

# Analysis and extraction of behaviors by students in lectures

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## ABSTRACT

In this paper, we discuss the influence the following behaviors on the behavior by a specific student in lectures; (i) the behavior by the lecturer, (ii) the behaviors by other students, and (iii) the behavior by oneself. First, we detect features for behaviors by lecturer and students by using image processing methods. Next, the relations among the above features are approximated by neural networks. Finally, we analyze the interaction between behaviors by lecturer and students based on the internal representations and show the synchronization between students.

## Keywords

Lecture, Lecturer, Student, Behaviors, Time series model

## 1. INTRODUCTION

In lectures, the change of behaviors (writing on the blackboard and explaining) by the lecturer play important roles on the interests and the understanding by students [1]. Authors have already discussed the relationship between behaviors by lecturers and students by using a neural network [3]. However, since students can see behaviors by other students, we should focus on the relations among students.

In this paper, we construct time-series models for the interaction between behaviors by lecturer and students by using neural networks [2]. Concretely, we detect behaviors by using image processing methods and construct a time-series model for their behaviors. Finally, we analyze the interaction between behaviors by lecturer and students based on the internal representations in neural networks.

## 2. ANALYSIS OF BEHAVIORS BY STUDENTS

Students listen to the explanation by the lecturer and look at contents on the blackboard. Moreover, a student can see behaviors by neighbor students and students are influenced by behaviors by other students. Furthermore, students are

listening to the lecturer and taking notes at their own paces. As shown in Figure 1, we can summarize the influences on behaviors by students as follows; (i) behaviors (explanation and writing) by lecturer, (ii) behaviors (listening and writing) by other students, (iii) behavior by oneself.

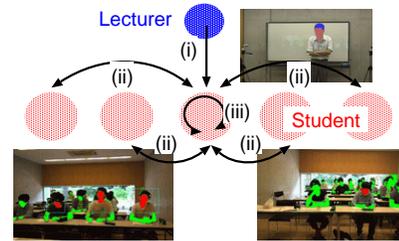


Figure 1: Influences on behaviors by students

### 2.1 Analysis of behaviors by students

Features for behaviors by lecturers and students can be extracted by image processing methods based on the color information [3]. Here, we define features as follows; the head position of the lecturer:  $x_{\text{head}}^L(t)$ , the number of skin-colored pixels in the face region of the lecturer:  $x_{\text{face}}^L(t)$ , and the number of skin-colored pixels in the face region of the  $p$ -th student:  $x_{\text{face}}^{S,p}(t)$ .

#### 2.1.1 Input-output relation of behaviors by students

Based on Figure 1, we approximate the number  $x_{\text{face}}^{S,p}(t)$  of skin-colored pixels in the face of the  $p$ -th student by the head position (horizontal)  $x_{\text{head}}^L(t)$  of the lecturer, the number  $x_{\text{face}}^L(t)$  of skin-colored pixels of the lecturer, and the number  $x_{\text{face}}^{S,q}(t)$  of skin-colored pixels of the  $q$ -th student as follows;

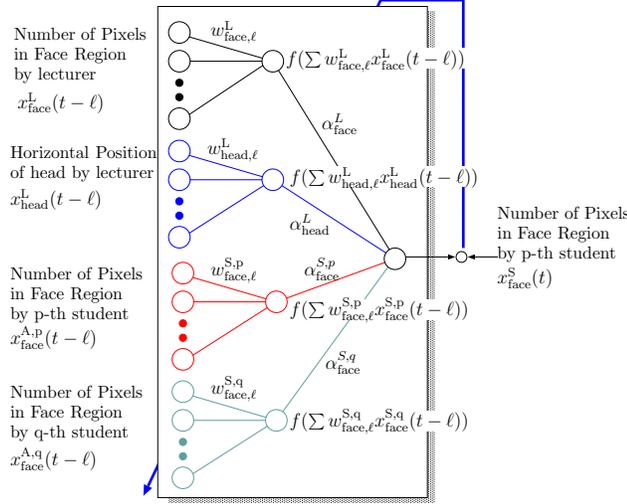
$$\begin{aligned}
 x_{\text{face}}^{S,p}(t) = & \alpha_{\text{face}}^L f\left(\sum_{\ell} w_{\text{face},\ell}^L x_{\text{face}}^L(t-\ell)\right) \\
 & + \alpha_{\text{head}}^L f\left(\sum_{\ell} w_{\text{head},\ell}^L x_{\text{head}}^L(t-\ell)\right) \\
 & + \alpha_{\text{face}}^{S,p} f\left(\sum_{\ell} w_{\text{face},\ell}^{S,p} x_{\text{face}}^{S,p}(t-\ell)\right) \\
 & + \sum_{q \neq p} \alpha_{\text{face}}^{S,q} f\left(\sum_{\ell} w_{\text{face},\ell}^{S,q} x_{\text{face}}^{S,q}(t-\ell)\right) + e(t), \quad (1)
 \end{aligned}$$

where  $q \neq p$  and  $\ell$  denotes the time delay. We assume that  $e(t)$  is a sequence of Gaussian noise. Here,  $\{\alpha\}$  denote weights for features by the lecturer and students and  $\{w\}$

denote weights for the time-delay of features. Moreover,  $f(\cdot)$  denotes a sigmoid function.

