Analysis of Behaviors by Audience in Lectures by Using Time-series Models

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Keywords: Lecture, Speaker, Audience, Behavior, Time Series Model, Synchronization.

Abstract: In this paper, the dominant behaviors defined by the face direction of the speaker and audience in lectures are analyzed by using the time-series models. First, we detect the face region of the speaker and audience by the image processing and we adopt the number of skin-colored pixels in face region as features for behaviors by them. Next, we construct piecewise time series models for behaviors by the speaker and audience. Finally, we analyze the synchronization phenomena in speaker and audience by comparing time series models. Concretely, we show that the parameters in the time series models denote the dominant section in lectures. Moreover, we discuss the relationships among notes, test and behaviors by audience.

1 INTRODUCTION

In diary life and education field, it is very important for human conversation to analyze gaze points and eye movements (Land and Taters, 2009). However, speaker and teacher have to talk with many audience and grasp their interests for given contents immediately in lectures. Specifically, in lectures and classes, lecturing with monotonous speech and gestures lose sometimes audience and audience interests for given contents. Good teachers and speakers can judge how audience and audience can understand and have interests for given contents and speech based on their expressions.

Experimentally, they focus on the eye movement by audience and expressions for the purpose of judgement of taking interests in the communication. Moreover, teachers and speakers can change the contents and repeat the same contents with slower speed according to the behaviors by students and audience. In these cases, the lecturer and speaker move face around and look at faces of audience for the purpose of evaluation of understanding and interests by audience. On the other hand, audience communicate their interests to speaker by their eye contacts and expressions. It is very important to analyze the interaction between behaviors by both speaker and audience.

Iso has shown that gestures by speaker has strong relations with the skill of speech (Iso, 2011). Moreover, it is shown that the frequency of gestures have positive correlation with the skill of speech by the speaker. On the other hand, Hatakeyama et al. have discussed a case that speaker can not see the behavior of audience (Hatakeyama and Mori, 2001). They have investigated how this case influenced with the speech and behaviors by the speaker. Therefore, from the viewpoint of evaluation of the interest and the understanding of audience, it is very important to investigate the interaction between speaker and audience. Moreover, Marutani et al. have proposed a method for the detection of behavior by speaker by using multiple cameras in the lecture on-line (T. Marutani and Minoh, 2007).

In this paper, the dominant behaviors define by the face direction of the speaker and audience in lectures are analyzed by using the time-series models. Here, the dominant section and model mean the change of the contents by the speaker and interests by the audience. The contents (words, images, figures and speech) and gestures by speaker are communicated to audience in lectures. The understanding and interest by audience are transformed to behaviors by them and their behaviors are communicated to speaker. Here, the interpersonal communication between the speaker and audience with speech and gestures occurs. Authors have discussed the extraction of relationships between them by using multi-layered

Watanabe E., Ozeki T. and Kohama T..
Analysis of Behaviors by Audience in Lectures by Using Time-series Models.
DOI: 10.5220/0004787801910196
In *Proceedings of the 6th International Conference on Computer Supported Education* (CSEDU-2014), pages 191-196
ISBN: 978-989-758-020-8

neural networks (E. Watanabe and Kohama, 2011b).

This paper can be summarized as follows; First, we detect the face region of the speaker and audience by the image processing and we adopt the number of skin-colored pixels in face region as features for behaviors by them. Next, we construct piecewise time series models for behaviors by the speaker and audience. Finally, we analyze the synchronization phenomena in speaker and audience by comparing with piecewise time series models. Concretely, we show that the parameters in the time series models denote the dominant section in lectures. Moreover, we discuss the relationships among notes, test and behaviors by audience.

2 ANALYSIS OF BEHAVIORS BY SPEAKER AND AUDIENCE

The speaker can communicate a lot of contents to audience by using words, figures, pictures, and speech information in lectures. Moreover, audience are sensitive to the behavior by the speaker including the loudness of the speech, the face and hand movements. On the other hand, the speaker can confirm the understanding and the interest of audience for given contents by asking questions on audience.

