.1	0.0	0.89
0.0	0.0	0.90
0.1	0.1	0.80
0.1	0.0	0.65
0.0	0.0	0.95

The averages of relative distance of Friendly-Hostile, Lively-Calm, and Casual-Formal are 0.73 0.86, and 0.92, respectively. The total average of relative distances is 0.84. This experiment is repeated in total four times. The results are shown in Table 2.10.

Table 2.10 Evaluations of each axis

No	Friendly	Lively	Casual	Evaluation
1	0.73	0.86	0.92	0.84
2	0.76	0.66	0.94	0.79
3	0.89	0.84	0.81	0.85
4	0.82	0.69	0.80	0.77

Finally, the average Evaluation of transform function is given as 0.81.

2.4 Legitimacy of transform functions

2.4.1 The case of two persons' conversation

2.4.1.1 Transform to Friendly-Hostile axis

Friendly mood appears in a cooperation phenomenon.

The cooperation phenomenon is seen in the only situation that two emotions are similar. Emotion similarity can be expressed as the length of difference vector between two emotional vectors in AAP.

The length of difference vector can express subtle relationships, such as beating the opponent aha. In such a case, an angle between emotional vectors is close, but the length of difference vector between their ones is at least longer than typically similar emotion. Therefore, a length of difference vector can express partly the friendly mood. And, friendly mood has some influence from affinity, because a degree of friendly depends on affinity.

A relation among friendly mood and each emotion is given by

$$Friendly \ \propto length\ of\ difference\ vector\ influence + affinity\ influence. \quad (2.16)$$

In other hand, a hostile mood cannot be written by only the length of difference, because a hostile-mood exists in a case that their emotions are similar each other. In this case, their emotions should be pointing low affinity because of opposing. Therefore, affinity influence is more important than the stage considering only friendly mood.

By containing affinity influence, proposal function can express the mood both of friendly and hostile.

Therefore, a relation among friendly mood and each emotion is given by

$$Hostile \ \propto length\ of\ difference\ vector\ influence + affinity\ influence. \quad (2.17)$$

Affinity Arousal-Pleasure space is defined with Euclid space. Therefore, the length of difference vector L can be calculated by

$$L = \sqrt{\left(Af_1 - Af_2\right)^2 + \left(Ar_1 - Ar_2\right)^2 + \left(Pl_1 - Pl_2\right)^2}\ . \tag{2.18}$$

where

Af_1 : Affinity value of agent1's vector,

Af_2 : Affinity value of agent2's vector,

Ar_1 : Arousal value of agent1's vector,

Ar_2 : Arousal value of agent2's vector,

Pl_1 : Pleasure value of agent1's vector,

Pl_2 : Pleasure value of agent2's vector.

The max length of difference vector between two emotions can be $2\sqrt{3}$. The max emotional value is (Affinity, Arousal, Pleasure) = (1, 1, 1). Its length is $\sqrt{1^2 + 1^2 + 1^2} = \sqrt{3}$. The minimum emotional value is (Affinity, Arousal, Pleasure) = (-1, -1, -1).Its length is also $\sqrt{(-1)^2 + (-1)^2 + (-1)^2} = \sqrt{3}$. Therefore, the max length of difference vector can be $2\sqrt{3}$. However, Atmosfield is defined $[-1, 1]^3$. The length of difference vector influence should be fixed to $[-1, 1]^3$. Both of friendly mood and hostile mood, the key is which participant feels pleasure or displeasure. A pleasure emotion is important as same as affinity one. In affinity arousal-pleasure space, this emotional information appears in a sign of pleasure axis. Therefore, transform function should have the term which is sign of pleasure. This pleasure information is not historical information, and compensates a length of difference vector the state friendly or hostile. Therefore pleasure information should be a coefficient of a length of difference vector.

Finally, the length of difference vector influence concluding pleasure effect is decided by

$$\text{length of difference vector influence} = \operatorname{sign}(\overline{P})\,\frac{L}{2\sqrt{3}}. \qquad (2.19)$$

In the Affinity Arousal-Pleasure space, an affinity axis was proposed to express the relation between two object as like human-human and human-robot [1]. Affinity value changes timely though an atmosphere should change slowly. Therefore, Affinity parameter should be contained in a transform function for friendly as hysteresis term, and the term should be summation from start of conversation to measuring time because of hysteresis. In friendly conversation, both of talkers should have high affinity emotion. If either one has low affinity emotion, it is that he endures the conversation time. Therefore, an influence of affinity should be focused on lower affinity.

This affinity influence should be also defined in [-1, 1].Think the dynamics of affinity influence converges to a smaller variation, a value of affinity influence can be average of anytime.

Therefore, affinity influence is defined by

$$\text{affinity influence}= \frac{\sum \min\left(Af_1(t), Af_2(t)\right)}{T}. \qquad (2.20)$$

Think a length of difference vector influence and an affinity influence are important as same as each other, a transform function should be given by

$$Friendly = \frac{1}{2}\left\{ sig\left(\overline{P}\right)\frac{L}{2\sqrt{3}} + \frac{\sum \min\left(Af_1(t), Af_2(t)\right)}{T} \right\}. \qquad (2.21)$$

2.4.1.2 Transform into Lively-Calm axis

In casual communication, situations that may occur about Lively or Calm are already stated in 2.1.3. These situations are summarized in the tabular form as in Table 2.11.

Table 2.11 The relation between lively atmosphere and average emotion

Condition		Result	
Arousal	Pleasure	High Affinity	Lively
Arousal	Pleasure	Low Affinity	Lively
Arousal	Displeasure	High Affinity	Lively
Arousal	Displeasure	Low Affinity	Calm
Sleep	Pleasure	High Affinity	Calm
Sleep	Pleasure	Low Affinity	Calm
Sleep	Displeasure	High Affinity	Calm
Sleep	Displeasure	Low Affinity	Calm

To express this table mathematically, think those conditions are average values of subjects, and conditions and results are Boolean values.

Then, this relation is expressed as

$$\begin{aligned}\text{Lively} = {} & \text{Arousal} \cap \text{Pleasure} \cap \text{Affinity} \cup \text{Arousal} \cap \text{pleasure} \cap \neg\text{Affinity} \\ & \cup \text{Arousal} \cap \neg\text{pleasure} \cap \text{Affinity}, \end{aligned} \tag{2.22}$$

$$\begin{aligned}\leftrightarrow & \text{Arousal} \cap (\text{Pleasure} \cap \text{Affinity} \cup \text{Pleasure} \cap \neg\text{Affinity}) \cup \text{Arousal} \\ & \cap \neg\text{Pleasure} \cap \text{Affinity}, \end{aligned} \tag{2.23}$$

$$\leftrightarrow \text{Arousal} \cap (\text{Pleasure} \cup \neg\text{Pleasure} \cap \text{Affinity}). \tag{2.24}$$

Table 2.11 can be uniquely expressed by function (2.24) under the Boolean assumption.

This Boolean function transform into continuous number by changing AND to multiplication, OR to addition, and NOT to negative addition. By changing operators, this transform function is given by

$$\text{Lively} = \text{Arousal} \times (\text{Pleasure} - \text{Pleasure} \times \text{Affinity})$$

$$\leftrightarrow \text{Arousal} \times \text{Pleasure}\,(1 - \text{Affinity}). \qquad (2.25)$$

This function can be unique one that expresses Table 2.11 under the Boolean assumption. Finally, the function transforming from emotion into Lively-Calm axis is given by

$$\text{Livery} = \overline{Ar}\;\overline{Pl}\,(1 - \overline{Af}), \qquad (2.26)$$

where

$\overline{Af}$: Average of Affinity value,

$\overline{Ar}$: Average of Arousal value,

$\overline{Pl}$: Average of Pleasure value.

2.4.1.3 Transform to Casual-Formal axis

In casual communication, situations that may occur about Casual or Formal are already stated in 2.1.4. These situations are summarized in the tabular form as in Table 2.12.

As like section 2.4.1.2, think that conditions are average values of subjects, and conditions and results are Boolean values.

In Casual-Formal axis case, however, table has the situation that does not exist in casual communication. And, Atmosfield is defined by negative connecting Casual axis [0, 1] and Formal axis [-1, 0]. Therefore, proposal function is necessary to consider each axis case, and connect Casual case and Formal case negatively.

And, Casual axis and Formal axis are very difficult to separate each case by using only emotional information because of influence from other atmosphere elements which Friendly-Hostile and Lively-Calm. And, Casual mood and Formal mood can change easily to each other.

Table 2.12 The relation of Casual-Formal atmosphere with other Parameters

Condition				Result
Friendly	Lively	Pleasure	Arousal	Casual
Friendly	Lively	Pleasure	Sleep	Casual
Friendly	Lively	Displeasure	Arousal	Casual $\left(\overline{Af} > 0.5\right)$ Formal $\left(\overline{Af} < 0.5\right)$
Friendly	Lively	Displeasure	Sleep	No exist
Friendly	Calm	Pleasure	Arousal	*
Friendly	Calm	Pleasure	Sleep	Casual
Friendly	Calm	Displeasure	Arousal	Formal
Friendly	Calm	Displeasure	Sleep	Casual
Hostile	Lively	Pleasure	Arousal	No exist
Hostile	Lively	Pleasure	Sleep	No exist
Hostile	Lively	Displeasure	Arousal	Formal
Hostile	Lively	Displeasure	Sleep	No exist
Hostile	Calm	Pleasure	Arousal	No exist
Hostile	Calm	Pleasure	Sleep	No exist
Hostile	Calm	Displeasure	Arousal	Formal
Hostile	Calm	Displeasure	Sleep	0

Then, Casual axis case is expressed as

$$\begin{aligned}&Casual =\\&Friendly \cap Lively \cap Pleasure \cap Arousal \cup Friendly \cap Lively \cap Pleasure \cap \neg Arousal\\&\cup Friendly \cap Lively \cap \neg Pleasure \cap Arousal \cap Affinity \cup Friendly \cap \neg Lively\\&\cap Pleasure \cap \neg Arousal \cup Friendly \cap \neg Lively \cap \neg Pleasure \cap \neg Arousal,\end{aligned} \tag{2.27}$$

$$\begin{aligned}&\leftrightarrow Friendly \cap Lively \cap Pelasure \cup Friendly \cap Lively \cap Arousal \cap Affinity\\&\cup Friendly \cap \neg Lively \cap \neg Arousal,\end{aligned} \tag{2.28}$$

$$\leftrightarrow Friendly \cap [Lively \cap (Pleasure \cup Arousal \cap Affinity) \cup \neg Lively \cap Arousal]. \tag{2.29}$$

Casual mood can be uniquely expressed by function (2.29) under the Boolean assumption in table 2.12. This Boolean function transform into continuous number by changing AND to multiplication, OR to addition, and NOT to negative addition. By changing operators, this function transforming into Casual axis is given by

$$\begin{aligned}&Casual =\\&Friendly \times [Lively \times (Pleasure + Arousal \times Affinity) + (-Lively) \times (-Arousal)],\end{aligned} \tag{2.30}$$

$$\leftrightarrow Casual = Friendly \times Lively \times [(Pleasure + Arousal \times Affinity) + Arousal]. \tag{2.31}$$

And, Formal axis case is expressed as

$$\begin{aligned}&Formal =\\&Friendly \cap Lively \cap \neg Pleasure \cap Arousal \cap \neg Affinity \cup Friendly \cap \neg Lively\\&\cap \neg Pleasure \cap Arousal \cup \neg Friendly \cap Lively \cap \neg Pleasure \cap Arousal\\&\cup \neg Frienldy \cap \neg Lively \cap \neg Pleasure \cap Arousal,\end{aligned} \tag{2.32}$$

$$\begin{aligned}&\leftrightarrow \neg Pleasure \cap Arousal \cap [Friendly \cap (Lively \cap \neg Affinity \cup \neg Lively)\\&\cup \neg Friendly \cap (Lively \cup \neg Lively \cup \neg Lively)],\end{aligned} \tag{2.33}$$

This Boolean function transform into continuous number by changing AND to multiplication, OR to addition, and NOT to negative addition. By changing operators, this function transforming into Formal axis is given by

$$Formal = (-Pleasure) \times Arousal \times [Friendly \times (Lively \times (-Affinity) + (-Lively)) + (-Friendly) \times (Lively - Lively)], \tag{2.34}$$

$$\leftrightarrow Formal = (-Pleasure) \times Arousal \times [(-Friendly) \times (Lively \times Affinity + Lively)], \tag{2.35}$$

$$\leftrightarrow Formal = Friendly \times Lively \times Pleasure \times Arousal \times (Affinity + 1). \tag{2.36}$$

The function transforming into Casual-Formal is given by negative connection Casual and Formal. This function is

$$Casual = Friendly \times Lively \times [(Pleasure + Arousal \times (Affinity + 1)] - Friendly \times Livelly \times Pleasure \times Arousal \times (Affinity + 1), \tag{2.37}$$

$$\leftrightarrow Casual = Friendly \times Lively \times [Pleasure + Arousal \times (Affinity + 1)(1 - Pleasure)]. \tag{2.38}$$

This function has influences from other atmosphere elements. These influence should not be thought as like as emotional values. Other atmosphere elements have influence directly. Therefore, their coefficient should have impact-factor 10.

Finally, the transform function is given by

$$Casual = \frac{1}{2} FrLv[\overline{Pl} + \overline{Ar}(\overline{Af} + 1](1 - \overline{Pl})] \times 100, \tag{2.39}$$

where

Fr : Friendly value,

Lv : Lively value,

$\overline{Af}$: Average of Affinity,

$\overline{Ar}$: Average of Arousal,

$\overline{Pl}$: Average of Pleasure.

2.4.2 The case of n persons' conversation

2.4.2.1 Transform to Friendly-Hostile axis

In n-persons' conversation, it is too subjective that using a length of difference vector to express Friendly mood.

Each emotion is occurred independently. If the number of sample is enough, the distribution should be normal distribution.

Therefore, it is redefined by standard deviation.

$$\sigma = \sqrt{\frac{1}{n-1}\sum_i \left\{\left(\overline{Af} - Af_i\right)^2 + \left(\overline{Ar} - Ar_i\right)^2 + \left(\overline{Pl} - Pl_i\right)^2\right\}} \tag{2.40}$$

where

$\overline{Af}$: average value of n-persons on Affinity,

Af_i : Affinity value of *i*-th person,

$\overline{Ar}$: average value of n-persons on Arousal,

Ar_i : Arousal value of i person,

$\overline{Pl}$: average value of n-persons on Pleasure,

Pl_i : Pleasure value of i person.

If n=2 then

$$\sigma = \sqrt{\sum_i \{\left(\overline{Af} - Af_i\right)^2 + \left(\overline{Ar} - Ar_i\right)^2 + \left(\overline{Pl} - Pl_i\right)^2\}}\ , \tag{2.41}$$

where $\overline{Af} = \frac{Af_1 + Af_2}{2}$, $\overline{Ar} = \frac{Ar_1 + Ar_2}{2}$, and $\overline{Pl} = \frac{Pl_1 + Pl_2}{2}$.

