Bayesian networks + reinforcement learning: Controlling group emotion from sensory stimuli

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As communication technology develops, various sensory stimuli can be collected in service spaces. To enhance the service effectiveness, it is important to determine the optimal stimuli to induce group emotion in the service space to the target emotion. In this paper, we propose a stimulus control system to adjust the group emotion. It is a stand-alone system that can determine optimal stimuli by utility table and modular tree-structured Bayesian networks designed for emotion prediction model proposed in the previous study. To verify the proposed system, we collected data using several scenarios at a kindergarten and a senior welfare center. Each space is equipped with sensors for collection and equipment for controlling stimuli. As a result, the system shows a performance of 78% in the kindergarten and 80% in the senior welfare center. The proposed method shows much better performance than other classification methods with lower complexity. Also, reinforcement learning is applied to improving the accuracy of stimuli decision for a positive effect on system performance.

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1. Introduction

The stimuli in an environment such as brightness and sound affect human emotion [1], and in most services, emotions are closely related with the effectiveness of the service [2]. In this context, there have been various approaches to finding optimal stimuli in service spaces [3]. Recently, the services that enhance the satisfaction of people with purchases or the effectiveness of education using sensory stimuli have been developed. These services are based on the conventional studies which find proper stimuli from the information of people in the space. However, such studies are based on many additional equipment to measure bio-signals such as electrodes attached to the subject’s skin that disturb action and can be a factor to change the subject’s emotion. They are not suitable in the real service spaces.

It can be a solution to this problem to use environment elements in finding current state instead of devices attached to the subject. To verify this, we designed a classroom to induce specific emotions that could enhance the effectiveness of education. Table 1 shows the elements that can be measured in an educational institute, especially kindergarten. These environmental factors are selected from the literature and proven by teachers of kindergarten about their effectiveness [4]. They affect children’s emotion, but do not interfere with the curriculum.

The environmental factors are measurable, but their effects are not deterministic. Some factors induce one emotion, whereas most do multiple emotions. Fig. 1 shows that emotions are subject to volume and sound. Even the same sound or volume can lead to different emotions. A probabilistic approach can be a solution to deal with the relationship between environmental factors and emotions.

In this paper, we propose a group emotion control system in an educational space and a welfare space by controlling the stimuli. The proposed system is composed of the two parts that predict emotion and determine stimuli as shown in Fig. 2. In the first part, Bayesian networks infer group emotions shared by people in the space, and they are classified into four classes of positive-arousal (P-A), negative-arousal (N-A), negative-relax (N-R), and positive-relax (P-R) by the stimulus-organism-response model of Russell [5]. The networks are constructed into a tree-structure and then divided into modules. In the second part, appropriate stimuli to change to the target emotion are determined by a utility function, which finds the proper stimuli using the utility table initialized by domain knowledge and adapted by reinforcement learning. We have applied the proposed method to two services of math and music classes in a kindergarten, and tai-chi class in a senior welfare center.

2. Related works

For emotional services, it is so important to recognize emotions accurately that several methods have been proposed for
recognizing human emotions through various input data. Facial expressions, voice, characters, and biological signals are typically used as the data sources for emotion recognition. Table 2 shows the studies related to emotion recognition.

Dobrishek et al. used a Gaussian mixture model with a universal background model to recognize user’s emotions with facial expressions and voice data [6]. Metallinou et al. proposed an emotion recognition model using voice and facial expression data based on Gaussian mixture model [7]. The proposed method showed better recognition accuracy of up to 22% by using two data mixed than by individually using data. In particular, the accuracy of “Anger” and “Sadness” was as high as 80% and the accuracy of “Neutral” was the lowest at 60% because the definition of “Neutral” state is very vague. Lee et al. used the features of speech data to recognize five emotions using a hierarchical binary decision tree [8]. The proposed method was tested with AIBO and USC IEMOCAP databases with the audio data that 51 children interacted with the toy robot. Chang et al. used the bio-signal information to recognize whether the user was angry with support vector regression [9].

