Modeling of Behaviors of Participants in Meetings for Decision Making

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Abstract: In this paper, we discuss (i) the modeling of the interaction between the behaviors of participants, (ii) the modeling of the holistic behaviors of all participants in the meeting for decision making. First, we detect the behaviors of participants based on their facial movements. Next, we propose a modeling method of the behaviors based on multi-layered neural networks. Moreover, based on experimental results, we discuss the relationships between the behaviors of participants and the parameters of multi-layered neural networks. Especially, we show that the parameters in the proposed models to be strongly related to the behaviors of participants and the meeting progress.

Keywords: Meeting, Decision making, Participant, Modeling, Behavior, Atmosphere

1. INTRODUCTION

Formal meetings can be mainly classified into two styles: (i) the information sharing (report and communication) and (ii) the problem-solving (brainstorming and decision-making). In decision-making meetings, some participants give opposing and other participants are approving opinions concerning those of the speaker. McCowan et al. have proposed an approach to the automatic meeting analysis that considers a meeting as a sequence of group-level events, termed meeting actions [1]. However, some participants indicate their opinions in their expressions and facial movements without voicing. Furthermore, participants can evaluate that the meeting had a friendly atmosphere with non-verbal behaviors.

Thus, it is essential for participants to analyze the behaviors of their fellow participants while considering their decisions regarding their opinions and to assess the progress of the meeting. If we can construct the model for representing the behaviors, we can evaluate the relationships between the behavior of participants [4]. Furthermore, we can apply the modeling methods of behaviors of participants to the analysis of the behaviors of students in collaborative learning [5].

In this paper, we discuss the modeling of the non-verbal behaviors of participants in the decision-making meeting. First, we detect the behaviors of participants based on their facial movements. Next, we propose models for the presentation of the behaviors by using neural networks. Lastly, from the experimental results, we discuss the relationships between the behaviors of participants and the model parameters.

2. DETECTION OF BEHAVIORS OF PARTICIPANTS

2.1. Decision-making meetings

We can observe participant non-verbal behaviors with respect to eye contact and facial movements as shown in Fig. 1 in decision-making meetings. When a speaker has comments, other participants (listeners) look at the speaker with non-verbal behaviors including negative/positive intentions. Furthermore, participants try to estimate negative/positive intentions based on the behaviors of other participants. Therefore, we have to detect the behaviors of participants for the analysis of the meeting.

![Fig. 1 Facial movements in decision-making meetings](image)

(a) Speaker (b) Listener

2.2. Detection of participant behaviors

First, we can detect the facial regions of participants via video images recorded by a camcorder in the center of the table [4]. As shown in Fig. 2, we can calculate the ratio \( r_{UL}, r_{UR}, r_{LL} \) and \( r_{LR} \) of each region by Eq. (1) by counting the number of pixels in each region (upper-left, upper-right, lower-left, lower-right),

\[
\begin{align*}
  r_{UL} &= \frac{1}{S} \sum_{x,y \in U_L} f(x,y), \\
  r_{UR} &= \frac{1}{S} \sum_{x,y \in U_R} f(x,y),
\end{align*}
\]

where \( S \) denotes the size of the facial region. When the object pixel \( f(x,y) \) is skin-colored, \( f(x,y) \) is set to 1.

Next, the feature \( r_U \) concerning the facial movements of participants is defined by \( r_U = r_{UL} - r_{UR} \). Here, \( r_U \) denotes facial movement in the horizontal direction and does not apply to eye movement. Moreover, participants often touch their faces, we focus on the upper facial regions.
3. MODELING OF BEHAVIORS OF PARTICIPANTS

As shown in Fig. 1, we can observe the behaviors of participants with respect to eye contact and facial movements. For the evaluation of the progress of the meeting, we have to monitor the behavior of each participant and the interactions between all participants. In this section, we introduce a modeling method for the interaction between participants based on a time-series model [4]. Here, we discuss (i) the modeling of the interaction between the behavior of each participant, (ii) the modeling of holistic behaviors of all participants.