Therefore, this function (2.41) can be arranged as

$$\sigma = \sqrt{\left(\frac{Af_1 - Af_2}{2}\right)^2 + \left(\frac{Af_2 - Af_1}{2}\right)^2 + \left(\frac{Ar_1 - Ar_2}{2}\right)^2 + \left(\frac{Ar_2 - Ar_1}{2}\right)^2 + \left(\frac{Pl_1 - Pl_2}{2}\right)^2 + \left(\frac{Pl_2 - Pl_1}{2}\right)^2}\ , \tag{2.42}$$

$$\leftrightarrow \sigma = \sqrt{\left(\frac{Af_1 - Af_2}{2}\right)^2 + \left(\frac{Af_1 - Af_2}{2}\right)^2 + \left(\frac{Ar_1 - Ar_2}{2}\right)^2 + \left(\frac{Ar_1 - Ar_2}{2}\right)^2 + \left(\frac{Pl_1 - Pl_2}{2}\right)^2 + \left(\frac{Pl_1 - Pl_2}{2}\right)^2}\ , \tag{2.43}$$

$$\leftrightarrow \sigma = \sqrt{\left(Af_1 - Af_2\right)^2 + \left(Ar_1 - Ar_2\right)^2 + \left(Pl_1 - Pl_2\right)^2} = L\ . \tag{2.44}$$

Essentially, standard deviation is the same as the length of difference vector. However, deviation is consisted by the length of difference vector from average vector to each emotional vector. Therefore, its objectivity is maintained.

In the normal deviation, 2σ can cover the 95% of data independently occurring.

Therefore, this transform function should be given by

$$Friendly = sign(\overline{P})\frac{2\sigma}{2\sqrt{3}} + \frac{\sum_t \min(Af_i(t) : 0 < i \le N)}{T}, \tag{2.45}$$

where

σ : standard deviation,

$sign(\overline{P})$: sign of average pleasure value,

T : number of sampling data,

$\min(Af_i(t) : 0 < i \le N)$: the minimum affinity value of n-persons on the time,

N (> 2): number of persons.

The standard deviation σ is calculated by

$$\sigma = \sqrt{\frac{1}{n-1}\sum_i \left\{ \left(\overline{Af} - Af_i\right)^2 + \left(\overline{Ar} - Ar_i\right)^2 + \left(\overline{Pl} - Pl_i\right)^2 \right\}}, \tag{2.46}$$

where

$\overline{Af}$: average value of n-persons on Affinity,

Af_i : Affnity value of i-th person,

$\overline{Ar}$: average value of n-persons on Arousal,

Ar_i : Arousal value of i person,

$\overline{Pl}$: average value of n-persons on Pleasure,

Pl_i : Pleasure value of i person.

2.4.2.2 Transform to Lively-Calm axis

In n-persons case, lively mood consists of lively person's influence. Therefore, it should be calculated personally. Personal liveliness is defined that one's emotional atmosphere calculated from emotion by Lively function. And, lively mood has much more influence from personal liveliness than calm one's one. Then, $Liveliness_{personal}$ is given by

$$Liveliness_{personal} = ArPl(1 - Af), \tag{2.47}$$

where

Af : one's Affinity value,

Ar : one's Arousal value,

Pl : one's Pleasure value.

Therefore, the transform function should be considered only lively mood. Finally, the transform function is given by

$$Lively = \frac{\sum_{i}^{N} Liveliness_{personal}, i}{\#(Liveliness_{personal} > 0)}, \tag{2.48}$$

where

N (> 2): number of persons.

2.4.2.3 Transform to Casual-Formal axis

In n-persons case, the relation between emotion and atmosphere is summarized in table 2.13. There is no change under the Boolean assumption. Therefore, the function is also given by

$$Casual = \frac{1}{2} FrLv[\overline{Pl} + \underline{Ar}(\overline{Af} + 1)(1 + \overline{Pl})] \times 100, \quad (2.49)$$

where

Fr : Friendly value,

Lv : Lively value,

$\overline{Af}$: Average of Affinity,

$\overline{Ar}$: Average of Arousal,

$\overline{Pl}$: Average of Pleasure.

Only difference point from two persons case is the case under the conditions that Friendly, and Calm mood, and average emotions are Pleasure and Arousal. In such a situation, the atmosphere is difficult to change. However, it can be both of casual and formal. The biggest factor determining an atmosphere is its earlier state.

In other words, an atmosphere of this case holds its state before. Therefore, this situation has no influence to function.Concluded this case, the casual function uniquely exists to express the table 2.13.

Table 2.13 The relation of Casual-Formal atmosphere with other Parameters for n-persons

Condition				Result
Friendly	Lively	Pleasure	Arousal	Casual
Friendly	Lively	Pleasure	Sleep	Casual
Friendly	Lively	Displeasure	Arousal	Casual $\left(\overline{Af} > 0.5\right)$ Formal $\left(\overline{Af} < 0.5\right)$
Friendly	Lively	Displeasure	Sleep	No exist
Friendly	Calm	Pleasure	Arousal	$Casual(t) =$ $Casual(t-1)$ $Casual(0) = 0$
Friendly	Calm	Pleasure	Sleep	Casual
Friendly	Calm	Displeasure	Arousal	Formal
Friendly	Calm	Displeasure	Sleep	Casual
Hostile	Lively	Pleasure	Arousal	No exist
Hostile	Lively	Pleasure	Sleep	No exist
Hostile	Lively	Displeasure	Arousal	Formal
Hostile	Lively	Displeasure	Sleep	No exist
Hostile	Calm	Pleasure	Arousal	No exist
Hostile	Calm	Pleasure	Sleep	No exist
Hostile	Calm	Displeasure	Arousal	Formal
Hostile	Calm	Displeasure	Sleep	0

Chapter 3

Atmosphere Understanding for Humans-Robots Interaction based on SVR and Fuzzy set

3.1 Atmosphere Representation using Fuzzy set

Various studies have been done for realizing a society in which humans and robots co-exist from a cognitive science perspective. Many proposals such as emotion recognition, atmosphere, gesture recognition, and thoughtfulness engine have been proposed for humans-robots interaction [11-16]. Most of the works, however, have been focused on emotions, especially in the case of one to one communication between a human and a robot. In the casual communication among many humans and many robots, however, atmosphere plays an important role rather than the emotions of individual humans/robots, e.g., during a virtual conference with twenty agents (humans/robots), or a home party with multiple humans and robots. Several studies have been done [1-9][15-18], in which atmosphere related factors are considered to define the attributes of the communication atmosphere.

Fuzzy set expression is necessary to make technological representation of subjective information such as atmosphere interpreted by an agent. The space representing atmosphere however, has not been studied enough except the fuzzy atmosfield (Fig. 3.1) [17] that is accepted in this paper. On the other hand many spaces representing emotions have been studied. Among them affinity arousal-pleasure space (Fig.3.2) [2] is used in this paper since it is used in most of the studies using fuzzy atmosfield [1][21][96].

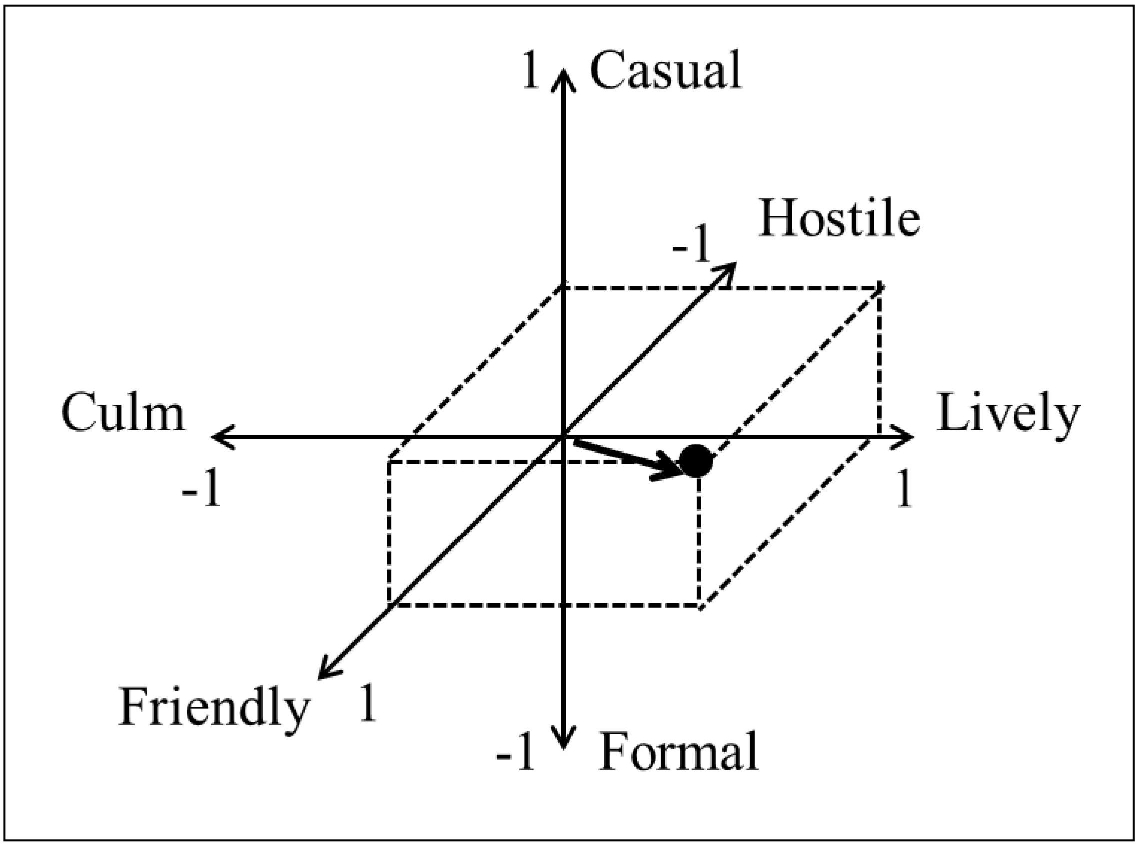


Fig 3.1 Fuzzy Atmosfield [17]

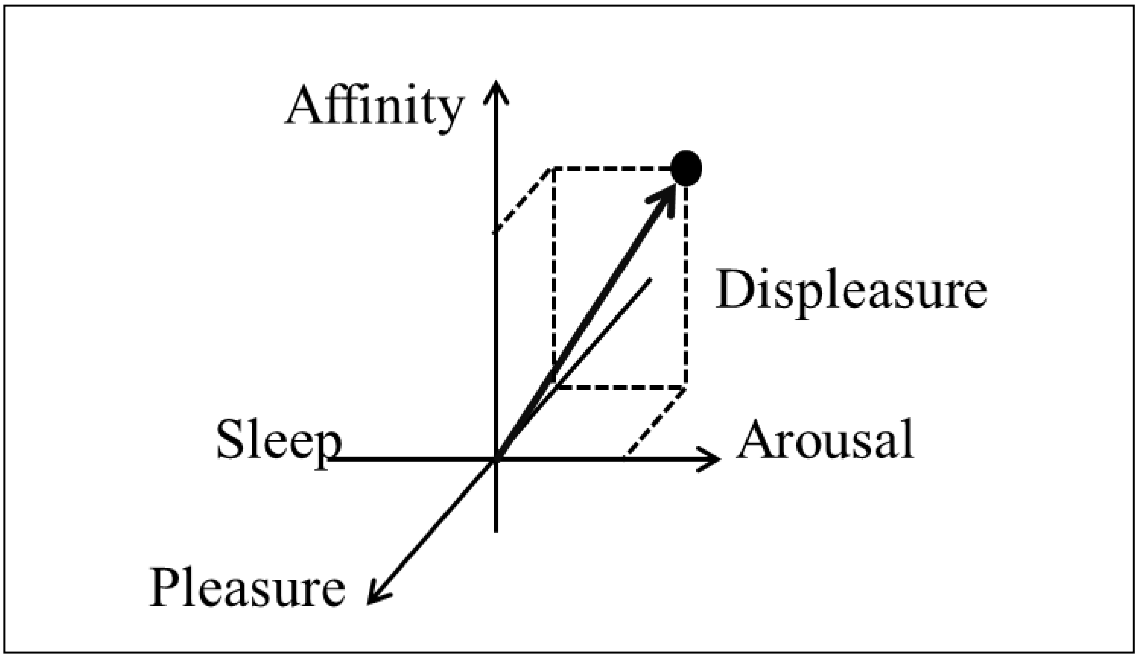


Fig 3.2 Affinity arousal-pleasure space [2]

In [10] transform functions are studied to obtain the atmosphere in fuzzy atmosfield from the emotions of all agents represented in affinity arousal-pleasure space. To confirm the validity of transform functions [10], a questionnaire consisting of 135 questions is done for 30 people in the age 20s and 30s regardless of nationality. Each subject is informed that two persons are talking each other and their emotion information is shown on the PC screen in the form of three tuple (x, y, z) where x ∈{sleep, neutral, arousal}, y ∈{displeasure, neutral, pleasure}, and z ∈{low affinity, neutral, high affinity} (Fig. 3.3 and 3.4). All 30 subjects are requested to give an answer on the PC screen (after looking the emotion information) about the atmosphere information by 0.2 interval value in each [-1,1]-interval of fuzzy atmosfield $[-1,1]^3$. The possible different emotion information of two persons is 135 (=9x9x3-108), where 9 dots in Fig.3.3 for each person is considered with the same 3 affinity levels in Fig.3.4 and 108 overlapped cases are subtracted. Hence each subject is supposed to give 135 answers.

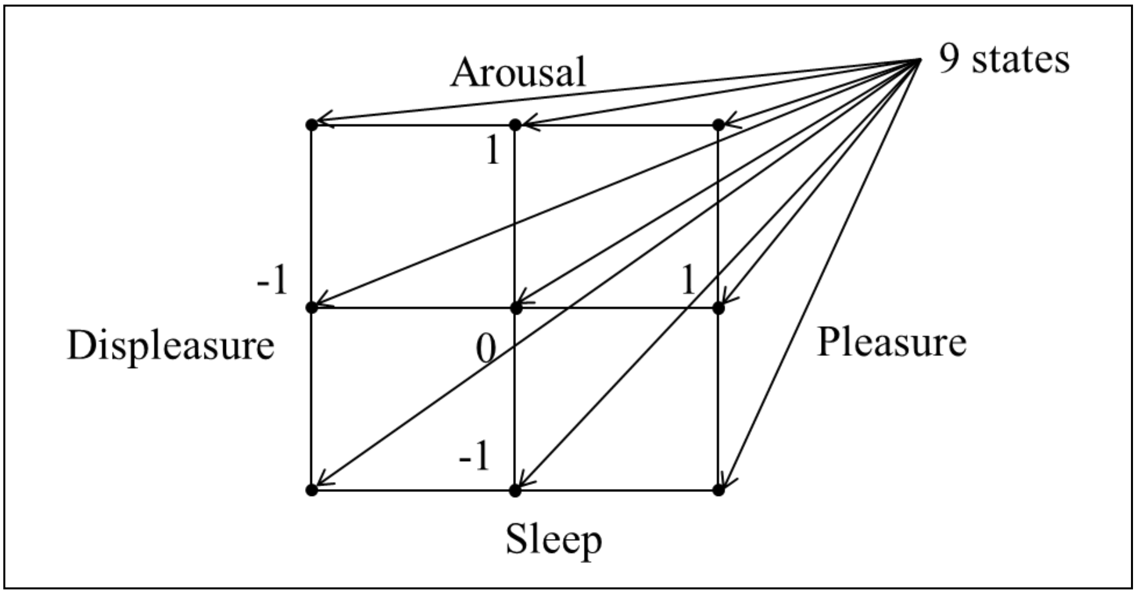


Fig.3.3 Nine states in Arousal-Pleasure plane

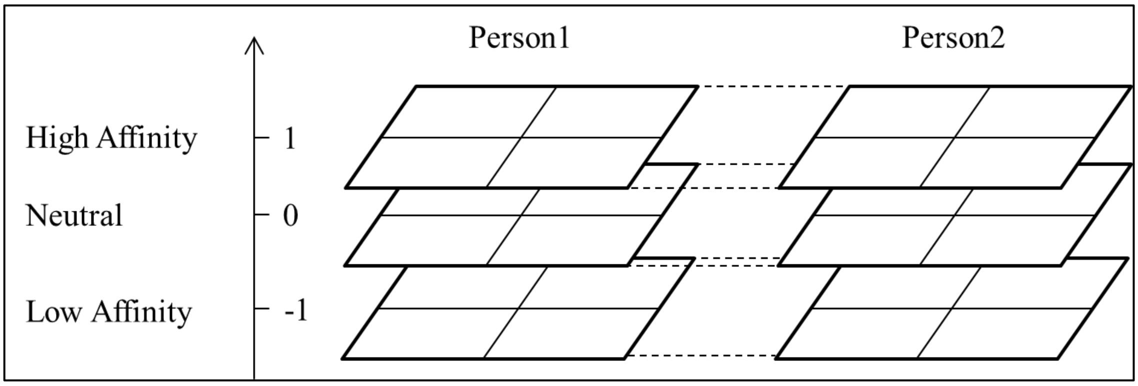


Fig.3.4 Three levels of Affinity

A few results are shown in 2 dimensional friendly-casual projection plane of 3 dimensional fuzzy atmosfield $[-1,1]^3$ by paying attention to the easiness of understanding. A uniformly distributed case (subject No.4) is illustrated in Fig.3.5 and a linearly distributed case (subject No.9) is shown in Fig.3.6. Having a look at other results, it becomes clear that the observed atmosphere varies from one subject to others even if the given situation is the same. Therefore the definite vector representation of the atmosphere is not appropriate, instead such scattered issues of atmosphere understanding should be taken into investigation in multi-agent society.