Park et al. proposed a method of recognizing three emotions with bio-signals such as EEG, EDA, and PPG using the fuzzy c-means clustering based on neural network when inducing emotions of the subjects by visual and auditory stimulation [10]. Praszyński et al. applied rule-based methods to the texts of blogs and social networks [11]. They perceived words of expressing emotions and the cause of emotion in these words, and constructed an ontology model that displayed semantic relations between them. Eyharabide et al. constructed an ontology model to recognize users’ emotions in the e-learning system [12]. Kim and Kwon developed a system that recommends music to users by recognizing the emotions expressed by the songs using the ontology model [13]. The system extracts feature data from the lyrics using a rule-based method and recognizes the emotions represented by the song using the ontology model. Lin et al. designed an ontology model for digital art based on the data entered by users in the form of texts after feeling the appreciation of digital art [14].

Table 1
The environmental stimuli in a kindergarten.

<table>
<thead>
<tr>
<th>Type</th>
<th>Stimulus</th>
<th>State</th>
<th>Controllable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auditory</td>
<td>Video: V1, V2, V3, V4</td>
<td>200 lx, 700 lx, 1000 lx</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Scent: Jasmine, Rose, Lavender, Lemon</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>Humidity: 30%, 40%, 50%, 70%</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

Table 2
Studies on emotion recognition.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Method</th>
<th>Input elements</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dobrishek et al. [6]</td>
<td>UBM-GMM</td>
<td>Facial expression, speech, head</td>
<td>HCI</td>
</tr>
<tr>
<td>Metallinou et al. [7]</td>
<td>HMM, GMM, MFB, SVD</td>
<td>Facial expression, speech, head</td>
<td>HCI</td>
</tr>
<tr>
<td>Lee et al. [8]</td>
<td>DT</td>
<td>Speech</td>
<td>HCI</td>
</tr>
<tr>
<td>Chang et al. [9]</td>
<td>SVR</td>
<td>Physiological signal</td>
<td>HCI</td>
</tr>
<tr>
<td>Park et al. [10]</td>
<td>FNN</td>
<td>Physiological signal</td>
<td>HCI</td>
</tr>
<tr>
<td>Praszyński et al. [11]</td>
<td>Ontology, rule</td>
<td>Text</td>
<td>HCI</td>
</tr>
<tr>
<td>Eyharabide et al. [12]</td>
<td>Ontology</td>
<td>Text</td>
<td>E-learning</td>
</tr>
<tr>
<td>Lin et al. [14]</td>
<td>Ontology</td>
<td>Text</td>
<td>Art</td>
</tr>
</tbody>
</table>
Previous studies have focused on recognizing emotions using personal data. However, in the emotional service, we cannot use the personal data such as facial expressions or voices. Emotions would be predicted based on specific environmental information coming from multimodal sensors in a real environment. We proposed a method for predicting group emotion based on the Bayesian network in previous research [15], and this paper extends it into a complete system.

3. The proposed system

The proposed system is as shown in Fig. 3, where inputs are environmental information and current emotion, and outputs are stimuli determined from the utility function. Bayesian networks predict the next emotion, and the utility function finds proper stimuli for target emotion using the utility table initialized by domain knowledge. As stimuli are coming in, the utility table is updated using reinforcement learning.

3.1. Emotion prediction using Bayesian networks

The proposed system predicts group emotion from environment information using Bayesian networks which are well-known to model the uncertainty with a causal relationship of events [16]. The network for predicting emotion is constructed based on domain knowledge [17], which can be provided by the literature, domain experts, and teachers in several service spaces. It includes the information of stimuli and the relations between stimuli, the emotional affection of each stimulus, and its process.

Since in most service spaces curricula are constructed minute by minute, the system should be fast to minimize the delay between the end of a current process and the start of the next process. The time of inferring Bayesian networks is determined by the complexity of the networks. To decrease the complexity of the networks, we have devised an efficient network structure in the previous study by transforming a single network into a modular tree-structured network. The tree-structured Bayesian network speeds up the inference time in realistic situations, and we employ the network to increase the service efficiency.

