A Sensory Control System for Adjusting Group Emotion Using Bayesian Networks and Reinforcement Learning

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Abstract. The relationship between sensory stimuli and emotion has been actively investigated, but it is relatively undisclosed to determine appropriate stimuli for inducing the target emotion for a group of people in the same space like school, hospital, store, etc. In this paper, we propose a stimuli control system to adjust group emotion in a closed space, especially kindergarten. The proposed system predicts the next emotion of a group of people using modular tree-structured Bayesian networks, and controls the stimuli appropriate to the target emotion using utility table initialized by domain knowledge and adapted by reinforcement learning as the cases of stimuli and emotions are cumulated. To evaluate the proposed system, the real data were collected for five days from a kindergarten where the sensor and stimulus devices were installed. We obtained 84 % of prediction accuracy, and 56.2 % of stimuli control accuracy. Moreover, in the scenario tests on math and music classes, we could control the stimuli to fit the target emotion with 63.2 % and 76.3 % accuracies, respectively.

1 Introduction

The emotion can affect human's mind. Recently, the services to promote user's purchase and educational satisfaction by sensory stimuli have been actively investigated. For an example, emotion can affect to the effect of education, and some curricula are designed so that the students feel specific emotion. Table 1 shows the elements that can be measured and controlled in an educational institute, especially kindergarten. These elements are selected by teachers in the kindergarten. They affect children's emotion, but do not disturb the curricula of kindergarten. Conventional studies utilize many devices like electrode attached on subject's skin, but they disturb education and can affect to subject's emotion.

In this paper, we propose a group emotion control system in kindergarten class by controlling stimuli. Even though kindergarten is a target domain in this paper, the proposed method can be easily applied to any space that requires to control stimuli for inducing appropriate emotion. The proposed system is composed of the two parts of predicting emotion and determining stimuli as shown in Fig. 1. At the first part, the next emotion is predicted using modular tree-structured Bayesian networks. At the second part, the proper stimuli to change it to the target emotion are determined by utility table, which is initialized by domain knowledge and adapted by reinforcement learning.

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Table 1. The elements to be measured and controlled in kindergarten

Type	Stimulus	State
Visual	Lux	200 lx, 700 lx, 1000 lx
	Color temperature	1000 K, 3000 K, 7000 K
	Video	V_1, V_2, V_3, V_4 (Pre-defined videos)
Auditory	Sound	S_1, S_2, S_3, S_4 (Pre-defined sounds)
	Volume	20 db, 40 db, 60 db
Olfactory	Scent	lavender, lemon, jasmine, rose
Tactile	Temperature	18 °C, 23 °C, 25 °C, 28 °C
	Humidity	30 %, 40 %, 50 %, 70 %

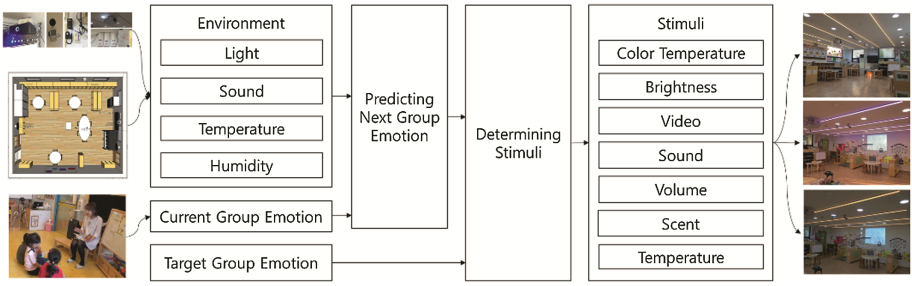

Fig. 1. A process of controlling stimuli for inducing emotion in the kindergarten

2 Related Works

Predicting emotion from data such as facial, vocal, and text has been the focus of a large number of studies over the past several decades. Table 2 shows the emotion recognition research which use raw-data.