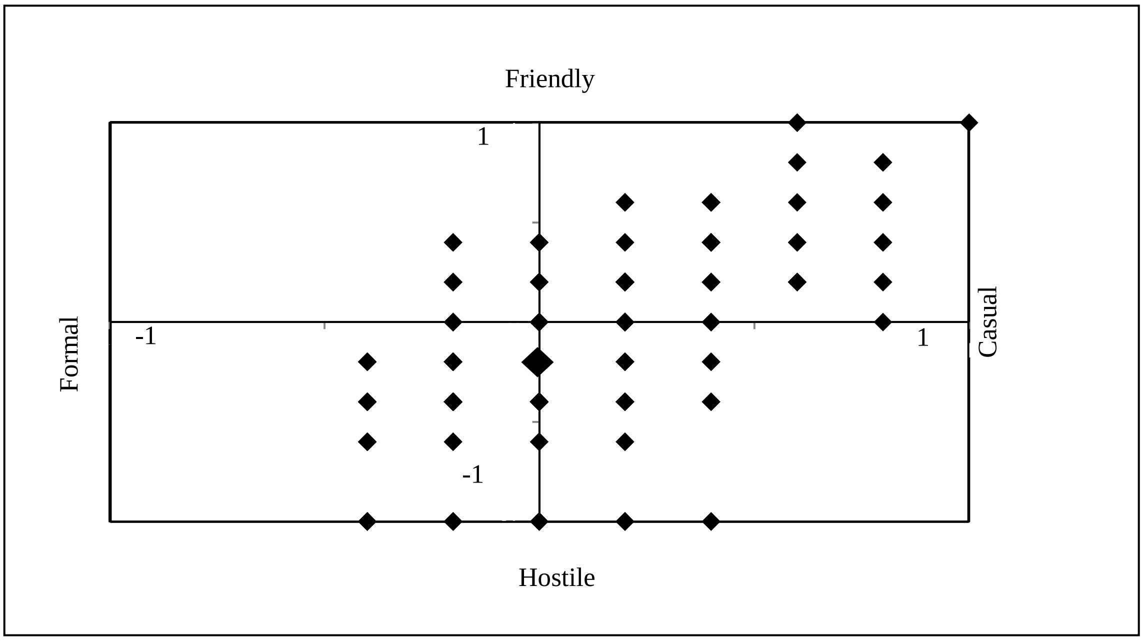


Fig 3.5 135 answers of subject No.4 (the most scattered case)

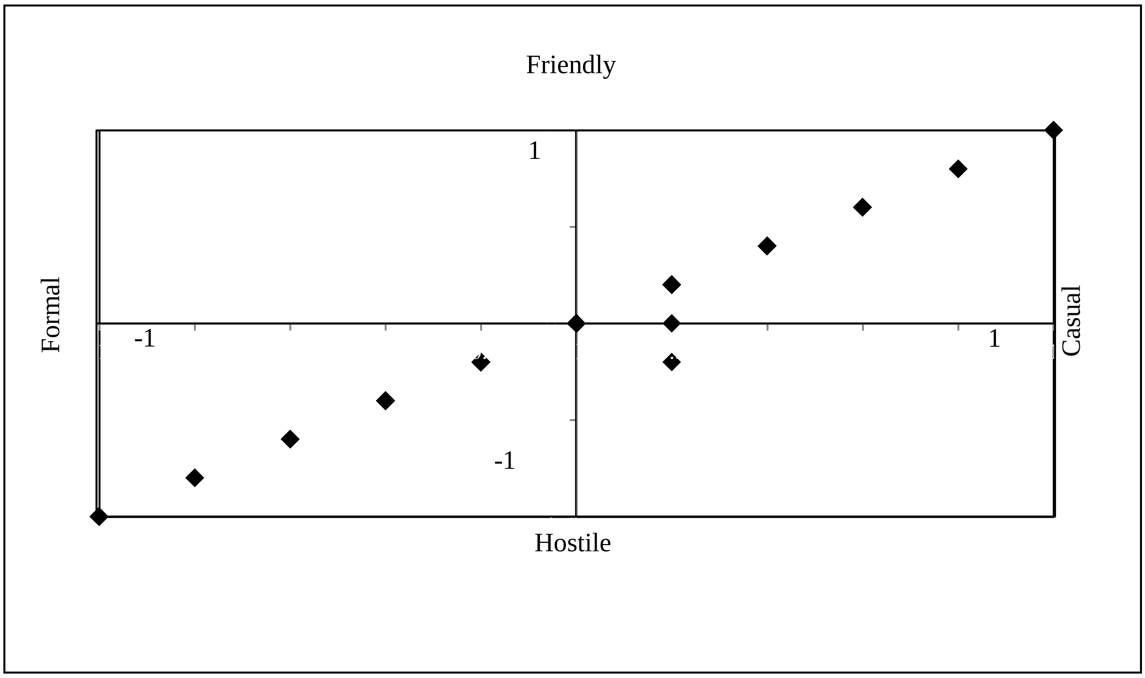


Fig 3.6 135 answers of subject No.9 (linearly distributed case)

Fuzzy set is a convenient tool to represent the dispersion of observed atmosphere induced by different agents. An atmosphere understanding method from emotions information of agents is proposed by using fuzzy set concept, where support vector regression (SVR) is introduced to represent the relationship between emotions of agents and the atmosphere in terms of fuzzy set. There are several possible methods other than SVR to represent the relationship such as statistical regression, probabilistic method, neural network, and auto regression. The relation between the emotions of agents and the atmosphere is usually non-linear, and maybe influence by the number of agents. Therefore, machine learning method maybe suitable. By taking the generalization ability and the accuracy into consideration, SVR is finally selected in the proposal.

3.2 Atmosphere Understanding for Humans-Robots Interaction based on SVR and Fuzzy set

As has been suggested in 3.1, learning method is necessary to obtain perception gap of the interpreted atmosphere among agents, e.g., the case that some agents feel formal, and another agents feel not so formal even the given situation is the same. In view of the generalization ability and the accuracy, SVR is selected in the proposal. Atmosphere understanding for humans-robots interaction based on SVR and fuzzy set is proposed for representing atmosphere in fuzzy atmosfield [21].

Let's consider a multi-agent society consisting of N agents (either humans or robots). Each agent is supposed to have emotion and to observe atmosphere time by time. The emotion is represented by a vector in three dimensional affinity arousal-pleasure space [2], whereas the atmosphere is represented by a vector in Fuzzy Atmosfield $[-1,1]^3$ [21].

The SVR is used for the estimation of the observed atmosphere by each agent from emotion information given by all N agents. The SVR training is done by using former emotion data of all N agents from other method and former atmosphere data of the target agent, i.e., the training is done agent by agent. The agent-wise trained SVR is used to estimate the observed atmosphere by the target agent from given current emotional information of an agent, and all N estimated atmospheres are represented as a fuzzy set on Fuzzy Atmosfield $[-1,1]^3$ [21]. The image is shown in Fig 3.7.

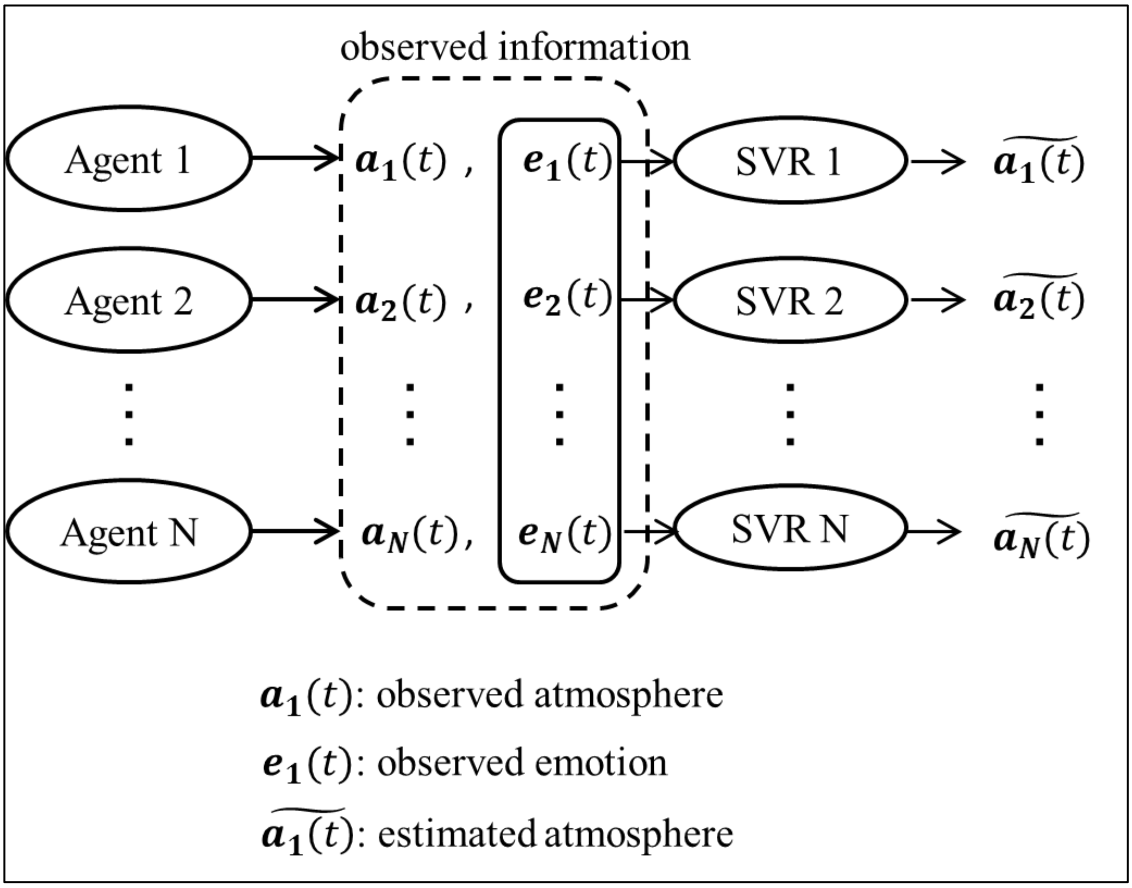


Fig 3.7 Overview of SVR estimation

The Radial Basis Function (RBF) kernel [22] of SVR is used for the proposed atmosphere understanding method since its faster calculating speed without any influence to the error estimation in comparison with the performance of other kernels. And its parameter is defined as $\varepsilon = 0.2$ uniform interval in questionnaire since each subject answers emotion/atmosphere data by 0.2 interval in [-1,1]. Therefore, the error of SVR in learning process is within a uniformly divided small interval in questionnaires.

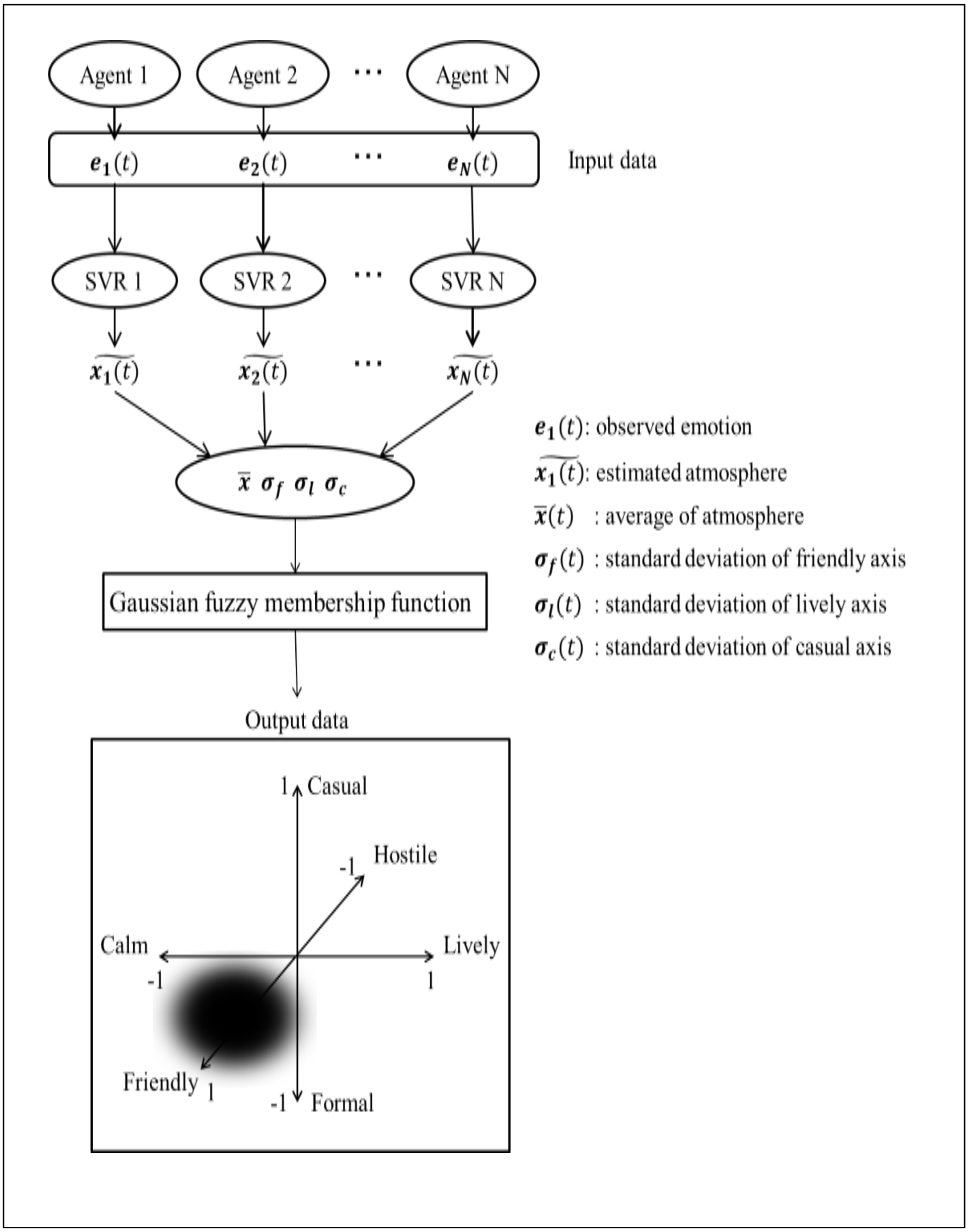


Fig 3.8 Overview of process to represent atmosphere

The represented fuzzy set on Fuzzy Atmosfield expresses distribution of observed atmospheres by all agents, and provides the whole atmosphere information to each agent, where Gaussian fuzzy membership functions in MATLAB are used to set specific value of gray-scaled color in representation atmosphere in fuzzy atmosfield, because the distribution of observed atmospheres is typically similar to Normal distribution (Fig. 3.8). The parameters of the Gaussian membership function are average $\overline{\boldsymbol{x}}$ and standard deviation $\boldsymbol{\sigma}$. The average $\overline{\boldsymbol{x}}$ of the atmosphere is given by

$$\overline{\boldsymbol{x}} = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{x_i}, \tag{3.1}$$

where $\boldsymbol{x_i}$ is the observed atmosphere by i-th agent and is a vector in fuzzy atmosfield $[-1,1]^3$ consisting of friendly, lively, and casual axes. The standard deviation $\boldsymbol{\sigma}$ is given by

$$\boldsymbol{\sigma} = \begin{bmatrix}\sigma_f \\ \sigma_l \\ \sigma_c\end{bmatrix}, \tag{3.2}$$

$$\sigma_f = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N}\left(x_{if} - \overline{x_f}\right)^2}, \tag{3.3}$$

$$\sigma_l = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N}(x_{il} - \overline{x_l})^2}, \tag{3.4}$$

$$\sigma_c = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N}(x_{ic} - \overline{x_c})^2}. \tag{3.5}$$

A typical example of the atmosphere is shown in Fig 3.9 by using the proposed SVR based atmosphere understanding method at t=40 sec in the scenario No.6 (in the relaxed mood, cf. experiments in 3.3).