3.1.1. Modular Bayesian networks

The Modular network first divides the Bayesian network into modules. To design a modular network that can be applied to a variety of environments, we use the Markov boundary to find the boundaries of the module [18]. After computing the Markov boundary, we find duplicate nodes in two or more boundaries. Since the overlapping nodes are the boundaries of the module, the modules are divided by the nodes, and the nodes are removed from both modules. To maintain the causality of the existing network, a virtual node is inserted in each module, and the node of the pair is connected to each other. The relationship between modules $\psi_i$ and $\psi_j$ is expressed in the below equation.

$$S(\psi_i, \psi_j) = (V_{\psi_{\text{out}}}, V_{\psi_{\text{in}}})$$

(1)

$S$ is a set of pairs of modules $\{< \psi_i, \psi_j | i \geq 1, j \geq 1, i \neq j\}$. The module pair $\{\psi_i, \psi_j\}$ has causality from module $\psi_i$ to module $\psi_j$. $V$ is a virtual node inserted into each module. The causality is reflected through the output node $V_{\psi_{\text{out}}}$ of one module and the input node $V_{\psi_{\text{in}}}$ of the other module. $V_{\psi_{\text{out}}}$ and $V_{\psi_{\text{in}}}$ have the same states and conditional probability table (CPT) with the overlapping node.

Through this process, the single Bayesian network is divided into six modules. Modules are classified into three categories based on type: four stimulus generation modules, one sensory integration module, and an emotion prediction module. The description of the modules and the nodes in the module is given in Table 3.

3.1.2. Tree-structured Bayesian networks

Each module is transformed into a tree structure to reduce inference complexity in the module. Tree-structured Bayesian networks can reduce the size of the CPT that determines the inference time by removing the arc of the nodes with low relevance [19]. To design the tree, the mutual information, which is the association between the nodes, is calculated using the following equation.

$$MI(X, Y) = \sum_{x \in X, y \in Y} p(x, y | C) \log \frac{p(x, y | C)}{p(x) p(y | C)}$$

(2)

where $X$ and $Y$ are attributes of each node, $C$ is a class, that is, an attribute of an output node of each module.

We use a maximum spanning tree algorithm to search the structure that can maximize the prediction performance. The proposed method finds the maximum spanning tree by setting the weight of the tree as the calculated mutual information. The transformation algorithm is shown in Fig. 4.

3.2. Stimuli determination using utility function

The Bayesian network for predicting the emotion outputs the probabilities for the four emotions as a result. The proposed system finds the appropriate stimuli to induce the target emotion
Table 3
Structure of modular Bayesian networks to predict emotion.

<table>
<thead>
<tr>
<th>Level</th>
<th>Module</th>
<th>Input nodes</th>
<th>Output nodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>Sensory</td>
<td>Sight emotion, hearing emotion, touch emotion, olfactory emotion</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Brightness module</td>
<td>Brightness, color, video</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hearing module</td>
<td>Sound, volume</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Touch module</td>
<td>Temperature, humidity</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Olfactory module</td>
<td>Scent</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Brightness module</td>
<td>200 lx, 700 lx, 1000 lx</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Color module</td>
<td>1000 K, 3000 K, 7000 K</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Video module</td>
<td>V1, V2, V3, V4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sound module</td>
<td>51, 52, 53, 54</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Volume module</td>
<td>20 db, 40 db, 60 db</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Temperature module</td>
<td>23 °C, 25 °C, 28 °C, 30%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Humidity module</td>
<td>40%, 50%, 70%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Scent module</td>
<td>Lavender, lemon, jasmine, rose</td>
<td></td>
</tr>
</tbody>
</table>

Input: Module $\psi$

Output: Tree-Structured Module $\psi'$

Node $\psi = \{n_1, n_2, ..., n_k\}$

$\psi' = \psi$;