3.1. Modeling of the interaction between behaviors of participants

When a participant speaks comments, other participants look at the participant and nod with negative/positive intentions. The behaviors of participants influence each other. Therefore, we have to the interaction between the behavior of each participant. For the modeling of the interaction between participants, we introduce a non-linear time-series model for the participant feature $r_U$, in which we define $x_p(t) = r_{U,p}(t)$ of the $p(=1,\cdots,P)$-th participant:

$$x_p(t) = \sum_{j=1}^{J} \alpha_{p,j} f \left( \sum_{q=1}^{P} \sum_{\ell=1}^{L} w_{j,q,\ell} x_q(t-\ell) \right) + e(t), \quad (2)$$

where $J$ denotes the degree of this model, $\ell(=1,\cdots,L)$ denotes the time-delay and the weight $\alpha_{p,j}$ denotes the influence of the behaviors of other participants on the behavior of the $p$-th participant. Moreover, the weight $w_{j,q,\ell}$ denotes the correlation with the behaviors $x_q(t)$ of other participants, $f(\cdot)$ denotes the sigmoid function, and $e(t)$ denotes Gaussian noise. We can evaluate the interactions between behaviors of participants based on the weight $\alpha_{p,j}$.

In Fig. 3, we show a neural network [3] for the non-linear time-series models defined in Eq. (2). Furthermore, we use the error function $E_I$.

$$E_I = \sum_p \sum_{t} (x_p(t) - \hat{x}_p(t))^2 \quad (3)$$

where $\hat{x}_p(t)$ denotes the prediction value of $x_p(t)$.

3.2. Modeling of holistic behaviors of participants

Participants try to estimate the atmosphere of the meeting base on non-verbal behaviors. The atmosphere of the meeting can be generated by not only the behavior of each participant but also the holistic behaviors of all students. Here, we define the holistic behavior as the sum $X(t) = \sum_{q} |x_q(t)| = \sum_q |r_{U,q}(t)|$ of behaviors of all participants. For the purpose of evaluating the atmosphere of the meeting, we introduce a non-linear time-series model for the holistic behavior $X(t)$ of all participants:

$$X(t) = \sum_{j=1}^{J} A_j f \left( \sum_{\ell=1}^{L} W_{j,\ell} X(t-\ell) \right) + e(t), \quad (4)$$

where $\ell$ denotes the time-delay and the weight $A_j$ denotes the characteristic of the holistic behaviors of all participants. Moreover, $W_{j,\ell}$ denotes the correlation with the holistic behavior $X_q(t)$ of all participants, $f(\cdot)$ denotes the sigmoid function, and $e(t)$ denotes Gaussian noise. We can evaluate the atmosphere of the meeting based on the weight $A_j$.

In Fig. 4, we show a neural network [3] for the non-linear time-series models defined in Eq. (4). Furthermore, we use the error function $E_{II}$.

$$E_{II} = \sum_t (X(t) - \hat{X}(t))^2 \quad (5)$$

where $\hat{X}(t)$ denotes the prediction value of $X(t)$.
4. ANALYSIS OF A MEETING

A decision-making meeting has been held under the following conditions; (i) Theme: selection of food menu for a party, (ii) Participants: four persons (undergraduate students), (iii) Camera: MR360 (King Jim Co. Ltd.). The timing of speaking by participants are shown in Fig. 5. Here, red lines indicate changes in the order (food menu and amount). Furthermore, the characteristics of the comments of each participant can be summarized as follows; (i) Participant-A: comments were different from the progress of the meeting, (ii) Participant-B: followed the comments of each participant can be summarized as (iv) Participant-D: commented on the management of the meeting progress.

4.1. Features of behaviors of participants

Figure 6 shows the features of behaviors of participants. Figure 6 (a) shows the feature $r_{U,p}(t) = r_{UL,p}(t) - r_{UR,p}(t)$. Here, $r_{U,p}(t)$ denotes the facial movement of the $p$-th participant. From this figure, it is shown that the facial movements of Participant-A and C are large and those of Participant-B and D are small. In Figure 6 (b), it is shown that the sum $\sum_p |r_{U,p}(t)|$ of the features $r_{U,p}(t)$ for all participants and their facial movements become comparatively larger with respect to the timing of the change in the order.