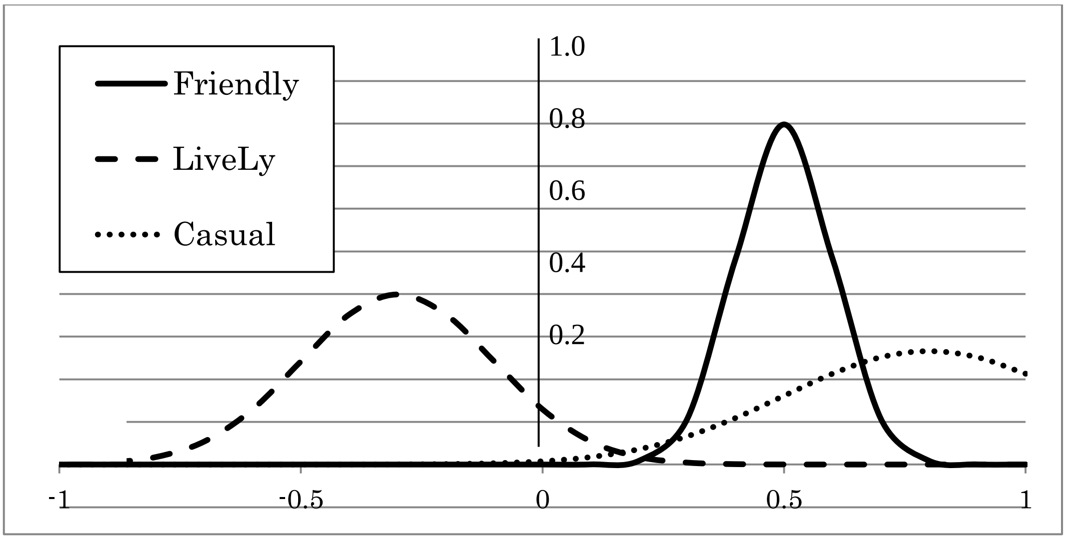


Fig 3.9 An example of atmosphere in terms of fuzzy set

The average value of friendliness is 0.5, and its standard deviation is 0.1. All N (=4) agents feel friendly mood commonly in this case. The value of lively axis represented by dashed line, however, is positioned in negative area. The average of liveliness is -0.3, and its standard deviation is 0.2. It means that someone feels silent but others do not feel so quiet but a little bit noisy. Therefore, the atmosphere from a view point of liveliness varies considerably from one agent to others. Finally, the casualness has a peak point near 1, which means most of the agents feel free for talking. The average of casualness is 0.8, and its standard deviation is 0.1. It is much larger than that of others, which means that varying degrees of individual human feeling is large.

3.3 Atmosphere Understanding Experiment for 13 Scenarios

To confirm the effectiveness of the proposal, four human agents are requested to play 13 scenarios, where each scenario continues for 100 sec on 10 sec intervals. Every 10 sec interval of each scenario, emotion and atmosphere information of all agents are provided by questionnaire, where emotion and atmosphere are expressed by 11 grades in [-1,1] of affinity arousal-pleasure space $[-1,1]^3$ and Fuzzy Atmosfield $[-1,1]^3$, respectively. By applying the proposed atmosphere understanding method based on SVR, atmospheres of all agents are obtained from emotions of all agents and are represented as a fuzzy set on Fuzzy Atmosfield for each 10 sec time interval of all 13 scenarios, where SVR training for all four agents is done in advance (one week before) by using the same 13 scenarios. The accuracy of the proposed method is confirmed by comparing the obtained atmosphere information by the proposal and the provided atmosphere information from all four agents.

Table 3.1 shows the existing area of the average position of provided atmosphere information from all four agents along 13 scenarios. In the Table 3.1, friendly, lively, and casual mean 1 on each axis, and hostile, calm, and formal mean -1 on each axis in Fuzzy Atmosfield $[-1,1]^3$. The first row in Table 3.1, for example, means that the 10 average atmosphere points along scenario 1 exist near the vertex (1, 1, 1) in Fuzzy Atmosfield $[-1,1]^3$. The second row in Table 3.1 means that the 10 average atmosphere points along scenario 2 starts from (-1, -1, -1), but move rapidly (within 10-20 seconds) to (1, 1, 1) by the end of the scenario. On the other hand, scenario 3 begins at (1, 1, 1) and changes slowly (for over 30 seconds) to (0, 0, 0) by the end of the scenario. By checking all 13 cases, it is concluded that most of the areas in Fuzzy Atmosfield are covered by the average atmosphere points along the 13 scenarios in Table 3.1 and that accuracy evaluation of the proposed method may be appropriate by using the experimental results.

Table 3.1 Existing area of each scenario in Fuzzy Atmosfield

Scenario No	Friendly-Hostile	Lively-Calm	Casual-Formal
1	friendly	lively	casual
2	from hostile to friendly (rapidly)	from calm to lively (rapidly)	from formal to casual (rapidly)
3	from friendly to neutral (slowly)	from lively to neutral (slowly)	from casual to neutral (slowly)
4	from friendly to hostile (rapidly)	from lively to calm (rapidly)	from casual to formal (rapidly)
5	from neutral to friendly (slowly)	from neutral to lively (slowly)	from neutral to casual (slowly)
6	friendly	from lively to calm, then lively (rapidly)	casual
7	friendly	from calm to lively (rapidly)	casual
8	friendly	calm	from formal to casual (rapidly)
9	friendly	calm	from neutral to casual (slowly)
10	friendly	from neutral to lively (slowly)	from formal to casual (slowly)
11	from neutral to friendly (slowly)	from calm to lively (slowly)	from formal to casual (slowly)
12	neutral	neutral	neutral
13	friendly	from lively to neutral (slowly)	casual

The proposed atmosphere understanding method is coded by MATLAB on a laptop PC (CPU: Core 2 duo P8700, 2.54/2.53 GHz, RAM: 4GB). It takes 40 sec for the offline learning process of SVR for each agent, and the online execution time of the proposal is 0.25 sec for each agent. If there are N agents in general, it takes for 0.25 x N sec for the SVR real time calculation of the atmosphere represented by a fuzzy set on Fuzzy Atmosfield. Therefore, the proposal is applicable for humans-robots interaction in relatively small number of agents' society from a view point of computation time.

The accuracy is investigated by the difference between the estimated atmosphere by the proposed method and the provided atmosphere from all agents, i.e., the accuracy of the proposed method for each scenario and for each agen**t** is defined by the one's complement of the averaged normalized distance by a series of ten atmospheres along the scenario

$$\mathbf{accuracy}(\mathbf{scenario},\mathbf{agent}) = \mathbf{1} - \frac{\boldsymbol{dist}\,(\boldsymbol{calculated\ atmosphere}, \boldsymbol{atmosphere\ from\ agent})}{\mathbf{2}\sqrt{\mathbf{3}}} \;, \tag{3.6}$$

where the distance between the calculated atmosphere by the proposed method and the given atmosphere from the agent is normalized by $\mathbf{2}\sqrt{\mathbf{3}}$, which is the maximal diagonal distance in the Fuzzy Atmosfield.

The best accuracy (0.97) is achieved in scenario No.1 Agent 4, scenario No.12 Agent 4, and scenario No.13 Agent 2, whereas the worst (0.84) in scenario No.5 Agent 1, and scenario No.4 Agent 4 as shown in Table 3.2. The relation between emotions and interpreted atmosphere becomes weak in atmosphere varies from hour to hour. Therefore, the atmosphere changing rapidly has a bad influence to stability of agent's perception shown as scenarios which the worst accuracy observed. The total average in Table 3.2 is 0.90, and its standard deviation is 0.036.

Table 3.2 Accuracy for each scenario/agent

Scenario No.	Agent 1	Agent 2	Agent 3	Agent 4	Average
1	0.92	0.90	0.86	0.97	0.91
2	0.86	0.86	0.86	0.94	0.88
3	0.94	0.92	0.92	0.86	0.91
4	0.87	0.92	0.90	0.84	0.88
5	0.84	0.94	0.92	0.91	0.90
6	0.90	0.92	0.86	0.90	0.90
7	0.92	0.92	0.86	0.90	0.90
8	0.86	0.92	0.86	0.94	0.90
9	0.94	0.90	0.86	0.90	0.90
10	0.87	0.95	0.92	0.94	0.92
11	0.91	0.86	0.94	0.86	0.89
12	0.92	0.92	0.86	0.97	0.92
13	0.87	0.97	0.92	0.86	0.91
Average	0.89	0.92	0.89	0.91	0.90

Since each agent answers emotion/atmosphere data with 0.2 interval in [-1,1] and the worst accuracy is 0.84 ($\geq$ 0.8), it is concluded that the proposed method provides enough atmosphere calculation ability in the experiment.

To represent the calculated atmosphere information of all agents for each scenario at time t=10,20,…,100 seconds in terms of a fuzzy set on Fuzzy Atmosfield, Gaussian fuzzy membership functions with average $\bar{\boldsymbol{x}}$ (3.1) and standard deviation $\boldsymbol{\sigma}$ (3.2) are used. Fig. 3.10 shows several examples of atmosphere in terms of fuzzy set for the scenario No.1 at t=10 sec (a), for the scenario No.1 at t=20 sec (b), for the scenario No.2 at t=10 sec (c), and for the scenario No.9 at t=20 sec (d). The atmosphere in terms of a fuzzy set in Fig. 3.10 seems something like a cloud in gray color. The center of the cloud corresponds to the average $\bar{\boldsymbol{x}}$, and the expansion size of the cloud is related to the standard deviation $\boldsymbol{\sigma}$, i.e., black part indicates within $1\boldsymbol{\sigma}$, gray part in between $1\boldsymbol{\sigma}$ and $2\boldsymbol{\sigma}$, and white part outside $2\boldsymbol{\sigma}$ inside of $[-1,1]^3$.

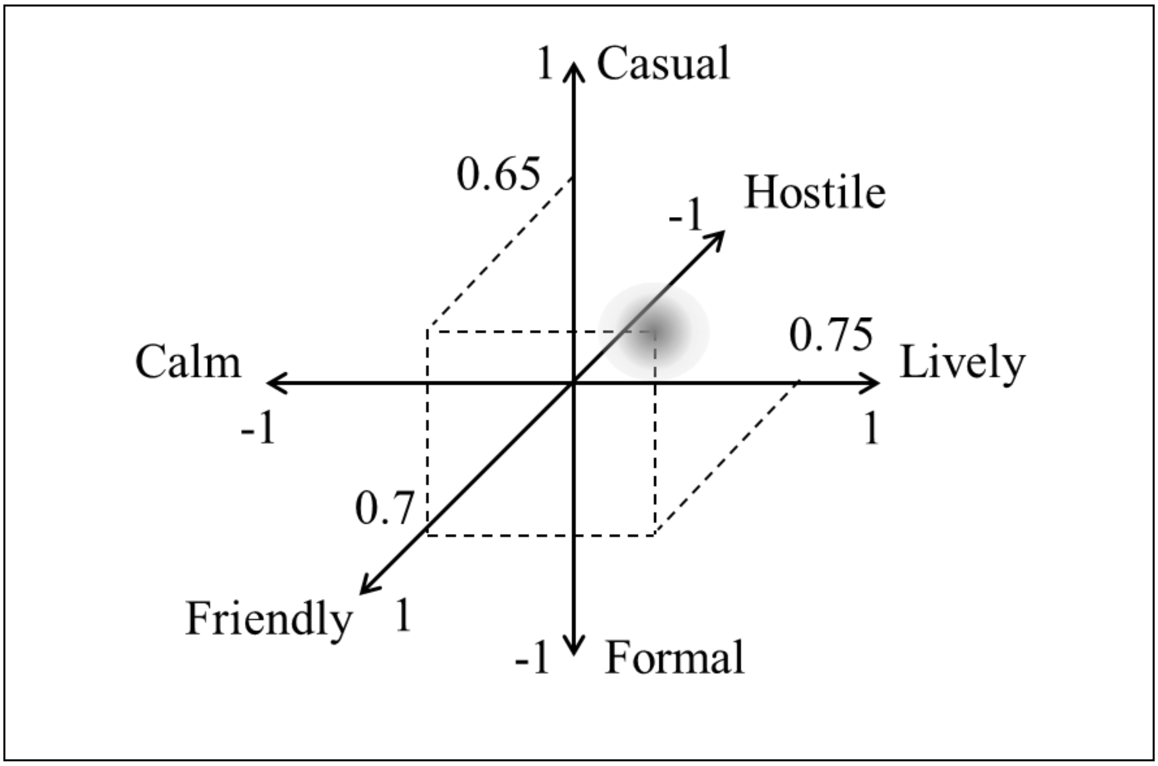


Fig 3.10(a) Atmosphere as fuzzy set in friendly, lively, and casual mood
(scenario No.1 t=10 sec)