Remove all arcs in $\psi'$;

for each node in $\psi$ do

Select node $n_i$;

Find edge set $\text{Edge}_i$ that contains all edge connected to $n_i$;

while $\text{Edge}_i$ is not empty do

Select edge $e_{ij}$ with maximum weight in $\text{Edge}_i$;

Connect node $n_i$ and $n_j$ in $\psi'$;

if Cycle exist in $\psi'$

Delete arc between $n_i$ and $n_j$;

Delete $e_{ij}$ from $\text{Edge}_i$;

end if

end while

end for

Fig. 4. An algorithm to induce tree-structured Bayesian network.

based on the probability of these emotions. Targeted emotion is the ideal emotion for the service at this moment. The emotion is set to one of P-A, N-A, N-R, and P-R.

The proper stimulus is determined using a utility function that calculates the utility values in utility tables, which is a three-dimensional table that defines the utility value indicating the influence of the stimulus on the target emotion in the predicted emotion. The utility value in the table is expressed as stimulus, target emotion, and predicted emotion. We define the utility value of stimulus as $UT(\text{stimulus}, s, \text{target emotion}, e_t, \text{predicted emotion}, e_p)$. To determine the optimal stimuli, the influence of each stimulus calculates an expected utility value $EU$ considering all four predicted emotions for the target emotion. The expected utility value $EU^{s}$ of each stimulus $s$ for target emotion $e_t$ is calculated by the following equation.

$$EU^s = \sum_{e_p \in \mathcal{E}} UT(s, e_t, e_p) \cdot \text{prob}_{e_t}$$

$\text{prob}_{e_t}$: predicted probability of emotion

$UT(s, e_t, e_p)$: utility value of stimulus

To induce target emotions, we find out what state each stimulus should have through the expected utility value. The set of states in each stimulus is $S_g = \{s_1, s_2, ..., s_n\}$, given the set of adjustable stimuli in Table 1 as $G = \{g_1, g_2, ..., g_m\}$. The optimal stimulus state for stimulus $g$ is determined by $\text{Opt}_g^s$ having the maximum expected utility value.

$$\text{Opt}_g^s = \arg \max_s \{EU(s_1), EU(s_2), ..., EU(s_n)\}$$

When the optimal stimulus state for all the stimuli is determined, the environmental stimulus is adjusted to the optimal state to the current environment to induce the target emotion.

3.2.1. Initializing utility table

The proposed system uses the domain knowledge to initialize the utility table. The initialization process consists of two rules. The first rule is to convert the domain knowledge provided in natural language into a two-dimensional numeric vector. One dimension represents the degree of valence, and the other dimension...
Input: Natural word set for a stimulus \( N = \{n_1, n_2, \ldots, n_k\} \)

Output: Converted vector \( C \)

R: Russell’s V-A model

Temp = Empty set of vectors

for \( n_i \) in \( N \) do

\( E = \) nearest emotion with \( n_i \) in \( R \)

Insert coordinate pair of \( E \) in Temp

end for

\( C = \) Center of Gravity in Temp

Fig. 5. An algorithm to convert natural word.

represents the degree of arousal. We employ Russell’s V-A model [20] to obtain each degree. The detailed procedure is shown in Fig. 5. The second rule maps the two-dimensional vector obtained in the first rule to the utility table. The value of the utility table is set according to the following equations based on the transformed vector \( C = \{c_v, c_a\} \) for each stimulus. Here, \( b \) is a constant for adjusting the utility table.

\[
\begin{align*}
UT(s, e_{pk}, e_p) &= c_v + c_a + b \\
UT(s, e_{nak}, e_p) &= -c_v + c_a + b \\
UT(s, e_{nk}, e_p) &= -c_v - c_a + b \\
UT(s, e_{pg}, e_p) &= c_v - c_a + b \\
\end{align*}
\]