Table 2. Studies to predict emotion

Authors	Input	Proposed method
Black and Yacoob [4]	Image	Rule-based
Eyharabide *et al.* [5]	Text	Ontology
Yacoub *et al.* [6]	Speech	k-Nearest neighbor, Support vector machine, Neural network, Decision tree
Lee *et al.* [7]	Speech	Decision tree
Utane and Nalbalwar [8]	Speech	Hidden Markov Model
Hayamizu *et al.* [9]	Facial image, Speech	Bayesian networks
Ivon, *et al.* [11]	Facial image, GSR, Accelerometer	Bayesian networks

Black extracted features from facial image and defined rules to classify emotion [4]. Eyharabide recognized emotion using ontology and applied it to e-learning service [5]. Yacoub compared four types of classification method using speech data [6]. Lee

classified speech data for human and robot interaction [7]. The robot recognizes emotion and responds depending on the current states of emotion. Utane applied emotion recognition to natural conversation between human and computer [8]. Hayamizu designed Bayesian network to recognize group emotion considering the previous state of emotion [9]. Previous works focused on accurate recognition using personal data. However, in the emotional service, we cannot use personal data like speech or face. We have to predict emotion from information on specific environment that usually come from multimodal sensors. We proposed the Bayesian network to predict group emotion before, but it is not constructed as a complete system [10].

3 The Proposed System

In this paper, we deal with not the specific emotions such as happiness, sadness, anger, etc., but four groups of emotions based on Valance-Arousal (V-A) model proposed by Russell [2]. In this model, emotions can be mapped on a space of positive-negative degree and arousal-relax degree, leading to one of four emotions such as positive-arousal (P-A), positive-relax (P-R), negative-arousal (N-A), and negative-relax (N-R) as shown in Fig. 2.

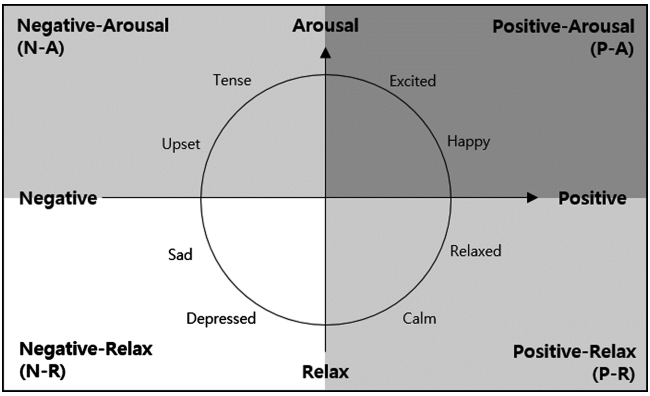

Fig. 2. Arousal-variance model for representing emotions

Based on this emotion model, the proposed system is as shown in Fig. 3. Bayesian networks predict the next emotion, and utility table finds proper stimuli for target emotion. The utility table is initialized by domain knowledge and adapted by reinforcement learning.