We focus on the intrapersonal communication in speaker and audience in this paper. The intrapersonal communication in lectures shows the changes of the face movement and the loudness of speech. Therefore, we extract the dominant rules in the intrapersonal communication by using piecewise time-series model.

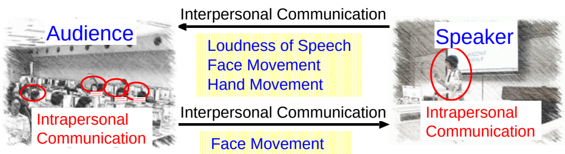


Figure 1: Interpersonal and intrapersonal communication for speaker and audience in lectures.

From Figure 1, we can summarize the following relations between behaviors by speaker and audience as follows;

- The influence of the behavior $x_S(t)$ by speaker on the p-th audience $x_A^p(t)$;
$$x_A^p(t) = f_{AS}(x_S(t-i), x_A^p(t-i)),$$
- The influence of the behavior $x_A^p(t)$ by p-th audience on audience $x_S(t)$;
$$x_S(t) = f_{SA}(x_S(t-i), x_A^p(t-i)),$$
- The intrapersonal communication in behavior $x_S(t)$ by speaker;
$$x_S(t) = f_S(x_S(t-i)),$$
- The intrapersonal communication in behaviors $x_A^p(t)$ by the p-th audience;
$$x_A^p(t) = f_A(x_A(t-i)).$$

In this paper, we treat the intrapersonal communication $x_A^p(t) = f_A(x_A(t-i))$ in behaviors $x_A^p(t)$ by the p-th audience.

2.1 Extraction of Features for Behaviors by Speaker and Audience

For the detection of the relations between behaviors by speaker and audience, we adopt the face movement as a feature. This feature can be extracted by image processing for images recorded by video camera.

Here, we detect the face region of the speaker and audience based on the color information. Moreover, the image for the face region has the skin-colored pixels. Therefore, we extract the skin-colored regions including face and hands based on the detection of pixels $\{f_{\text{Red}}(x,y),\ f_{\text{Green}}(x,y),\ f_{\text{Blue}}(x,y)\}$ with the following conditions;

$$\begin{aligned} f_{\text{Red}}(x,y) &> \varepsilon_{\text{Red}}, \\ f_{\text{Red}}(x,y) &> f_{\text{Green}}(x,y) + \Delta_{\text{Green}}, \\ f_{\text{Red}}(x,y) &> f_{\text{Blue}}(x,y) + \Delta_{\text{Blue}}, \end{aligned} \tag{1}$$

where ε_{Red} denotes a threshold for the detection of the red-colored pixel. Also, Δ_{Green} and Δ_{Blue} denote thresholds for the evaluation of the objective pixel.

Figure 2 shows changes of the number of skin-colored pixels in the face region detected by image processing in a lecture. In this Figure, it is shown that the number of skin-colored pixels changes according to the position and direction of the face region.

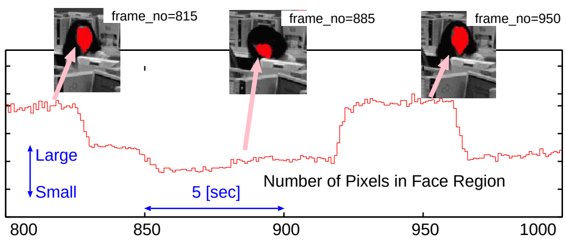


Figure 2: Changes of the number of skin-colored pixels in face region.

2.2 Analysis of Behaviors by Speaker and Audience by using Time-series Models

Features for the behavior by the speaker detected by image processing method can be summarized as follows; (i) the loudness of speech by speaker, (ii) the number of skin-colored pixels in the face region, and the number of skin-colored pixels in the face region of audience. In lectures, the speaker has to talk with many audience and grasp their interests for given contents immediately. Accordingly, they focus on the face movement by the audience for the purpose of judgement of taking interests in the lecture.