\( UT: \) utility value of stimulus

\( b: \) Basis of Utility Table

3.2.2. Updating utility table

The utility tables initialized with domain knowledge may not be perfect, because there may be a difference between domain knowledge and the actual environment. The proposed system updates the table using Q-learning, one of the reinforcement learning methods [21]. It uses Q-value \( Q_{s,t} \) to indicate the fitness of the stimulus \( s \) in the environment at time \( t \), and finds the parameters to maximize the Q-value. The Q-value is updated by the reward, and the reward at \( t \) \( r(t_{\text{target}}, e_t) \) is determined by the following equation.

\[
r(t_{\text{target}}, e_t) = \begin{cases} 
R & \text{if } e_{\text{target}} \text{ and } e_t \text{ completely match} \\
0 & \text{if } e_{\text{target}} \text{ and } e_t \text{ partially match} \\
-R & \text{if } e_{\text{target}} \text{ and } e_t \text{ are completely different}
\end{cases}
\]

\( R: \) Constant reward of the system

(6)

In the proposed system, the Q-value is defined as the value in the utility table. It means that \( Q_{s,t}(e_{\text{target}}, e_t) \) is the same as \( UT(s, e_t, e_p) \) at \( t \). Then, updating the Q-value means updating the value in the utility table. The updating formula of the Q-value is shown in the following equation.

\[
Q_{t+1,s}(e_{\text{target}}, e_t) = (1 - \alpha)Q_{t,s}(e_{\text{target}}, e_t) + \alpha r(t_{\text{target}}, e_t)
\]

\( \alpha: \) Updating ratio of Q-value

(7)

4. Experiments

4.1. Experimental data

We collected datasets in two real spaces, kindergarten and senior welfare centers. Color temperature sensor, illuminometer, hygroscope, thermometer, illuminometer, and volume indicator were installed for data collection in both spaces. Also, color temperature, brightness, sound, video, scent, and temperature were controlled to induce group emotion. VIBRA system [22] was used to measure the emotion, and teachers in the class observed group emotion. The system using vibrazione technology can collect the emotion of children and elderly people based on Russell’s emotion model by detecting the sensitivity as the non-contact sensing. A detailed description of the collection process is given in Table 4 and Fig. 6.

The collected environmental information is color temperature, brightness, video, sound, volume, humidity, temperature, scent, current emotion, and next emotion. The collection was performed in every minute. The number of data in each space is two hundred instances in the kindergarten and two hundred twenty-seven instances in the senior welfare center.

4.2. Emotion prediction evaluation

4.2.1. Emotion prediction accuracy

The accuracy for emotion prediction is measured to verify the performance of the emotion prediction model. We compare the accuracy with a single Bayesian network, decision tree (DT), multi-layer perceptron (MLP), k-nearest neighbors (k-NN), and support vector machine (SVM) for objective evaluation. We empirically set the parameters of other methods as follows: The MLP is set the number of hidden layers as six and learning rate as 0.3, the k-NN is set \( k = 1 \), the DT is set the minimum number of instances per leaf as two and the maximum depth of the tree as none, and the SVM with radial basis function kernel is set gamma = 0.0 and cost = 1.0.

The performance is measured by 5-fold cross validation that the training set is randomly partitioned into 5 equal sized subsets. A single subset is retained as the validation data for testing the model of the 5 subsets, and the remaining 4 subsets are used as training data.

Experiments were performed with the data of kindergarten and elderly welfare facilities, respectively. The performance of the proposed model in kindergarten is 84%. This is slightly lower than a single Bayesian network, but higher than other methods. The performance in the senior welfare center was similar. The accuracy of the proposed method was 81%, which was the same as that of a single Bayesian network and higher than other methods. However,
Table 4
Sensors installed in each domain for data collection.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Event</th>
<th>#Subjects</th>
<th>#Days of experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kindergarten</td>
<td>Math, music classes (20 min per class)</td>
<td>10 children</td>
<td>5 days (two classes in a day)</td>
</tr>
<tr>
<td>Senior welfare center</td>
<td>Tai chi class</td>
<td>10 elderly people (over 50 years old)</td>
<td>10 days (a class in a day)</td>
</tr>
</tbody>
</table>

Fig. 6. Experiments for data collection: kindergarten (above) and senior welfare center (below).