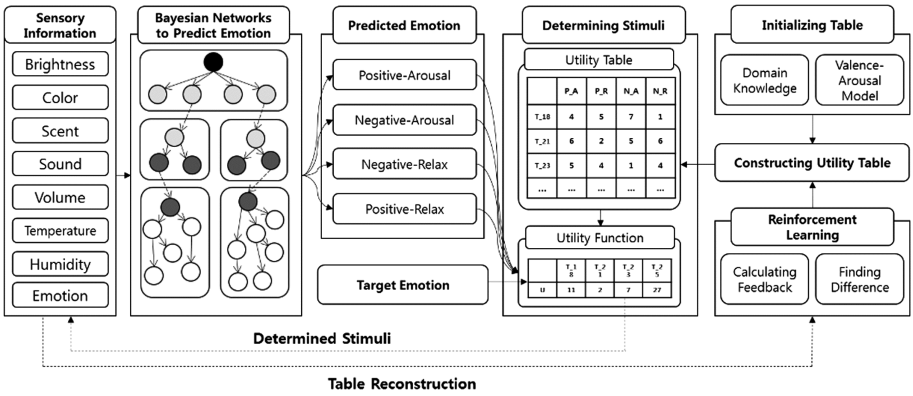

Fig. 3. The overall structure of the proposed system

3.1 Emotion Prediction by Bayesian Networks

To determine the proper stimuli, the emotion of a group of people has to be predicted from environment information. Bayesian networks are used to predict emotion because they are well-known to model the uncertainty with causal relationship among events. We can construct single Bayesian network from domain knowledge provided by the literature and teachers in kindergarten. However, in the real situation, there are quite many events and evidences that hinders from efficient prediction.

In order to reduce the complexity of Bayesian network, we devise a sophisticated method to model it with modular tree-structured Bayesian networks. At first, we design the modular Bayesian networks to adopt different environments easily by utilizing Markov boundary to find boundaries between modules [12]. After calculating the Markov boundary, we find the middle nodes that are overlapped more than two Markov boundaries. Because they are border of modules, modules are divided by the middle nodes, and they are removed from both modules connected with a pair of virtual nodes inserted in each module. Modules M_i and M_j can be represented as follows:

$$\begin{aligned} M_i &= \left(B_i(TBN) - Md_{ij}\right) \cup V_{ij} \\ M_j &= \left(B_j(TBN) - Md_{ij}\right) \cup V_{ji} \\ V_{ij} &= V_{ji} = \{S_0, S_2, \ldots, S_n\} \end{aligned} \tag{1}$$

Md_{ij} is a middle node between M_i and M_j, and V_{ij} means the virtual node that is in M_i and connects M_i and M_j. Virtual nodes have the same states and conditional probability table with the middle node. Virtual nodes in a pair have the same probability in each state. By this process, we can construct modular Bayesian networks.

Next, each module of Bayesian network is converted into a tree-structured Bayesian network. Maximum spanning tree algorithm is used to find connections that strongly affect to prediction performance. Figure 4 shows the conversion algorithm. The weight of edge means the influence when the edge is removed. Suppose the states of two nodes

Input: Single Bayesian Network (SBN)
Output: Tree-Structured Bayesian Network (TBN)

TBN = SBN;
Remove all nodes in TBN;
while (N_i is node in SBN)
  Select node N_i;
  Select edge set E_i that includes every edge of N_i;
while (E_i is not empty)
  Select edge E_{ij} that has maximum weight in E_i;
  Make connection N_i and N_j in TBN;
  if (cycleExist(TBN))
    Delete connection between N_i and N_j;
    Delete E_{ij} from E_i;
  else
    Escape the loop;

Fig. 4. A conversion algorithm to tree-structured Bayesian network

be X and Y, and the state of output node be C. Then, we can represent the weight of each node I_p as follows:

$$I_p(X,Y) = \sum_{x\in X, y\in Y, c\in C} P(x,y,c) log \frac{p(x,y|c)}{p(x|c)p(y|c)}. \quad (2)$$

After calculating the weight of each edge, we can construct a maximum spanning tree from a module of Bayesian network. Edges are sorted in decreasing order, and is selected every edge that makes no cycle.

The final Bayesian networks constructed to predict emotions in the kindergarten classes have six modules and fifty-five nodes as shown in Fig. 5. The constructed modules are grouped to three parts: "Collecting stimuli data" part, "Combining stimulus" part, and "Predicting emotion" part. There are four modules for collecting stimuli data: touch, sight, hearing, and olfactory sensors. They collect stimuli data from each sense like sound type or volume. "Combining stimuli" module gathers their results, and combines data and the emotion classified from the stimuli. "Predicting emotion" module predicts emotion from the previous emotion, current emotion, and the result of "Combining stimuli" module.