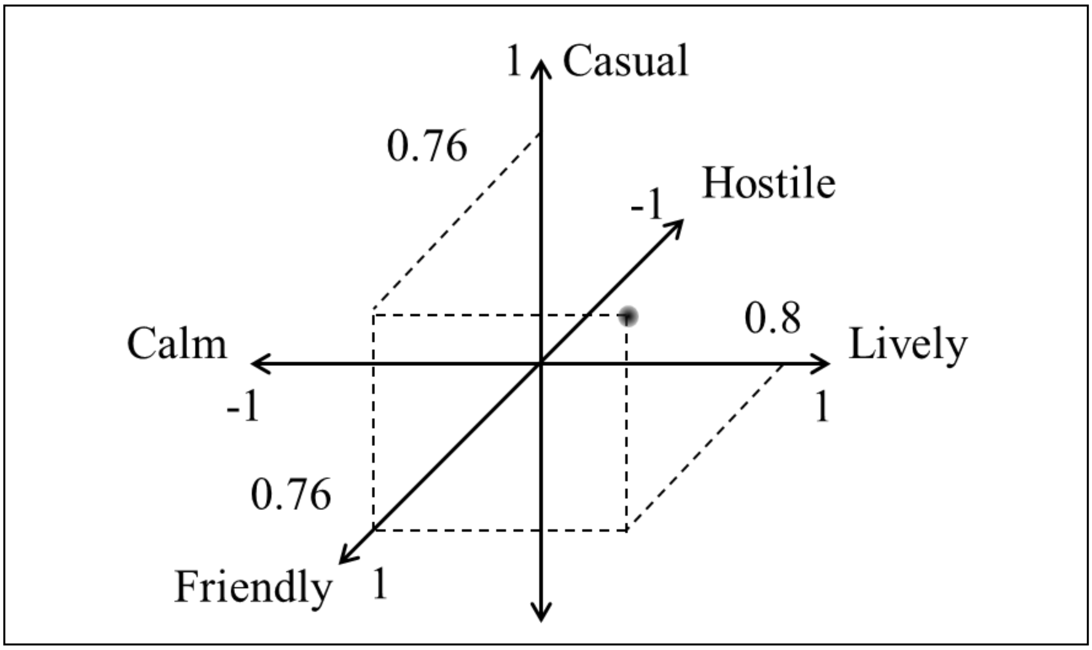


Fig 3.10(b) Atmosphere as fuzzy set in friendly, lively, and casual mood (No.1 t=20 sec)

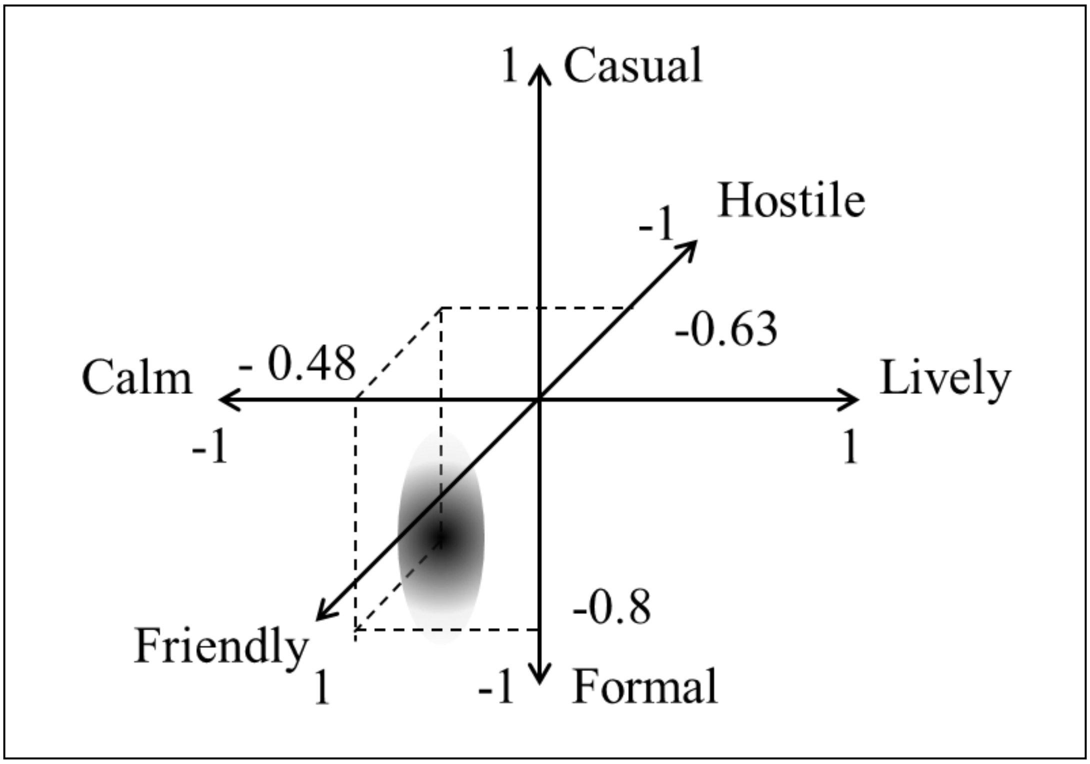


Fig 3.10(c) Atmosphere as fuzzy set in hostile, calm, and formal mood (No.2 t=10 sec)

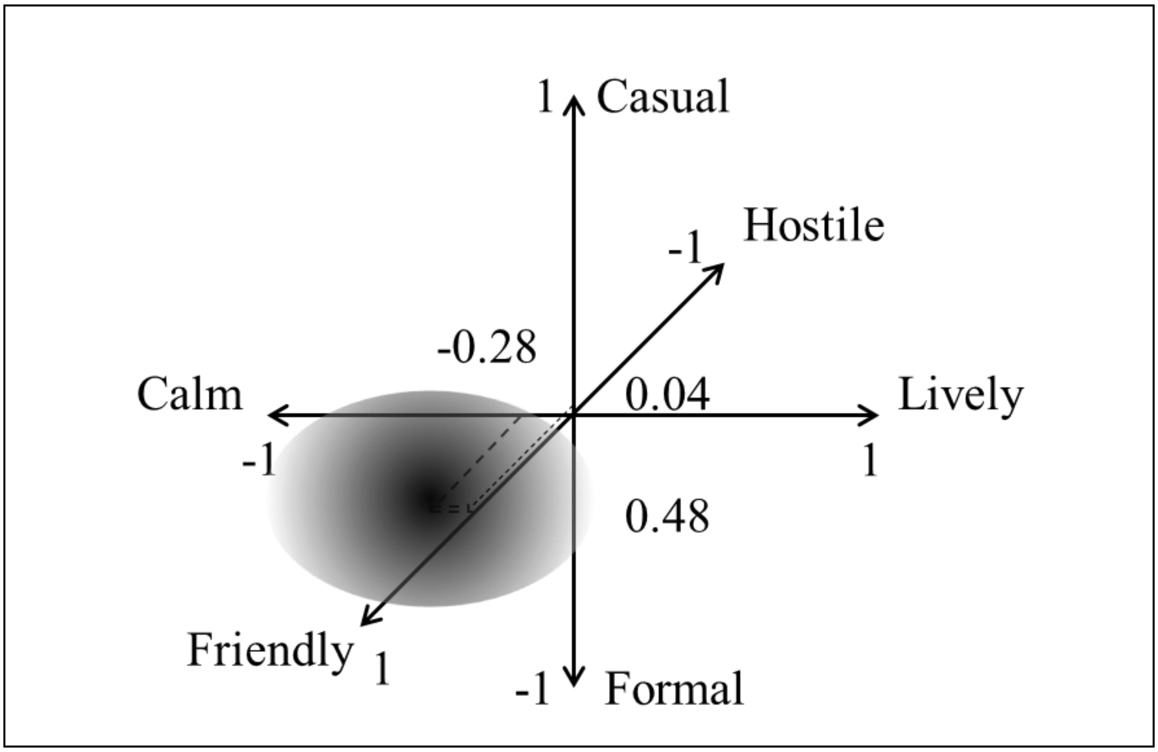


Fig 3.10(d) Atmosphere as fuzzy set in friendly, calm,

and neutral (on casual-formal) mood (No.9 t=20 sec)

The size of the cloud in Fig. 3.10(a) is the most commonly observed in the experiment, where the standard deviation $\boldsymbol{\sigma}$ takes values from 0.16 to 0.2 that means there is relatively small difference among atmospheres felt by agents. Fig. 3.10(b) shows the smallest cloud in all experiments, in which the cloud is concentrated into a singleton, i.e., all agents feel the atmosphere in almost the same manner. In the case of Fig. 3.10(c) the standard deviation varies very big from one axis to others. Lastly the biggest cloud case ($\boldsymbol{\sigma_f = 0.10, \sigma_l = 0.64, \sigma_c = 0.56}$) is shown in Fig. 3.10 (d), i.e., there exist big difference of atmospheres felt by agents. It becomes clear through the experiment that the atmosphere in the same situation is felt differently by each agent and that the proposed method provides such spreading atmosphere information systematically.

The comparison accuracy for each agent of SVR and neural network with back propagation which is widely known as a solution for non-linear problem is shown in Table 3.3. Some models of node are tested by using the same data set with SVR, because the most suitable number of node in neural network is uncertain. The best accuracy of neural network is lower SVR's one for all agents. And, customization of neural network is necessary to use for each agent, because optimal number of node is different by agent as shown in Table 3.3. The worst accuracies (0.71 in Agent1, 0.64 in Agent2, 0.77 in Agent 3, 0.76 in Agent4) indicate that neural network may estimate the wrong atmosphere. These differences between SVR and neural network are attributing to design concept. SVR is suited to the data of emotion and atmosphere which has fluctuation noise rather than neural network, because **ε**-tube of SVR allows a bit of errors in its learning process. Therefore, versatility of SVR is increasing ability to respond adequately to fluctuation of human's perception. SVR is suitable to estimate the atmosphere interpreted by an agent rather than neural network from view point of implementation, accuracy, and generalization ability.

Table 3.3 Accuracies of SVR and neural network

node	Agent1	Agent2	Agent3	Agent4
5	0.77	0.68	**0.84**	0.81
6	0.73	0.68	**0.84**	0.82
7	0.73	0.67	0.80	0.80
8	0.75	0.65	0.80	0.79
9	0.73	0.70	0.83	0.81
10	0.75	0.66	0.79	**0.84**
11	0.74	0.69	0.78	0.79
12	0.74	0.71	0.81	0.79
13	0.74	0.69	0.82	0.82
14	0.75	0.65	0.79	0.82
15	0.75	0.69	0.80	0.82
16	0.72	0.69	0.83	0.77
17	0.74	0.68	0.82	0.82
18	0.72	0.64	0.82	0.79
19	0.72	0.68	0.79	0.80
20	0.73	0.69	0.78	0.80
21	0.74	0.66	0.77	0.77
22	0.74	0.71	0.79	0.78
23	0.75	0.69	0.81	0.79
24	0.72	0.69	0.78	0.82
25	0.78	0.67	0.79	0.79
26	0.74	0.67	0.77	0.79
27	**0.79**	0.66	0.77	0.76
28	0.71	**0.73**	0.81	0.81
29	0.73	0.69	0.77	0.79
30	0.73	0.65	0.80	0.79
31	0.74	0.66	0.78	0.79
32	0.73	0.64	0.77	0.78
MAX	**0.79**	**0.73**	**0.84**	**0.84**
SVR	0.89	0.92	0.89	0.91

A robot project entitled “Multi-Agent Fuzzy Atomosfield” is ongoing by authors’ group sponsored by JSPS (Japan Society for the Promotion of Science) where the interaction is studied for the multi-agent society consisting of several humans and several eye-robots with Kinect® and RTM (Robot Technology Middleware developed by AIST). The deep level understanding in humans-robots interaction is also studied, where emotion understanding, intention understanding, and atmosphere understanding with customized knowledge and thoughtfulness engine are investigated. In the project the proposed atmosphere understanding method is planning to be applied to the thoughtfulness engine using the output information from the emotion engine developed, and a demonstration DVD entitled ‘Routine of a beloved employee’ is created to show the availability of the proposed atmosphere understanding method. Moreover, the proposal aims to support humans’ and robots’ decision making by providing atmosphere information in terms of a fuzzy set about the state of the current atmosphere, where many humans and robots are coexisting in the society. A new way is opened for humans-robots interaction based on the proposed method by providing atmosphere information appropriately using a fuzzy set expression.

Chapter 4
Distance education system with visualized atmosphere information based on fuzzy inference with customized knowledge

4.1 Distance education system using atmosphere information

Effects and satisfaction of distance education becomes important issue recently [23-55]. Several adoptive system based on learner's user model have been proposed for effective distance education [56-87], they show improvement of the learner's satisfaction. Learner's stress is focused to realize more effective distance education by analyses of learner's performance, where not only system's adaptation to learner but also learner's adaptation is necessary [88-95]. The best effective learning is not easy to realize under using only the unilateral system's adaptation because the learning process depends on learner's emotion. On the other hand, unilateral learner's adaptation to the system is also not simple to make enough efficiency for each learner because it requests high motivation of the learner. The motivation of learners becomes an important issue for learners' performance [95]. The learner's isolation and stress feelings in distance education are still open research topics [88-95]. The classroom lecture which has learners' sufficiency has many interactions among learners and lecturer, where the atmosphere of the lecture is shared by the learners and the lecturer. Therefore, educational environment which has interaction among learners and system such as virtual classroom lecture is necessary to realize effective distance education.

A distance education system is proposed to realize indirect interaction among learners and system, to decrease the learner's stress and isolated feelings, and to inspire learners, where visualized atmosphere information in a virtual classroom is shared by all learners based on fuzzy inference, where the fuzzy inference is suited to represent assessment of atmosphere because it includes humans' fuzzy expression. A multimodal interface such as Kinect® is introduced to each learner's learning environment in order to transfer the learner's state, i.e., facial expression, gesture/posture, and sound, to the system. The learner's state is mapped into a learner's emotion in affinity arousal-pleasure space [2]. Atmosphere information in the virtual classroom is obtained as an emotional vector on fuzzy atmosfield $[-1, 1]^3$ [21][96] by applying rule based fuzzy inference to learner's emotion information. A visualization program provides the atmosphere information of the virtual classroom to each learner.

Each learner studies by communicating with the system and is able to recognize the atmosphere of all other leaners that are supposed to stay in the same virtual classroom at the same time. Each learner gets much more motivation, decreases isolated feelings, reduces stress, and increases the feeling of acceptance by the system via visualized virtual classroom atmosphere. System manager gets each learner's psychological status, obtains individual difference of atmosphere recognition by learners, and makes use of educational contents improvement or business strategy.

A distance education system is designed, where a concept of atmosphere in a virtual classroom is introduced, a multimodal interface device is requested to each learner's learning environment, visualized atmosphere information in the virtual classroom is indicated on the screen of traditional distance education, and records of atmosphere information are provided to system manager.