4.2.2. Inference time

The operating time is important for the proposed system, because the curriculum is provided in minutes in the education service. Especially, the inference time of Bayesian network for emotion prediction determines the speed of the system process. To evaluate the time of the proposed modular tree-structure Bayesian networks, we compared the networks with the single Bayesian network and the tree-structure Bayesian network. For each network, the average time for a hundred test results was calculated.

As a result, the proposed network was about 24 times faster than the single network and 1.5 times faster than the
tree-structured network. These results showed the moderate speed in the limited number of nodes. However, if the number of nodes would increase, the inference time of a single network would increase more dramatically than the proposed network. Fig. 9 shows the results.

4.3. Stimuli determination evaluation

The performance of the stimulus determination algorithm depends on whether the determined stimulus correctly induced the target emotion. To verify the performance, stimuli determination accuracy was measured by comparing the target emotion and emotion after the determined stimuli had output. We measured the accuracy before and after applying reinforcement learning in each space.

When Kindergarten outputted the stimulus as domain knowledge, it showed the average accuracy of about 70%, but it increased to 78% after reinforcement learning was applied. In the elderly welfare center, the accuracy of 63% was improved to 80%. By learning the parameters optimized for the environments, the difference between the minimum and maximum accuracies decreased in both cases. Fig. 10 shows the accuracies of the proposed method.
4.4. Scenario test

To verify the performance of the system, experiments were conducted based on scenarios in each space. Kindergarten classes consisted of mathematics and music scenarios, and in the senior welfare center, the class was based on Tai Chi scenario. Detailed information on each scenario is given in Table 5.

Emotional achievement was measured according to the scenario. The emotional achievement means the extent to which the proposed system has induced the target emotion. If the target emotion and the current emotion match, the achievement is 100%, and if the emotion is only one of positive-negative or arousal-relaxation, 50% is given, and otherwise, 0% is given.

Figs. 11 and 12 show the degree of achievement for each scenario. In the kindergarten, music scenario was more likely to be achieved overall than mathematical scenario, because students tend to be more emotional in music than in math. In the elderly welfare center, the achievement level of tai chi class was 80%. This was similar to the achievement of music lesson.

In all three scenarios, achievement has fallen at similar points. These points were all the points where the target emotion changed. The decrease in achievement seems to be due to the fact that the emotional changes of the subjects were slower than the stimulus changes.
5. Conclusions

In this paper, we have proposed a group emotion adjusting system by sensory information in IoT space. The proposed system consists of emotion prediction and stimuli determination. Modular tree-structured Bayesian networks were used to predict emotion from the environment. The stimulus was determined using the utility value calculated by the utility function, with the predicted emotions and the utility table for the target emotion. The utility table was initialized based on domain knowledge and adapted by reinforcement learning from the collected data.

The proposed system was evaluated in the two spaces of kindergarten and senior welfare center. The spaces contained several sensors to measure the environments and controlling devices to adjust the stimuli. The system showed the performance of 78% in kindergarten and 80% in senior welfare center. The proposed Bayesian networks achieved more than 80% accuracy. The method had lower complexity and much better performance than the other methods. Reinforcement learning also had a positive impact on the stimuli determination accuracy. In scenario tests, the system showed more than 70% emotional achievement.

For the future works, the system can be improved in three ways. First, the Bayesian networks to predict emotion can be constructed from data. The proposed networks were constructed with domain knowledge, and it can be learned with the data acquired in real environments. Second, the number of stimuli can be increased. If the system controls more stimuli, the performance of the system would increase. Finally, the system can be applied to several practical domains such as coffee shop, department store, and so on.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References


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