3.2 Stimuli Control by Utility Table

Because emotion is given as probabilities, which represent the uncertainties of emotion, decision making problem can be modeled as POMDP. Q-value would be calculated as weighted sum of Q-values (denoted as EQ) with each probability, as shown in Eq. (3).

The final stimulus is selected as O^a_{j*} s.t. $\mathrm{EQ}\left(O^a_{j*}\right) > \mathrm{EQ}\left(O^a_j\right)$ for $\forall j$, where j = value index of the ath stimulus given, and k = index of emotion.

$$\mathrm{EQ}(O^a_j) = \sum \mathrm{P}(k) * \mathrm{Q}(s, a) \tag{3}$$

Because the effect of actions can be known after the action has been taken, we do not know whether unchosen actions are good or bad. The proposed system uses the domain knowledge to initialize the utility table, substituting exploration process manually. Since the data represent the effect to individual emotion, positive, negative, arousal and relax, the proposed system first maps these values onto the V-A plane. Figure 6 shows the mapping algorithm ($N_i\left(O^a_j\right)$ = number of descriptions with the jth value given and the ath stimulus to the ith emotion). In the first step, $N_i\left(O^a_j\right)$ values are counted for all i's.

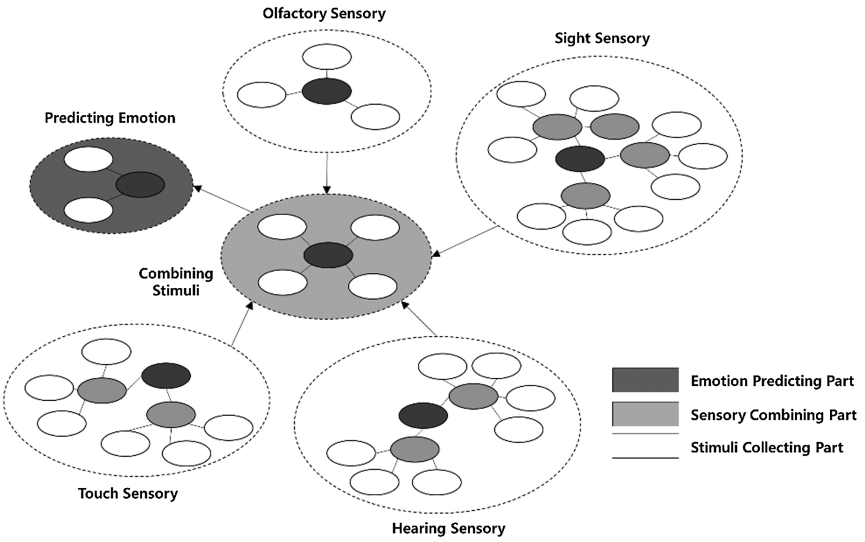

Fig. 5. Modular Bayesian networks to predict emotion in the kindergarten classes

Then, $P\left(O^a_j\right)$, mapped point, is calculated by their distance. Steps 3 and 4 in Fig. 6 approximate $P\left(O^a_j\right)$ to the nearest *NWc* point, with Euclidian distance. Since each *NWc* represents the membership value to each quadrant, utility values are calculated by a set of linear transition functions using *NWc* (S = adjusting constant, NWc = (Xc, Yc), f_i = utility value for the ith quadrant).

Step 1: for $\forall\ 1 \leqq i \leqq 4$, count the number of words describing O_j^a with given i, and set $N_i(O_j^a)$.

Step 2: calculate $\mathrm{P}(O_j^a) = (P_x, P_y) = (N_1(O_j^a) - N_2(O_j^a), N_3(O_j^a) - N_4(O_j^a))$.