In this paper, we assume that the face direction by speaker and audience show non-stationary characteristics with the time. Namely, that characteristic of the behavior by the audience changes with the time and the content of the lecture. In this section, we propose an extraction method of “dominant section” and model for speaker and audience based piecewise AR (auto-regressive) modeling. Here, the “dominant section” and model mean the change of the contents by the speaker and interests by the audience. Therefore, it is very important for the analysis of the objective lecture to extract dominant section.

We assume that the face direction by speaker and audience can be modeled by the following non-stationary AR model with time varying parameters $a_i(t)$; Let us consider the following non-stationary AR model with time varying parameters $a_i(t)$;

$$x(t)+\sum_{i=1}^{p} a_i(t)x(t-i)=e(t), \tag{2}$$

where p denotes the degree of the AR model, and a sequence $\{e(t)\}$ of white noise has the following statistics:

$$E[e(t)]=0,\ \ E[e(t)e(\tau)]=\sigma^2\delta_{t\tau}, \tag{3}$$

where $\delta_{t\tau}$ denotes the Kronecker delta function.

When the Yule-Walker method is applied to non-stationary time series data, we have to pay attention to the following trade-off problems; (i) Too long local section: While the reliability of the statistics becomes increased, it is difficult to grasp the changing property of time varying parameters. As a result, the estimation performance of such parameters becomes worse. (ii) Too short local section: In the contrast, while it is easy to grasp the changing property of time varying parameters, the reliability of the statistics becomes decreased.

It is very important to develop a modeling method by taking account of these non-stationary properties.

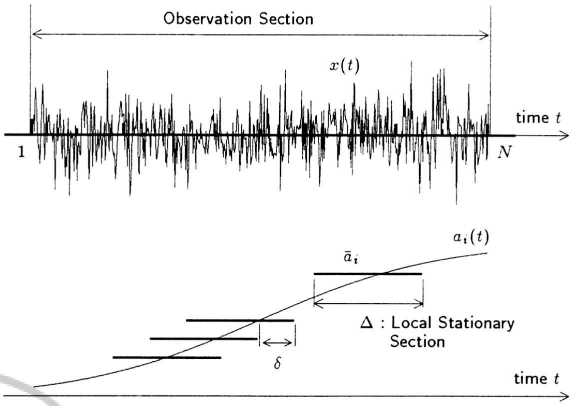


Figure 3: Observation section and local stationary section Δ in the non-stationary time-series data.

From the viewpoint of the statistical approach, several kinds of estimation methods of time varying parameters in AR model have been already discussed by many researchers. They can be categorized into the following two approaches: (i) Estimation method by introducing the local stationary section (Y. Miyanaga and Hatori, 1991), (Y. Miyoshi and Kakusho, 1987), (ii) Estimation method by introducing the time varying parameters (E. Watanabe and Mitani, 1997). In block-wise processing for the non-stationary time series data, it is necessary to consider three factors (i.e., the length of the local stationary section, the learning ability of the local stationary model, and the structure of the local stationary model). These factors are mutually connected and it is very difficult to determine appropriate values for such factors in prior.

In this paper, we propose a method for the extraction of “dominant section” and model for speaker and audience based on time-series models. Authors have already proposed an extraction method for the dominant sections based on the prediction error (E. Watanabe and Kohama, 2011a). Here, the dominant section and model mean the change of the contents by speaker and interests by audience. In this paper, we propose a new extraction method for the dominant sections based on the change of estimated parameters. The prediction value $\hat{x}(t)$ in the k-th local stationary section can be calculated by

$$\hat{x}(t)=-\sum_{i=1}^{p} a_i^k x(t-i), \tag{4}$$

where a_i^k denotes the estimated parameter in the k-th section. Also, the prediction error E_P^k in each section can be calculated by

$$E_P^k=\frac{1}{\Delta}\sum_{t=k\Delta}^{(k+1))\Delta}(x(t)-\hat{x}(t))^2. \tag{5}$$

When the prediction errors E_P^k in the k-th section and E_P^ℓ in the ℓ-the section are small and the estimated parameters a_i^k satisfy the following condition, the k-th and ℓ-th sections can be modeled by the same time-series model.

$$E_a^{k,\ell} = \frac{1}{P}\sum_{i=1}^{p}(\hat{a}_i^k - \hat{a}_i^\ell)^2 \leq \varepsilon_a, \tag{6}$$

where ε_a denotes the threshold value. As shown in Figure 4, if the k-th and ℓ-th section have the same characteristics, that is, the behaviors by the speaker and audience, we can model the above two sections with same time-series model. Therefore, the behaviors by the speaker and the audience in the k-th and ℓ-th sections can be modeled by the same time-series model.