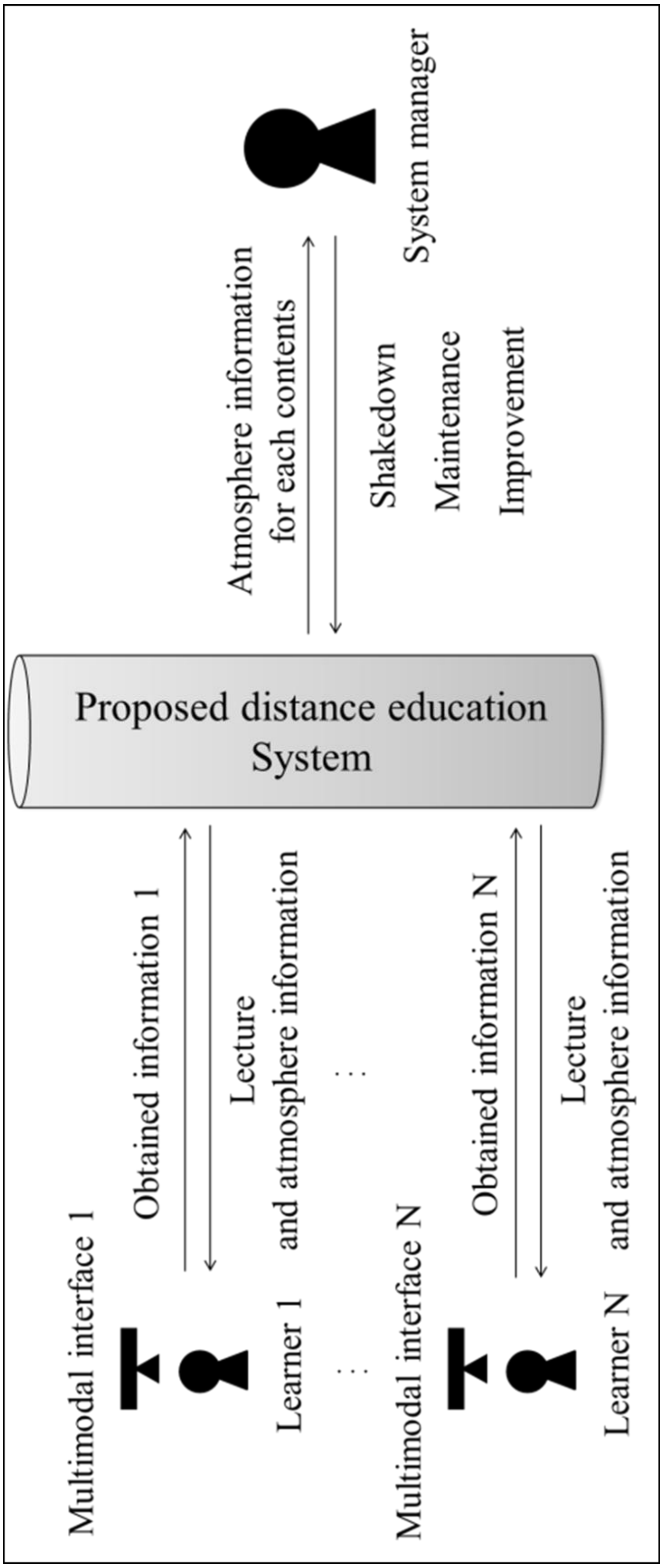


Fig. 4.1 Interactions among learners, system, and system manager in proposal

The mutual interaction among learners, system, and system manager in the virtual classroom is shown in Fig. 4.1. The virtual classroom consists of learners, system, and system manager. It has interactions among them, where the locations and learning instances of learners are generally different one after another. A concept of virtual classroom actualizes new learning environment in such a way that each learner feels as if he/she is supposed to attend in a real classroom by sharing the same atmosphere. The atmosphere of virtual classroom is formed mainly by emotions of all learners and a virtual lecturer in the system, and reminds each learner the existence of other learners and a virtual lecturer. A multimodal interface device such as Kinect® is introduced to capture each learner's states from facial expression, gesture/posture, sound information, and so on. Feelings of atmosphere information by each learner are obtained from each learner's emotions by using rule based fuzzy inference. They are unified into final atmosphere information in virtual classroom by using average and standard deviation operations. Finally the atmosphere information in the virtual classroom is visualized/displayed on the screen of each learner's learning environment by two figures, where one indicates average atmosphere with shape-color-length model and another shows standard deviations of three atmosphere components by 1/8 ellipsoidal body model.

Each learner is easy to forget other learners' existence even if he/she basically recognize that the other learners are also learning the same contents, because there is no information of other learners' existence in traditional distance education system. The traditional distance education system provides mainly educational contents only, and accordingly the learner may feel isolation and frustration. The learner may know the existence of other learners if the system proffers real classroom like environment. In the proposed distance education system it is supposed to exist a classroom in the education environment, called a virtual classroom, and to be located by all learners, system, and system manager. Each learner may think that he/she is studying with other learners in the virtual classroom via the visualized atmosphere information on the screen of learner’s terminal, therefore the isolated feelings of learners may be decreased. The learner’s mood is also reflected immediately to the atmosphere information of the virtual classroom from instance to instance, consequently the learner may relieve the frustration by watching the change of atmosphere information in response to his/her mood. In such a way like this, the proposed system improves affinity of learners gradually to the lecture in the virtual classroom.

The atmosphere information in the virtual classroom is recorded for each learning instance. The atmosphere for each screen of learning contents will be changed successively according to the accession by learners. Such history of atmosphere information is stored in the system, including 1) the atmosphere of the virtual classroom at the scene and the accessed learner, and 2) the accessed learner’s feeling of atmosphere at the scene. The history of atmosphere information in the virtual classroom includes the information, i.e., which contents inspire learners and whether the learning is completed in appropriate atmosphere or not. It is one of the most important elements for the system manager to brush up the distance education system to the direction of better customization for each learner and better business chance.

4.2 Atmosphere estimation of virtual classroom based on fuzzy inference

4.2.1 Fuzzy set representation on fuzzy atmosfield of virtual classroom atmosphere

Fuzzy atmosfield [21][96] shown in Fig.4.2 is accepted to represent atmosphere in a virtual classroom, including learners, system, and system manager.

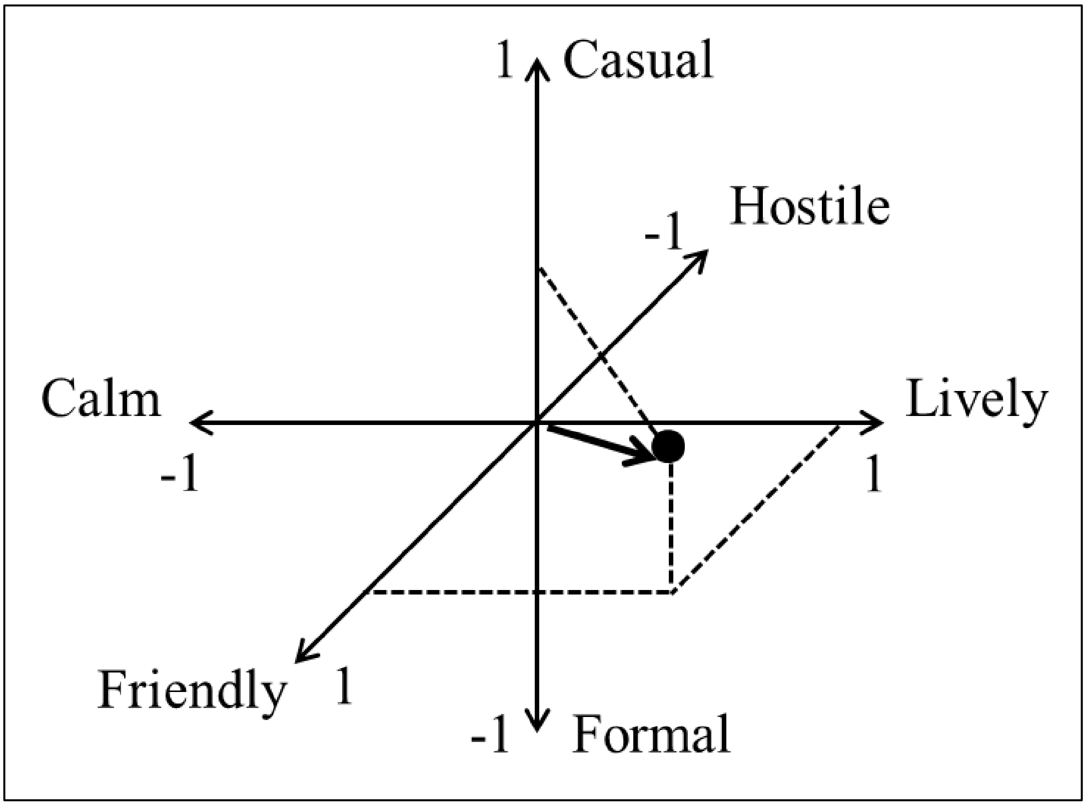


Fig. 4.2 Fuzzy atmosfield representing the atmosphere [21]

A concept of virtual classroom is introduced in the proposed distance education system, and its atmosphere is supposed to be changed successively. The Atmosphere in the virtual classroom for each learning instance is estimated by using rule based fuzzy inference. The input of fuzzy inference is 3D emotional vector in affinity arousal-pleasure space [2] shown Fig. 4.3, and is fed by learners' multimodal interface device with neural network and fuzzy set [99]. It should be noticed that the affinity axis is suit to represent the relationship between a learner and learning contents because affinity arousal-pleasure space represents emotion and learner's impression to the learning contents in a space.

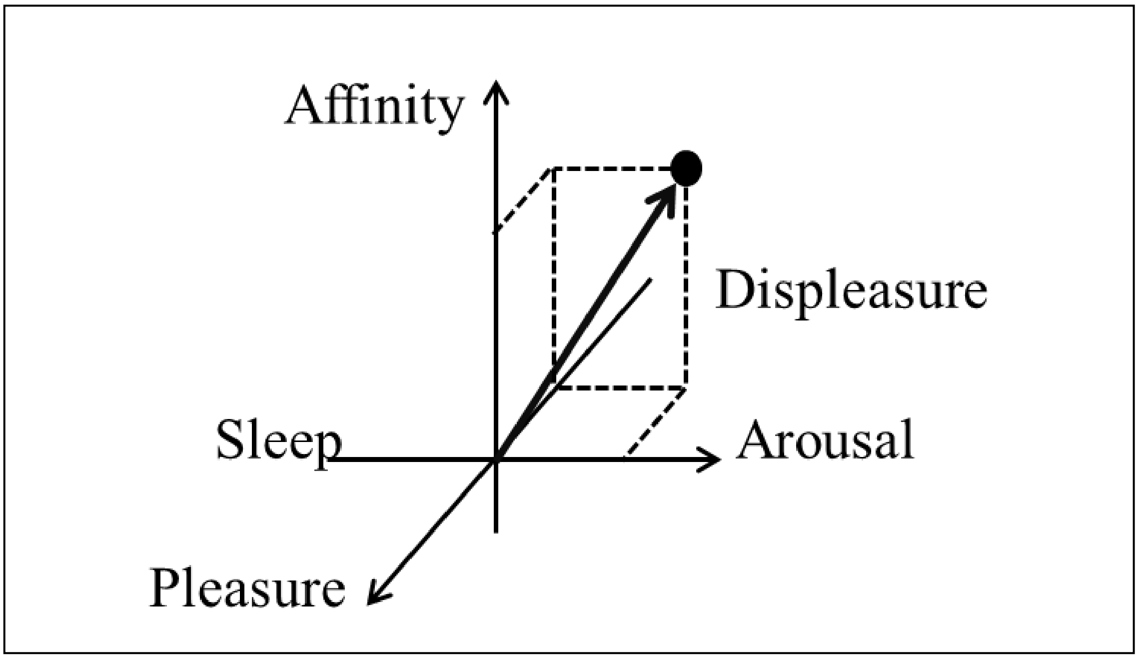


Fig. 4.3 Affinity arousal-pleasure space [97]

4.2.2 Fuzzy inference rules using customized knowledge

Each learner's feelings of the atmosphere in the virtual classroom are estimated by max-min center of gravity method of the fuzzy inference using a 3D emotional vector of each leaner as input information. Because there is an individual difference in feelings of atmosphere [100], some kinds of knowledge customized to each leaner is necessary to estimate correctly each learner's feelings of atmosphere. The relations between learner's emotion and feeling of atmosphere, which are obtained by questionnaire in virtual classroom lecture for each learner, are used as customized knowledge. The customized knowledge in a database is used to create if-then fuzzy inference rules.

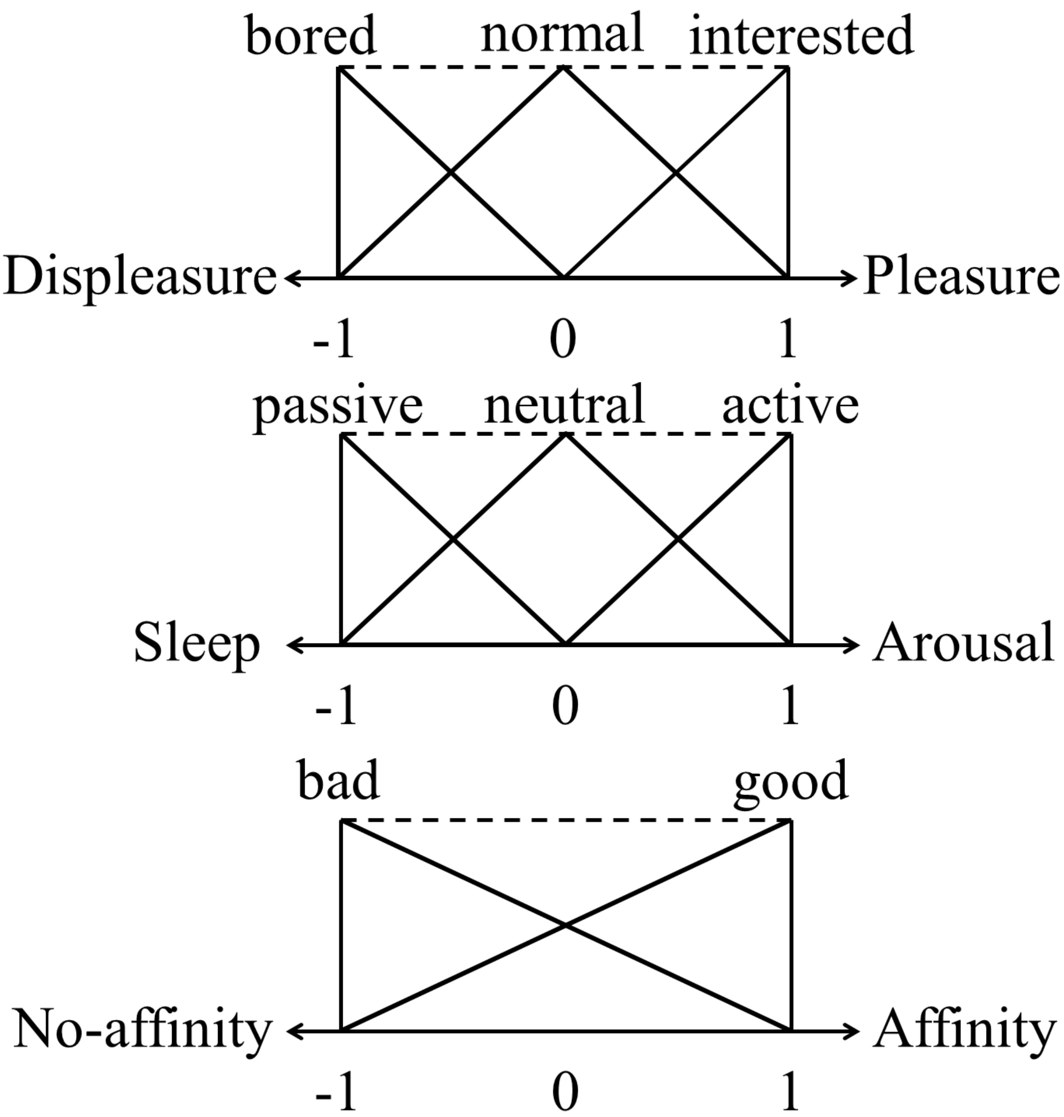


Fig. 4.4 Membership functions in affinity arousal-pleasure space [2]

Fuzzy membership functions shown in Fig.4.4 represent emotions estimated for each leaner in affinity arousal-pleasure space $[-1, 1]^3$ (i.e. pleasure-displeasure, arousal-sleep, and affinity-no affinity) [4] and are used in antecedent part of if-then fuzzy inference rules. Each learner's feelings of atmosphere are represented in fuzzy atmosfield $[-1, 1]^3$ (i.e. Friendly-Hostile, Lively-Calm, and Casual-Formal) [21]. The membership functions shown in Fig. 4.5 are used in consequent part.