Step 3: for $\forall\ 1 \leqq c \leqq 12$,
calculate $d_c(\mathrm{P}(O_j^a)) = \sqrt{(Px - Xc)^2 + (Py - Yc)^2}$

Step 4 : select $NWc*$ s.t. $d_{c*}(\mathrm{P}(O_j^a)) < d_c(\mathrm{P}(O_j^a))$ for $\forall\ 1 \leqq c \leqq 12$

Fig. 6. An algorithm to initialize utility table

$$\begin{aligned} f_1(X_c, Y_c) &= (X_c + Y_c) + S \\ f_2(X_c, Y_c) &= (X_c - Y_c) + \mathrm{S} \\ f_3(X_c, Y_c) &= (-X_c + Y_c) + S \\ f_4(X_c, Y_c) &= (-X_c - Y_c) + S \end{aligned} \tag{4}$$

The proposed system uses the current emotion and selected stimuli for every period except the first period, and calculates reward $r_{t+1}(s_t, a_t)$ so to update utility table as follows.

$$Q_{t+1}(s_t, a_t) \leftarrow (1 - \alpha) Q_t(s_t, a_t) + \alpha r_{t+1}(s_t, a_t) \tag{5}$$

In this equation, α means the reflection rate of data that are gathered from the stimuli control system. If α is zero, the table will not be updated; if α is 1, the table will be reconstructed entirely.

4 Experimental Results

4.1 Data Description

The real data were collected from ten children at the kindergarten classes, where volume indicator, thermometer, hydroscope, illuminometer, and color sensor were installed, as shown in Fig. 7. Thermometer, humidity sensor, microphone, brightness sensor, and color sensor were installed at the wall. We can control temperature, light (for brightness and color temperature), video, sound, and scent. VIBRA system [13] was used to measure the emotion, and the teacher in the class was asked to provide the group emotion.

The data at the classes were collected for five days, and two classes in a day. Sensor data were sampled at every minute and each class was given in twenty minutes. In total, the dataset for all classes amounts to two-hundred instances of brightness, color temperature, humidity, volume, sound, video, scent, current emotion, and next emotion.

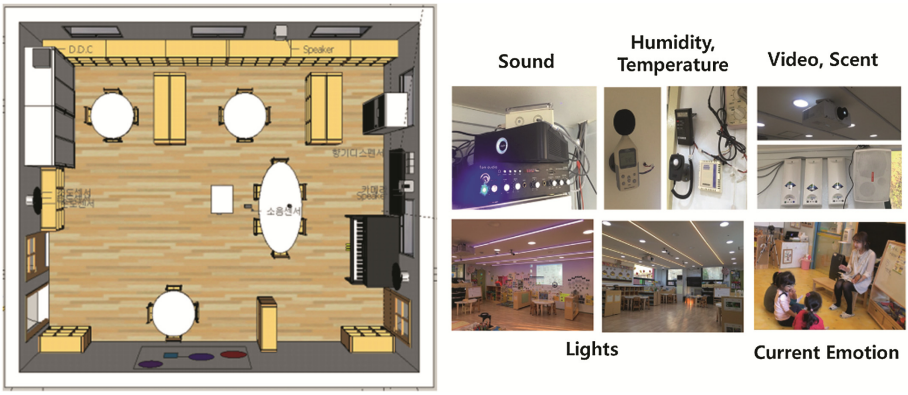

Fig. 7. The kindergarten class that data were collected

4.2 Experiments on Emotion Prediction

The accuracy of emotion prediction was compared with single and tree-structured Bayesian networks, and other classification methods: Decision Tree (DT), Multi-Layer Perception (MLP), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). Classification methods were evaluated by five-fold cross validation.