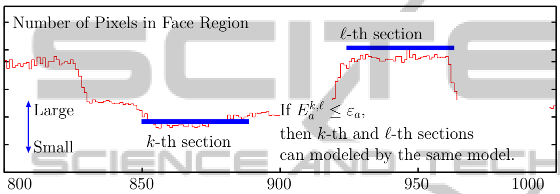


Figure 4: Observation section and local stationary section Δ in the non-stationary time-series data.

On the other hand, if $E_a^{k,\ell}$ is greater than ε, the k-th and ℓ-th sections can not be modeled by the same time-series model. When the number of local sections are large, the objective local sections can be modeled by a dominant time-series model.

3 ANALYSIS RESULTS

3.1 For Artificial Data

First, we consider the following non-stationary AR model with time-varying parameters $a_i(t)$:

$$x(t) + \sum_{i=1}^{2} a_i(t)x(t-i) = e(t). \tag{7}$$

We assume that time-varying parameters $a_i(t)$ changes with time t as follows:

$$\begin{cases} a_1(t) = 0.5, a_2(t) = -0.2, \\ \quad (1 \leq t \leq 150, 301 \leq t \leq 450), \\ a_1(t) = -0.5, a_2(t) = 0.2, (\text{otherwise}). \end{cases} \tag{8}$$

Here, the prediction error E_P and the estimated error E_a for time-varying parameters can be evaluated by the following equations;

$$E_P = \frac{1}{N}\sum_{t=1}^{N}(x(t) - \hat{x}(t))^2,$$

$$E_a = \frac{1}{2N}\sum_{t=1}^{N}\sum_{i=1}^{2}(a_i(t) - \hat{a}_i(t))^2,$$

where $\hat{x}(t)$ and $\hat{a}_i(t)$ denote the predicted value and the estimated parameter respectively. Figure 5 shows the prediction error E_P and the estimated error E_a for time-varying parameters with various Δ for artificial time-series data. As shown in Figure 5, when Δ becomes smaller, the prediction error E_P and the estimated error E_a for time-varying parameters can be improved.

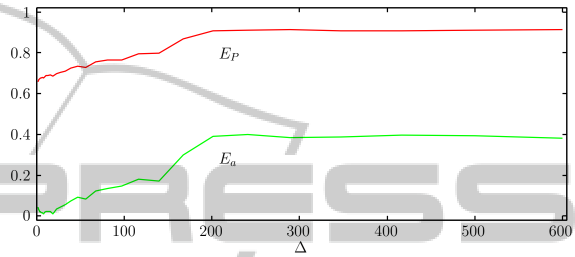


Figure 5: Prediction error E_P and estimated error E_a for time-varying parameters with various Δ for artificial time-series data.

Moreover, Figure 6 shows the estimated parameters $\{\hat{a}_i(t)\}$ for $\Delta = 10, 600$. In case of $\Delta = 10$, the estimated parameters $\{\hat{a}_i(t)\}$ can catch up the characteristic for parameters $\{a_i(t)\}$. Therefore, we adopt the shorter local section Δ as modeling the time-series model with time-varying parameters.

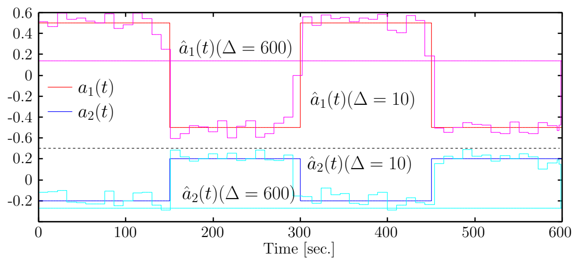


Figure 6: Estimated parameters $\{\hat{a}_i(t)\}$ for $\Delta = 10, 600$.