4.2.3 Approximate representation of atmosphere information in virtual classroom

For each learning instance, the atmosphere in virtual classroom is initially set to zero vector in fuzzy atmosfield. When a new learner accesses the learning instance, the learner's feelings of atmosphere is provided as a vector in fuzzy atmosfield by using fuzzy inference based on customized knowledge. The atmosphere in virtual classroom of the learning instance is updated at the new learner's access by adding (max operation) the provided vector to the former set of vectors, i.e., the atmosphere is expressed by a set of vectors in the same number of accessed learners. Although the atmosphere information is represented by a set of vectors in fuzzy atmosfield, it is complicated and boring if the information of a set of all vectors is presented directly to learners. Instead, easily understandable approximate information may be welcomed by learners. As such an approximate expression, average vector in fuzzy atmosfield $[-1,1]^3$ and standard deviations vector in $[0,1]^3$ of the set of all atmosphere feeling vectors are accepted. A pair of these two vectors are visualized, and presented to the learner by displaying the visualized images on the learner's screen (in the right bottom).

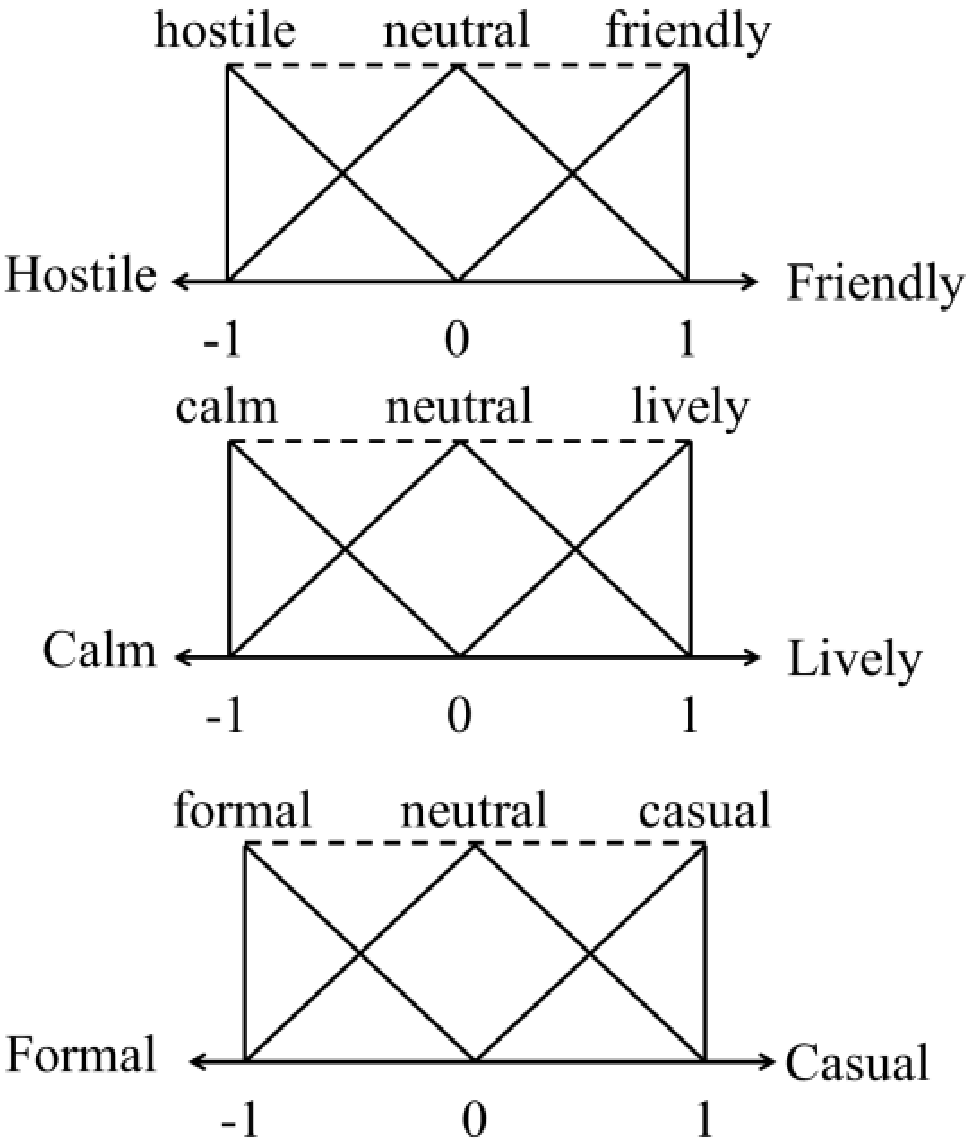


Fig. 4.5 Membership functions in fuzzy atmosfield [21]

4.2.4 Visualization of Approximated Atmosphere Information in Virtual Classroom

Atmosphere information of each learning instance is represented by a fuzzy set (a set of vectors in the same number of accessed learners) in fuzzy atmosfield $[-1, 1]^3$, and changes one learner's access after another. It is represented approximately by a pair of vectors, i.e., average vector in $[-1,1]^3$ and standard deviations vector in $[0,1]^3$. Visualization of approximated atmosphere information is proposed to inform the atmosphere in virtual classroom to learners.

An average vector is illustrated by shape-color-length model [21] as shown in Fig.4.6. A standard deviations vector is illustrated by using 1/8 ellipsoidal body model in $[0, 1]^3$ as shown in Fig. 4.7, where the surface is colored by the correspondence from [0, 1] to [red, purple].

As an example, visualized approximated atmosphere information in the case of average vector (0.4, 0.7, -0.4) and standard deviations vector (0.1, 0.5, 0.2) is shown in Fig. 4.8, where the atmosphere is assessed as friendly in uniformly, lively with split whether strongly live or not so strong, and a little casual in uniformly.

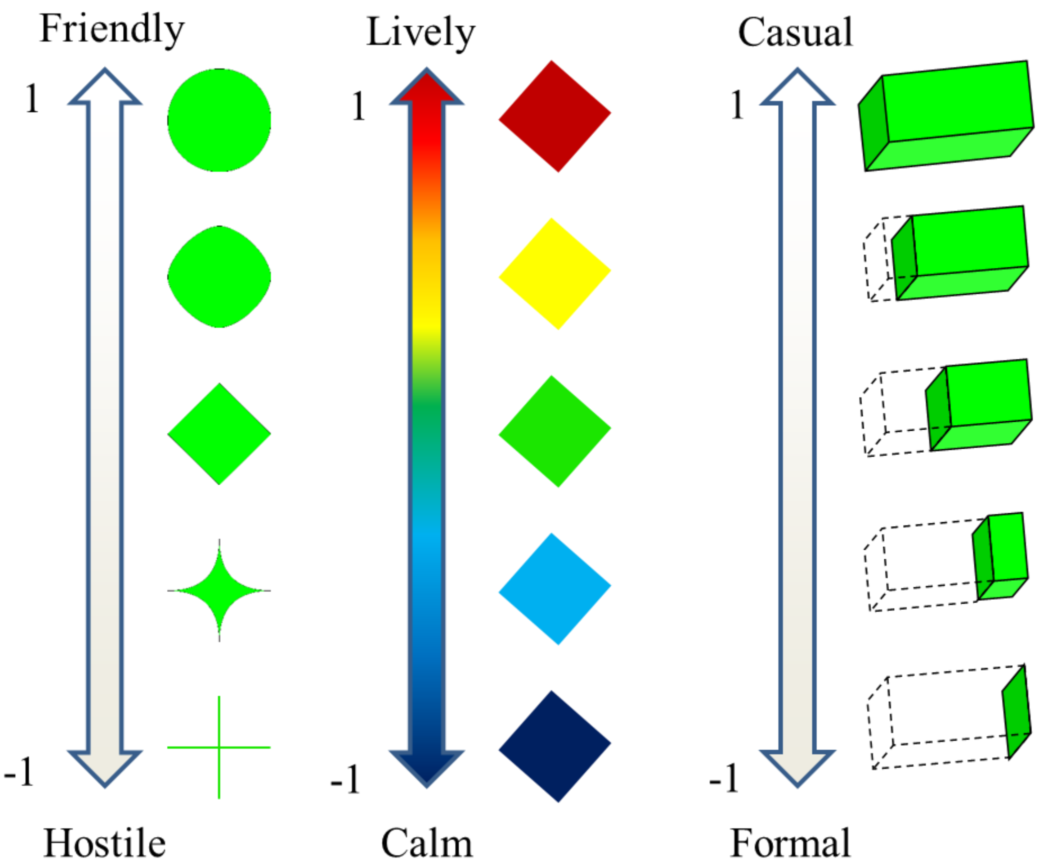


Fig. 4.6 Visualized representation of atmosphere average vector
by shape-color-length model [21]

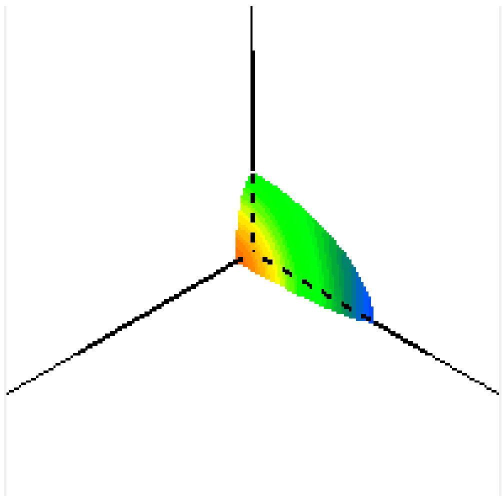
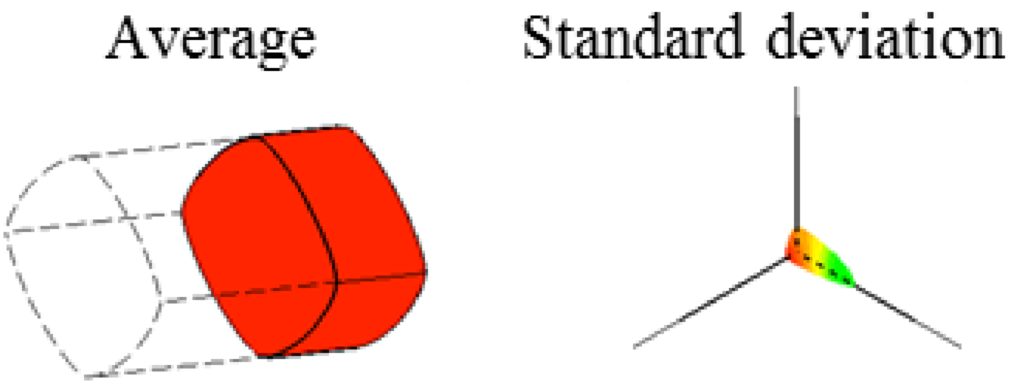


Fig. 4.7 Visualized atmosphere standard deviations vector
by 1/8 ellipsoidal body model



(0.4, 0.7, -0.4) (0.1, 0.5, 0.2)

Fig. 4.8 An example of visualized atmosphere

4.3 Evaluation of Visualized Atmosphere Information based on Learners' Mood with POMS

4.3.1 Visualization experiment of atmosphere information

A part of '2-3 Fuzzy Logic and Reasoning' in CAI contents on computational intelligence [97] is accepted for the experiment to 15 learners (graduate students) to confirm the availability of visualized atmosphere information in the virtual classroom. An example of screen of CAI contents with the visualized atmosphere information (in the right bottom area) is shown in Fig. 4.9. It should be noticed that the atmosphere information in the right bottom area in Fig. 8 changes as a new learner accesses to this screen, i.e., from average (0, 0, 0) with standard deviation (0, 0, 0) in the case of no average (0.3, 0.2, 0.2) with standard deviation (0.2, 0.3, 0.2) as shown in Fig. 4.9 right bottom area when the 15th and the last learner finished to study this screen.

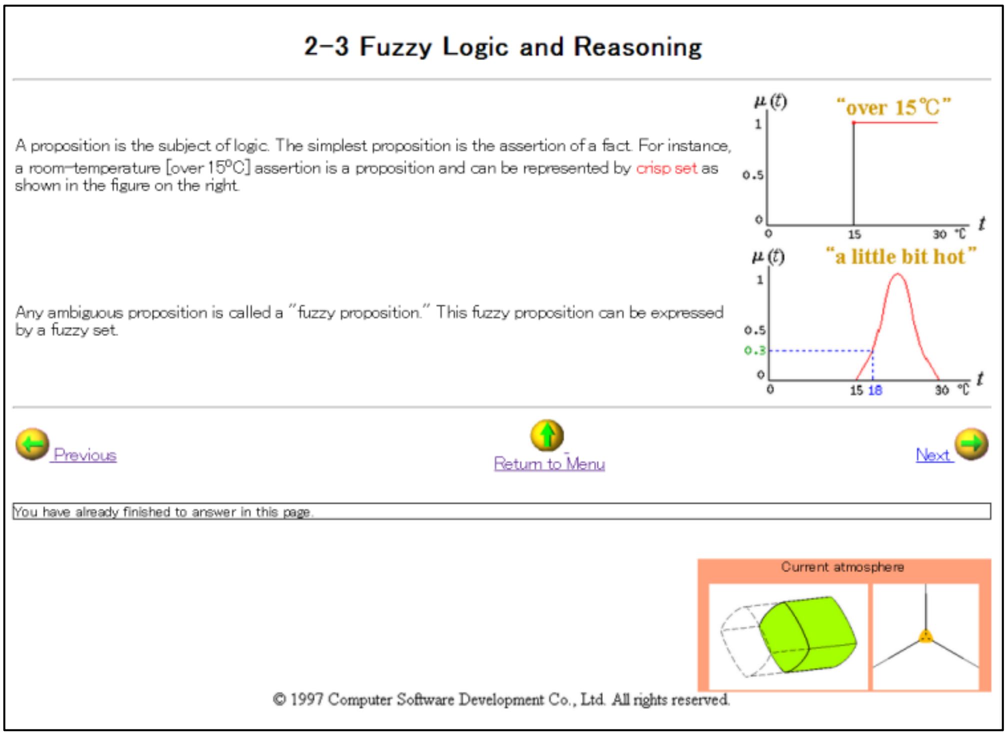


Fig. 4.9 A scene of CAI contents with visualized atmosphere information

4.3.2 System evaluation by learners' mood based on POMS

A traditional style distance education, i.e., without no atmosphere information, is practiced as a preliminary experiment for 15 learners (4 master and 11 Ph-D students) on two sections '2-1 What is Fuzzy Logic?' and '2-2 Fuzzy Set Operations' in 2nd chapter of CAI contents [97]. Profile of Mood States (POMS) test [98] is done to obtain learners' mood for 15 learners after finishing two sections. Then main experiment by proposed distance education with atmosphere information is accomplished using a section '2-3 Fuzzy Logic and Reasoning' in 2nd chapter of CAI contents [97] for the same 15 learners. The POMS test is also carried out to the 15 learners after finishing the study.

In both experiments, each learner is expected to input the 5 grade answers to 65 questions in POMS. Table 4.1 shows T scores for 15 learners in the POMS test for traditional style distance education, where T-A, D, A-H, V, F, and C are Tension-Anxiety, Depression-Dejection, Anger-Hostility, Vigor, Fatigue, and Confusion, respectively. And T scores for 15 leaners in the POMS test for proposed distance education are listed in Table 4.2. The difference that T scores in Table 4.2 minus the scores in Table 4.1 is summarized in Table 4.3.