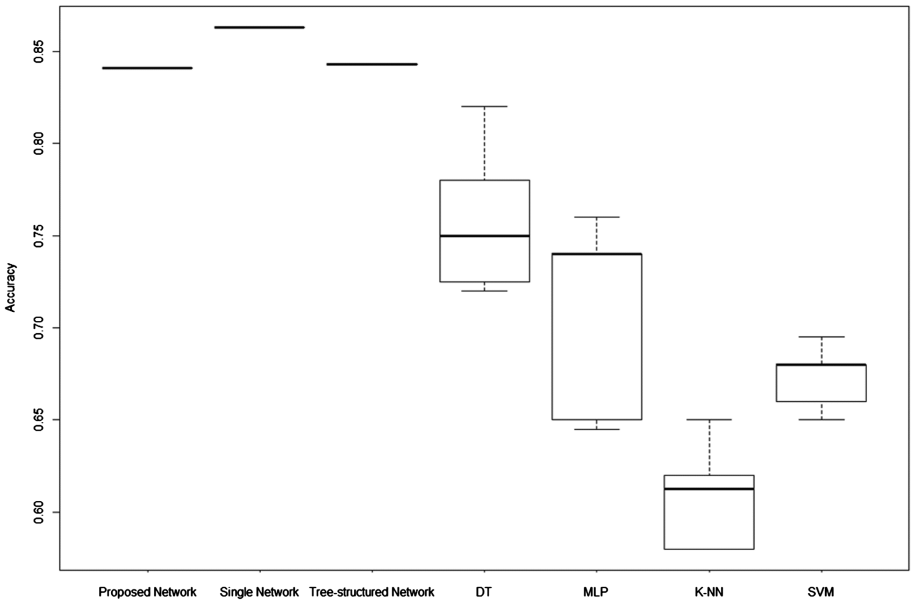

Fig. 8. Accuracy of emotion prediction

Figure 8 shows the accuracy of emotion prediction. The proposed method shows the accuracy of 84 %, which is little lower than single Bayesian network, but much higher than other classification methods. This means the proposed method has better performance than other classification methods, and similar performance with single Bayesian network. When we need faster method with competitive accuracy, the proposed method might be better than single Bayesian network.

4.3 Experiments on Stimuli Control

Figure 9 shows the accuracies of a baseline system without reinforcement learning and the proposed system. 65-minutes data with unclean data excluded were used for the test and 10-fold cross validation was conducted. An accuracy of the baseline system is 39.66 % with standard deviation of 8.82 %, and 15.51 % increase of accuracy is obtained by applying reinforcement learning. Since the utility values of failed cases in the baseline system are not incremented, the specificity is calculated as 100 % for given data.

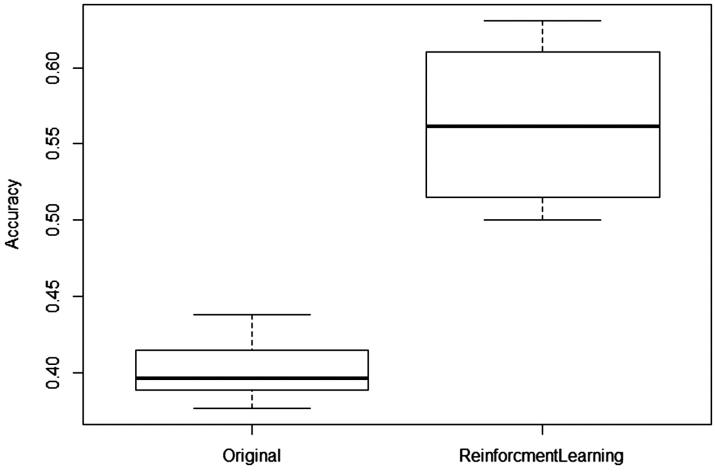

Fig. 9. Accuracy of stimuli control

Figure 10 shows the improvement of accuracy for each update of utility table. As the baseline system does not update, its accuracy is constant at initial accuracy (39.66 %). Improvements are mainly occurred in the 45~50-minutes and 60~65-minutes sections, primarily contributions of success of the second class' color temperature of 6,800 K to the correction of the third class' mis-controlled color temperature of 5,000 K. As shown in the result, enough time is needed to exploit the result of learning, as improvements are mainly occurred in the latter part.