### 2.1.2 Learning of the input-output relation by using a neural network model

For the approximation of Eq. (1), we use a neural network model as shown in Figure 2. Obviously, the connection between input and hidden units is sparse and such a connection intends to the clarification of the role of weights  $\alpha$  for each feature. Moreover, weights  $\{w\}$  between input and hidden layers play the role of the clarification of the time-correlation among features. The object for the learning for a neural net-



**Figure 2: Neural network for approximation of the input-output relation defined by Eq. (1)**

work model in Figure 2 is to minimize  $E$ .

$$E = \sum_t E_t = \sum_t (x_{\text{face}}^{\text{S},p}(t) - \hat{x}_{\text{face}}^{\text{S},p}(t))^2, \quad (2)$$

where  $\hat{x}_{\text{face}}^{\text{S},p}(t)$  denotes the prediction value for  $x_{\text{face}}^{\text{S},p}(t)$ . The learning law for weights  $\alpha_{\text{face}}^L$  can be represented by

$$\alpha_{\text{face}}^L = \alpha_{\text{face}}^L - \eta \frac{\partial E_t}{\partial \alpha_{\text{face}}^L}, \quad (3)$$

where  $\eta$  denotes the learning coefficient. On the other hand, the learning law for weights  $w_{\text{face},\ell}^L$  can be represented by

$$w_{\text{face},\ell}^L = w_{\text{face},\ell}^L - \eta \frac{\partial E_t}{\partial w_{\text{face},\ell}^L}. \quad (4)$$

## 3. EXPERIMENTAL RESULTS

We have recorded images (640×360 [pixels], 10 [fps]) for four lecturers and five students in lectures concerning on the derivation of the formula for some trigonometric functions. Table 1 shows weights  $\alpha$  between hidden and output layers. These weights denote the strength for each feature in Eq. (1) and we can show the followings;

- The behavior by Student-1 is strongly influenced by the change of the face of oneself from the relation between  $\alpha_{\text{head}}^L = 0.73$  and  $\alpha_{\text{face}}^{\text{S},p} = 1.35$  for Student-1.

- Weights  $\alpha_{\text{face}}^{\text{S},1}$  by Student-1 satisfy  $|\alpha_{\text{face}}^{\text{S},1}| > |\alpha_{\text{face}}^{\text{S},q}|$  for all lecturers. This means that the behavior by Student-1 is not influenced by behaviors by other students.
- Weights  $\alpha_{\text{face}}^{\text{S},3}$  by Student-3 satisfy  $|\alpha_{\text{face}}^{\text{S},3}| < |\alpha_{\text{face}}^{\text{S},2}|$  for all lecturers. This means that the behavior by Student-3 is strongly influenced by the behaviors by Student-2.
- Weights  $\alpha_{\text{face}}^{\text{S},p}$  satisfy the relations  $|\alpha_{\text{face}}^{\text{S},p}| > |\alpha_{\text{head}}^L|$  and  $|\alpha_{\text{face}}^{\text{S},p}| > |\alpha_{\text{head}}^L|$  for all students. This means that the behaviors by students are strongly influenced by them rather than the behaviors by lecturers.

**Table 1: Weights between hidden and output layers (Results for other lecturers are omitted due to limitations of space)**

(a) Lecturer-1							
Student	$\alpha_{\text{face}}^{\text{S},p}$					$\alpha_{\text{head}}^L$	$\alpha_{\text{face}}^{\text{S},p}$
	A	B	C	D	E		
A	-1.57	-0.26	0.43	-0.02	0.40	0.73	1.35
B	-0.68	-1.39	-0.46	-0.33	-0.43	0.04	0.32
C	0.32	2.31	0.34	-0.27	-0.39	-0.36	-0.35
D	0.50	0.28	1.20	-2.60	-0.47	0.32	0.66
E	-0.25	0.31	-0.45	-2.16	-1.13	-0.11	0.31

(b) Lecturer-2							
Student	$\alpha_{\text{face}}^{\text{S},p}$					$\alpha_{\text{head}}^L$	$\alpha_{\text{face}}^{\text{S},p}$
	A	B	C	D	E		
A	1.87	0.33	-0.05	0.30	-0.24	-0.25	-0.31
B	0.81	1.43	0.30	-0.26	0.26	0.52	0.26
C	0.29	1.62	0.40	0.08	0.29	0.23	0.06
D	-0.26	0.29	1.13	-1.06	-0.36	-0.24	0.31
E	-0.34	0.43	0.27	-3.24	-0.64	-0.23	-0.30

## 4. CONCLUSIONS

In this paper, we have analyzed the interaction between behaviors by lecturer and students by using neural networks and shown the followings; (i) a specific student is strongly influenced by only the behavior by oneself, (ii) other students are strongly influenced by other students, (iii) all students are strongly influenced by the behavior by oneself and other students rather than lecturers.

## 5. ACKNOWLEDGMENTS

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