Table 4.1 Results of POMS test in traditional distance education

learner	T-A	D	A-H	V	F	C
1	55	42	42	45	41	49
2	53	60	49	37	66	57
3	56	54	58	58	50	51
4	54	46	49	50	44	57
5	45	49	40	69	40	49
6	56	51	50	48	40	45
7	45	45	44	63	41	47
8	50	43	42	55	50	51
9	37	49	40	51	43	64
10	34	42	43	63	40	40
11	55	62	64	41	66	61
12	53	43	47	50	38	49
13	53	58	58	58	56	51
14	48	56	59	66	50	47
15	37	48	40	58	41	44

Table 4.2 Results of POMS test in proposed distance education

learner	T-A	D	A-H	V	F	C
1	42	43	39	43	37	42
2	56	67	48	30	70	66
3	56	53	54	56	43	51
4	53	45	50	46	44	53
5	39	44	38	69	38	40
6	48	51	48	51	46	55
7	45	43	44	74	41	47
8	45	42	40	53	48	49
9	36	41	38	43	43	49
10	37	44	37	61	37	38
11	60	71	66	53	58	61
12	55	46	48	51	48	46
13	48	55	47	60	51	44
14	45	56	56	66	45	49
15	39	44	40	45	41	49

Table 4.3 Difference of T Scores between Traditional and Proposal

learner	T-A	D	A-H	V	F	C
1	-13	1	-3	-2	-4	-7
2	3	7	-1	-7	4	9
3	0	-1	-4	-2	-7	0
4	-1	-1	1	-4	0	-4
5	-6	-5	-2	0	-2	-9
6	-8	0	-2	3	6	10
7	0	-2	0	11	0	0
8	-5	-1	-2	-2	-2	-2
9	-1	-8	-2	-8	0	-15
10	3	2	-6	-2	-3	-2
11	5	9	2	12	-8	0
12	2	3	1	1	10	-3
13	-5	-3	-11	2	-5	-7
14	-3	0	-3	0	-5	2
15	2	-4	0	-13	0	5

Table 4.3 indicates that the effect of visualized atmosphere information is different one learner after another. The best efficiency is found in Tension-Anxiety of leaner 1 and vigor of learner 15, so it is concluded that learner 1 decreases frustration and learner 11 becomes lively. In the interview after experiments, learner 1 says that he relaxes to see the visualized atmosphere information rather than the case of traditional style distance education with no atmosphere information, and learner 11 mentions that he takes an interest in watching transition of visualized atmosphere information in proposed distance education, which coincides with lower stress of learner 1 and high affinity of learner 11. Anger-Hostility of learner 13 is comparatively lower than that of others, which means that his angry emotion is reducing. Learner 13 answers in the interview that he learns comfortable by feeling that other learners learn in the same virtual classroom through atmosphere information. It indicates that lower isolate feelings of learner 13. Confusion of learner 9 attains the lowest score in the experiments, which is concluded that learner 9 decreases confusion. In the interview learner 9 says that he read the contents carefully when he feels difficulty of contents because visualized atmosphere information becomes hostile at that time. It means that high aspiration of learner 9.

To make the statistical difference between results of the proposed distance education and that of traditional distance education clear, F-test and paired t-test are practiced for each T score. The p-values of F-test in T scores, i.e., T-A, D, A-H, V, F, and C are 0.473, 0.125, 0.468, 0.216, 0.107, and 0.307, respectively. The results are not significant at the 5% significance level, so paired t-test is possible to be done. As the result, the p-values of paired t-test are T-A=0.087, D=0.431, A-H=0.011, V=0.334, F=0.205, and C=0.192. The result of A-H is significant at the 5% significance level except for those of others, which means the visualized atmosphere information has effect to 15 learners from a view point of A-H. On the other hand, the evaluations of T-A, D, V, F, and C have a relation between learning environment and learner’s state of mood though the effect of visualized atmosphere information is confirmed in Anger-Hostility parameter of POMS statistically.

The history of atmosphere information with proposed distance education is shown in Fig. 4.10(average) and Fig. 4.11(standard deviation). Average of Friendly-Hostile in 1st, 2nd, 4th, and 5th page are higher than that of other pages, which indicates that 15 learners study smoothly. The 4th page has higher average of Casual-Formal, which means that 15 leaners are inspired by contents. It also shows that the 4th page is appropriate instance to realize effective discussion. Studying by 15 learners is done under appropriate atmosphere in the virtual classroom because whole contents have no prominent atmosphere. The system manager says in the interview that the history of atmosphere information includes the characteristics of the CAI contents and leads to make a strategy for business.

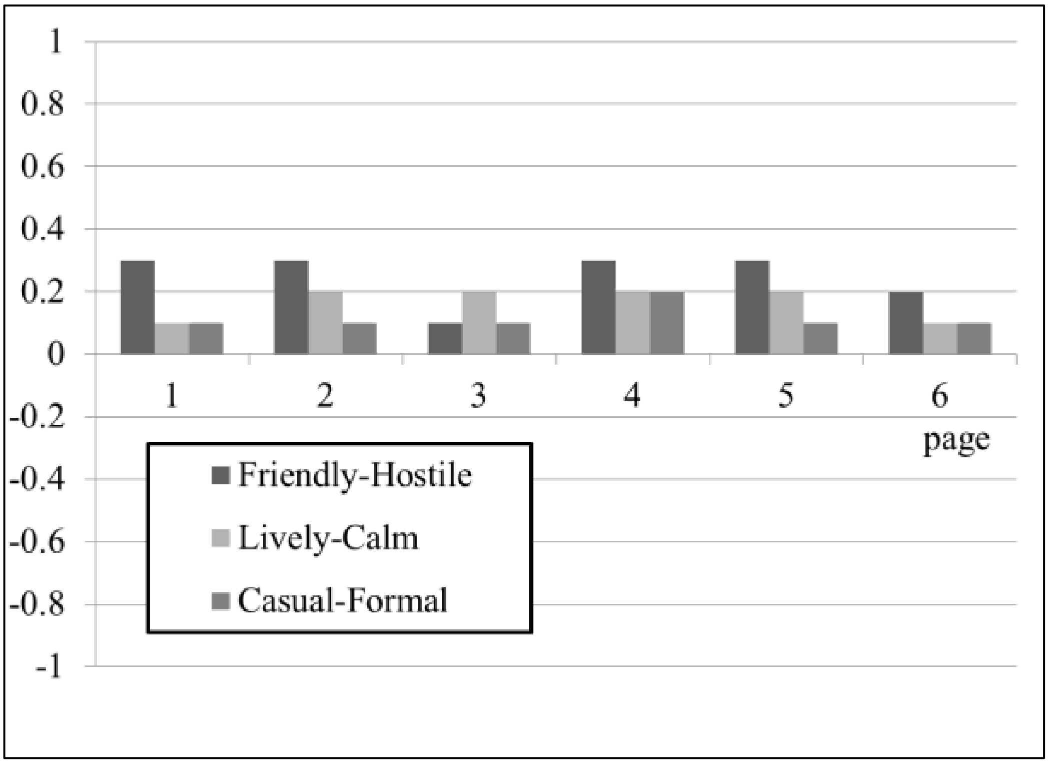


Fig. 4.10 History of average atmosphere information
in the proposed distance education system

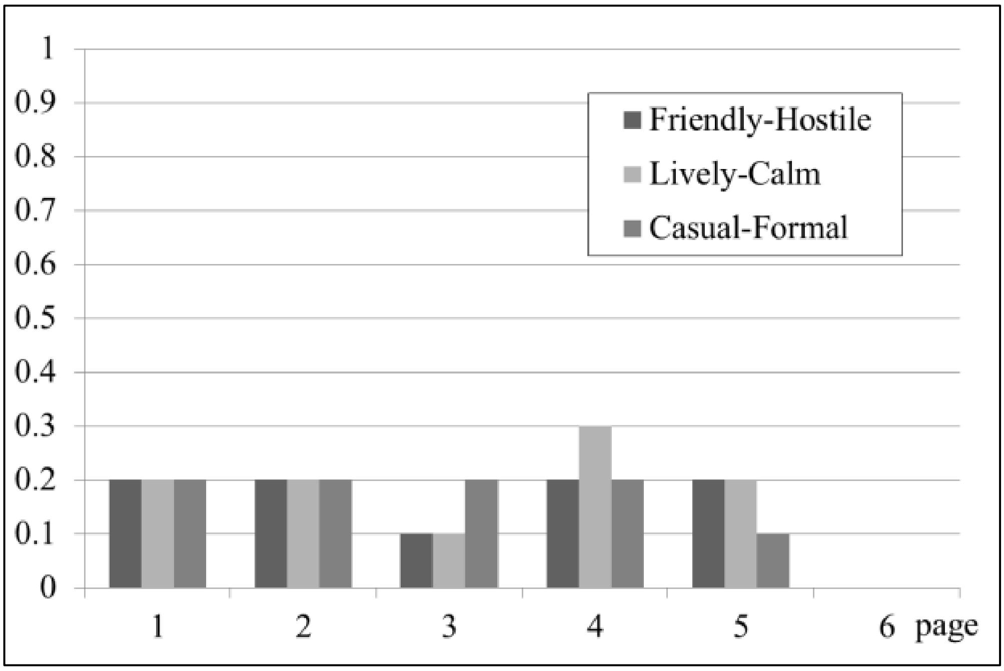


Fig. 4.11 Standard deviation records of atmosphere information
in the proposed distance education system

In the experiment of two persons communication by measuring each emotion, the proposed transform function shows that it can represent the atmosphere with the accuracy 0.81. This basic experimental results will give an enough background to ongoing research project of casual communication between robots and humans, where it is being applied to the demonstration play “enjoying home party by 5 eye robots and 4 human beings”.

Chapter 5

Conclusion

Atmosphere information extraction based on transform function from affinity-arousal pleasure space to fuzzy atmosfield

In chapter 2, the proposed transform function shows that it can represent the atmosphere with the accuracy 0.81 in the experiment of two people's communication by measuring each emotion. These basic experimental results will give an enough background to ongoing research project of casual communication between robots and humans, where it is being applied to the demonstration play "enjoying home party by 5 eye robots and 4 human beings".

Atmosphere understanding for Humans-Robots interaction based on SVR and Fuzzy set

In chapter 3, the 13 scenarios which cover most of the cases in Fuzzy Atmosfield are played by four human-agents to confirm the availability of the proposed method in the multi-agent society consisting of a relatively small number of agents. An evaluation is done through questionnaires to the four human-agents by asking the emotion/atmosphere of each agent in every 10 seconds for all 13 scenarios. The distance between the answered atmosphere by the agent and the calculated atmosphere by the proposed method is normalized by $\mathbf{2\sqrt{3}}$ that is the maximal diagonal distance in the Fuzzy Atmosfield $[-1,1]^3$. The accuracy of the proposed method for each scenario and for each agent is defined by the one's complement of the averaged normalized distance by ten scenes. The average accuracy for 13 scenarios and four agents is 0.90 with the standard deviation 0.036, where the best and the worst average accuracy are 0.97 and

0.84, respectively. Since each agent answers his/her emotion/atmosphere data by 0.2 interval in [-1,1] for 3 axes of Fuzzy Atmosfield, and the worst average accuracy is 0.84 ($\geq$ 0.8), the proposed method shows enough atmosphere understanding accuracy in the experiment.

The 130 (=13 scenarios $\times$ 10 scenes/scenario) scenes in the experiment covers most of the typical positions and there is no big vacant spaces in Fuzzy Atmosfield. Hence, the proposed atmosphere understanding method may be concluded to be available for humans-robots interaction consisting of a relatively small number of agents (four agents in the experiment). From a view point of computational complexity in the experiment, a real time computation is possible by using MATLAB coding on a laptop PC (CPU: Core 2 duo P8700, 2.54/2.53 GHz) whereas it takes for 40 seconds in SVR learning process. Because the computation time for real time computation increases linearly as the number of agents increases, the proposed method provides the necessary information for each agent (human/robot) in the case of bigger number of agents to understand the atmosphere correctly and to make appropriate behavioral decisions thereafter. Therefore, the robot agent may be able to respond appropriately with proposal to situations such that a discussion with a polarized group, uncomfortable conversation, and, serious meeting.

A robot project entitled “Multi-Agent Fuzzy Atomosfield” is ongoing by authors’ group, where the deep level understanding consisted of emotion understanding, intention understanding, and atmosphere understanding with customized knowledge and thoughtfulness engine has been investigated. The proposed method is planning to be applied to the atmosphere understanding part of the project. Moreover, it aims to give humans for assisting behavioral decision making by providing information in terms of fuzzy set about the state of atmosphere. The proposed method opens a new way for humans-robots interaction by providing atmosphere information appropriately.

Distance education system using visualized atmosphere information based on fuzzy inference with customized knowledge

In chapter 4, the availability of atmosphere information visualization for each learner is confirmed by simulation using CAI contents on computational intelligence [97]. An effect of the proposed distance education system is tested by 15 graduate students using implemented distance education with CAI contents [97]. It is confirmed in Anger-Hostility parameter of POMS by comparison with traditional distance education method in terms of F-test and paired t-test. The p-values of F-test in T scores are 0.473(T-A), 0.125(D), 0.468(A-H), 0.216(V), 0.107(F), and 0.307(C), and those of paired t-test are 0.087(T-A), 0.431(D), 0.011(A-H), 0.334(V), 0.205(F), and 0.192(C). The homoscedasticity of experimental results is verified in results of F-test for each T score. The significance of the proposal in Anger-Hostility (A-H) is validated in comparison with traditional distance education method using paired t-test.

The record of atmosphere information during learning process of each learner shows that the visualization of atmosphere information improves the atmosphere assessed by the learner, and figures out which contents make the learner interesting. The improvement of atmosphere during learning process leads to increase the learner's performance, such as providing the learner's high affinity feeling and decreasing the learner's isolated feelings. The availability of atmosphere information for the system manager is also confirmed by analyzing records of atmosphere information during learning processes of all learners, e.g., the analysis of records of atmosphere information may help the system manager to detect which contents are effective for the learner.

The proposal of displaying atmosphere information in a virtual classroom aims to establish an innovative distance education system which exceeds face-to-face traditional education system, in the sense of affinity of classroom atmosphere, e.g., the system detects what the atmosphere is the best for each learner and realizes the effective distance education via controlling atmosphere during their learning processes. No learners dislike studying and feel any stress such as isolation, confusing, and disgust, because all educational contents customized to each learner inspire all learners and make them interesting. The system manager may work out his/her strategy of the business by analyzing the records of atmosphere information.

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Related Publications

Journal

[1]. **Kazuhiro Ohnishi,** Fangyan Dong, Kaoru Hirota, “Atmosphere Understanding for Humans-Robots Interaction Based on SVR and Fuzzy set”, Journal of Advanced Computational Intelligence and Intelligent Informatics(JACIII), Vol.18 No.1, 2014.

[2]. **Kazuhiro Ohnishi,** Jesus A. Garcia-Sanchez, Yongkang Tang, Fangyan Dong, Kaoru Hirota, “Visualization of Atmosphere Information for Distance Education System based on Fuzzy Inference using Customized Knowledge”, Journal of Aoutomation, Mobile, Robotics & Intelligent Systems (JAMRIS), 2015**(submitted)**

Conference

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[3]. **K. Ohnishi,** Jesus Garcia, F. Dong, K. Hirota, Distance Education System with Visualized Atmosphere Information based on Fuzzy Inference, 7th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control (HNICEM), November, 2014, Palawan, Philippines.

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[1]. **Kazuhiro Ohnishi,** Yojiro Adachi, Yoichi Yamazaki Fangyan Dong ,Kaoru Hirota, 親和型快－覚醒空間から雰囲気場への変換関数の提案 (Transform Functions from Affinity Arousal Pleasure Space to Atmosfield in natural conversation), 28th Fuzzy System Symposium（FSS2012), Japan Society for Fuzzy Theory and Intelligent Informatics.

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[3]. **Kazuhiro Ohnishi**, Fangyan Dong, Kaoru Hirota, Atmosphere Representation/Understanding for Humans-Robots Interaction, The Robotics and Mechatronics Conference 2014.

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