3.2 For Real Data

We have recorded images and speech for speaker and audience in a lecture concerning on “C language”. In this lecture, the speaker explained “the role of the pointer” during about 20 [min].

As shown in Figure 7, four audience (21-22 years old) had this lecture and the images for speaker and audience were recorded by digital video cameras. These images were recorded by the rate 10 [fps] and the size of 640×360 [pixels].

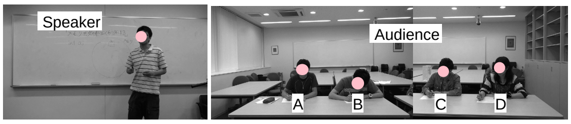


Figure 7: Speaker and audience recorded by digital video cameras.

Moreover, in Figure 8, the transition of behaviors (speaking and silent) by speaker is shown. In "Silent" phase, the speaker is waiting for finishing of taking notes by audience.

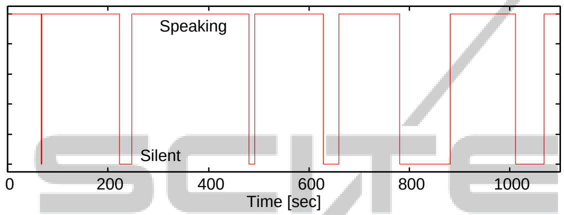


Figure 8: Behaviors (speaking and silent) by speaker.

3.2.1 Features by Speaker and Audience

In this paper, we adopt the number of skin-colored pixels in the face region as the feature for the behaviors by speaker and audience. Figure 9 shows the numbers of skin-colored pixels in speaker and audience.

When the value by the speaker is small, the speaker is writing the content on the whiteboard. On the other hand, when the value by the speaker is large, the speaker is turning the face to audience. When the value by audience is small, the audience is writing the content on the note. Furthermore, when the value by audience is large, the audience is turning the face to the speaker. From Figure 9, we can see that the behaviors by audience-C and audience-D have high correlation each other.

3.2.2 Prediction Error and Estimated Parameters

Figure 10 shows the prediction error E_P and estimated parameters $\{\hat{a}_i(t)\}$ in each section for audience-A. Here, the length Δ of the local stationary section is set as 10 [sec].

In Figure 10 (a), we have the sections with large prediction error at 230, 340, 900 and 1,070 [sec]. On the other hand, prediction errors in other sections are smaller than 0.1. Therefore, we can confirm that the behaviors by audience-A can be modeled by the piecewise auto regressive models with adequate precision. Moreover, Figure 10 (b) shows the estimated parameters $\{\hat{a}_i(t)\}$ in each local section defined by Δ.

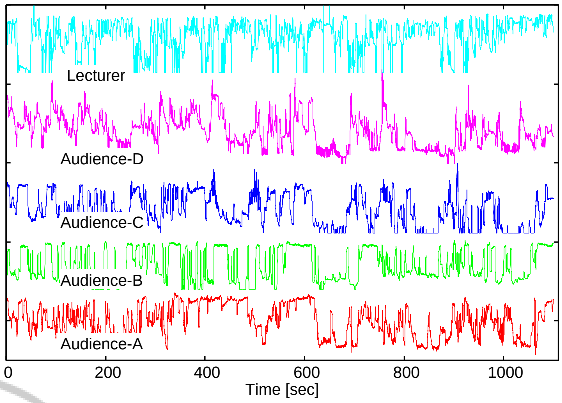
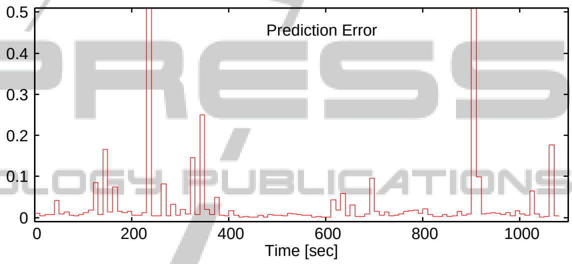
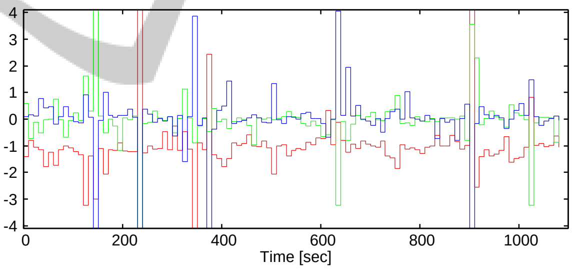