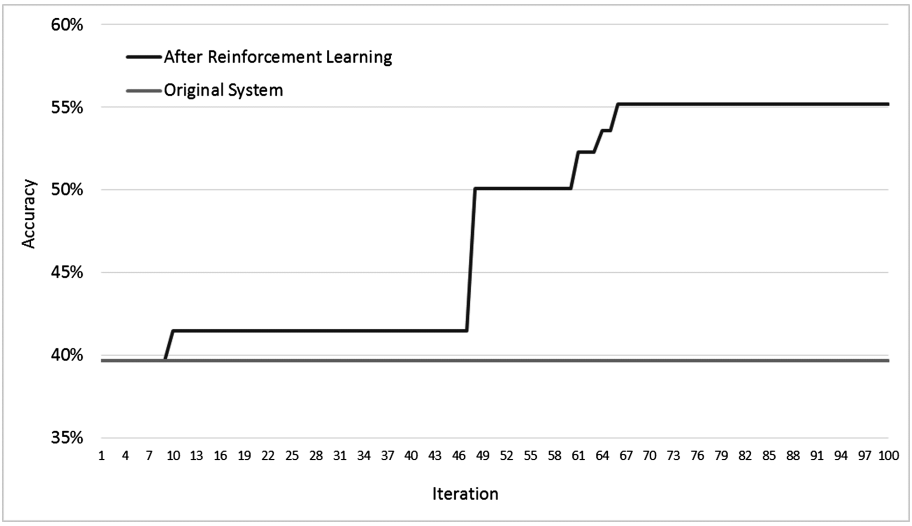

Fig. 10. Accuracy improvements with reinforcement learning

4.4 Scenario Test

To confirm the operational performance, we conducted experiments on a couple of scenarios that include math and music contents at the kindergarten (see Table 3). A scenario composed of three parts was performed in twenty minutes.

Table 3. Two scenarios of math and music classes at the kindergarten

Type		0~5 min	5~15 min	15~20 min
Math	Activity	Finding number	Calculating number	Presenting result
	Target emotion	P-A	P-R	P-A
Music	Activity	Listening	Singing together	Singing alternately
	Target emotion	P-A	P-A	P-R

Figure 11 shows the achievement for math and music scenarios. Achievement is calculated by comparing target and real emotions. If two emotions are the same, it is calculated as 100 %. If two emotions are the same at only one dimension (positive-negative or arousal-relax), it is calculated as 50 %. In the figure, the music scenario has higher achievement than the math scenario, possibly because music is more emotional than math.

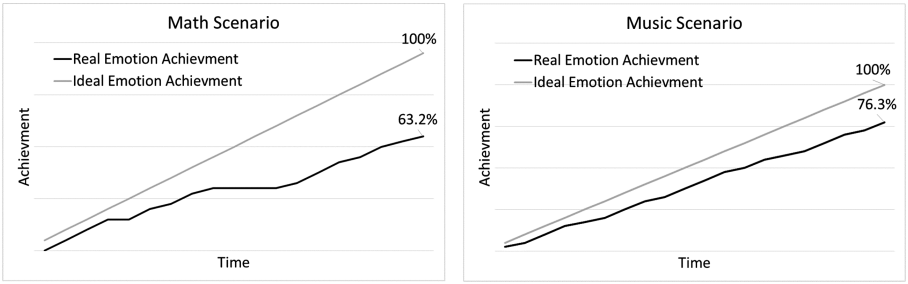

Fig. 11. Emotional achievements for the two scenarios

5 Concluding Remarks

In this paper, we have proposed a sensory stimuli control system to change group emotion at kindergarten classes. The proposed system consists of emotion prediction part and stimuli determination part. Modular tree-structured Bayesian networks are used to predict emotion from environment. They produce more than 80 % accuracy with less complexity, and the performance is much better than other classification methods. It shows better performance for classifying positive and arousal emotions than negative and relax emotions. Utility values are used to determine the stimuli from targeted and predicted emotions, and reinforcement learning is used to adapt the utility table from cumulated data. For the future works, we need to collect more data to verify the proposed system, especially for negative emotions, and apply the system to a variety of domains.

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