4.2. Modeling of behaviors of participants

Figure 7 (a) shows the modeling results of the feature $x_p(t) = r_{U,p}(t)$ in Eq. (2). Here, the length of the modeling section is 10 [sec] and the numbers of input units, hidden units and output units are $30 \times 4$ (30 [fps] $\times$ the number of participants), 4, and 4 (the number of participants). Figure 7 (b) shows the modeling results of the sum of the feature $X(t) = \sum_p |x_p(t)|$ in Eq. (4). Here, the numbers of input units, hidden units and output units are $30 \times 4$, 4, 1. In these figures, we can see that the features $x_p(t) = r_{U,p}(t)$ and $X(t) = \sum_p |x_p(t)|$ in Eq. (2) and Eq. (4) can be approximated by the neural networks with adequate precision (Figs. 3 and 4).

4.3. Weights in modeling of behaviors of participants

4.3.1. For interaction between behaviors of participants

We discuss the weight $\alpha_{p,j}$ of the non-linear time-series model (Eq. (2)) for the participant feature $r_U$, in which we define $x_p(t) = r_{U,p}(t)$ of the $p$-th participant. Here, $\alpha_{p,j}$ denotes the weight between the $j$-th hidden unit and the $p$-th output unit concerning on the $p$-th participant. Figure 8 shows the sum $\sum_j |\alpha_{p,j}|$ of the weight $\alpha_{p,j}$ of Eq. (2). Therefore, we can interpret the sum $\sum_j |\alpha_{p,j}|$ as the influence receiving from the behaviors of all participants. In Fig. 6 (a) and Fig. 8, when the behavior of $p$-th participant $|r_{U,p}(t)|$ becomes large, the sum $\sum_j |\alpha_{p,j}|$ becomes large. Therefore, the weights $\sum_j |\alpha_{p,j}|$ can represent the change of the behavior.

4.3.2. For holistic behaviors of participants

We discuss the weight $A_j$ of the time-series model (Eq. (4)) for the holistic behavior $X(t) = \sum_q |x_q(t)| = \sum_q |r_{U,q}(t)|$ of all participants. From Fig. 6 (b) and Fig. 9, it is shown that the change of the holistic behavior $X(t)$ of all participants is not corresponded with the change of the weight $\sum_j |A_j|$ of Eq. (4). We would like to discuss the relationship between the holistic behavior $X(t)$ and the weight $\sum_j |A_j|$.
4.4. Evaluation of the meeting by other individuals

We discuss the evaluation results by other individuals (three undergraduate students) who had not attended to this meeting. They detected the timing of characteristic comments and behaviors based on the meeting video. Figure 10 shows their evaluation results of the behaviors and comments of participants.

4.4.1. Evaluation of behaviors

We can summarize the evaluation results as follows; (i) In section [109,136], some participants were looking at the menu and nodding while commenting “We need three types of food.” (Participant-D exhibited behavior corresponding to this comment)), (iii) In section [350,390], the meeting was stagnating. However, the meeting finished based on the comment by Participant-C, and (iv) In section of [390,395], one participant exhibited the behavior (Participant-C pointed to the menu and made a comment, “We need one more food.”).

4.4.2. Evaluation of comments

We can summarize the evaluation results as follows; (i) In section [28,40], other individuals pointed out the comment concerning “Pizza”. However, they did not consider any of the characteristic behaviors exhibited, (ii) In section [180,195], other individuals pointed out the comment “Japanese, Western-style, and Chinese foods.” and they considered the characteristic behaviors, (iii) In section [260,280], other individuals the comments “Sandwich” and “For breakfast if it were left over”. However, other individuals did not consider any characteristic behaviors, and (iv) In section [390,395], other individuals pointed out the comment “We need one more Western-style food” as well as the characteristic behaviors.

5. CONCLUSIONS

In this paper, we have discussed the modeling of the behaviors of participants in a decision-making meeting by using neural networks. From the analysis results, we have discussed the relationships between the model parameters and the behaviors as follows; (i) the weights $\alpha_{p,j}$ of Eq. (2) show the characteristics of each participant, (ii) the weights $A_j$ of Eq. (4) show the characteristics of holistic behaviors of all participants. Finally, from the evaluation of the meeting by other individuals, we have confirmed that the change of the weight $A_j$ of Eq. (4) has a strong relation with the evaluation by other individuals.

As future work, we would like to discuss the followings; (i) the detection of behaviors by OpenPose [6], and (ii) the relationship among the behavior, the model parameters, and the progress of the meeting.

REFERENCES