Figure 9: The numbers of skin-colored pixels in speaker and audience.



(a) Prediction Error E_P



(b) Estimated Parameters $\{\hat{a}_i(t)\}$

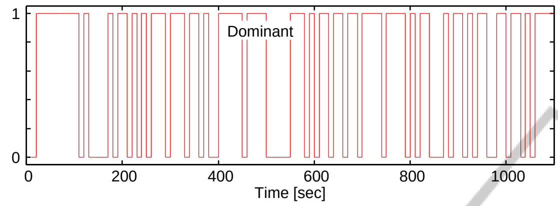
Figure 10: Prediction error E_P and estimated parameters $\{\hat{a}_i(t)\}$ in each section for audience-A.

For example, the change of estimated parameters is small in the section [780,820] and this section can be classified to the same time-series model by the condition Eq. (6).

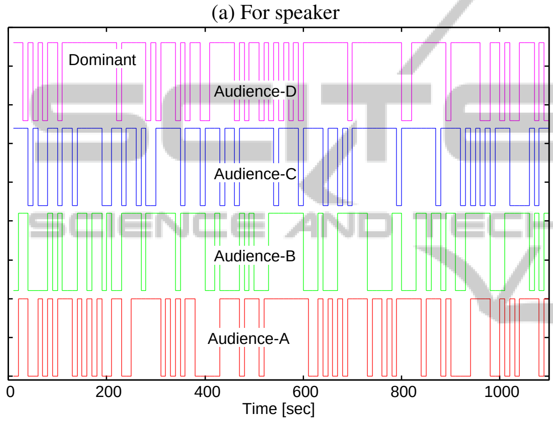
3.2.3 Extraction of Dominant Time-series Model

Figure 11 shows the sections modeled by the dominant time-series models for behaviors by speaker and audience. Here, the value "1" denotes that the objective section defined by Δ can be modeled by the dominant time-series model.

In Figure 11 (a), we can see that the number of the dominant time-series models by speaker is small. Because the speaker has to pay attention to all audience and he often is turning the face here and there. On the other hand, in Figure 11 (b), we can see that the numbers of the dominant time-series models by audience are large. Especially, the changes by audience-C and audience-D are very similar in the section [600,900].



(a) For speaker



(b) For audience

Figure 11: Changes of the dominant time-series models by speaker and audience.

From this figure, we can see that the synchronization phenomena occurs in audience-C and audience-D by comparing time series models. Furthermore, we evaluated hand-written notes by all audience after lecture and hand-written notes by audience-C and audience-D had good contents compared with other audience.

4 CONCLUSIONS

This paper have discussed the analysis of behaviors by speaker and audience in lectures. First, we have extracted the face direction as behaviors by speaker and audience. Next, we have constructed piecewise time-series models for their behaviors. Finally, we have shown the estimated results of dominant sections in a real lecture based on the piecewise time-series models. From experimental results, we have shown that the synchronization phenomena in two audience as shown in Figure 11 and the hand-written notes by the two audience had good contents compared with other audience.

As future work, we would like to discuss many cases with many audience and speakers. Moreover, we would like to analyze the eye movement by the speaker for the purpose of detection of the key person in audience.

ACKNOWLEDGEMENT

This work has been partly supported by the Grant-in-Aid for Scientific Research (C) from the Japan Society for the Promotion of Science (Grant No. 25350308).

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