an Article from

Journal of Advanced Computational Intelligence

Paper:

Automatic Video Recording of Lecture's Audience with Activity Analysis and Equalization of Scale for Students Observation

Satoshi Nishiguchi*, **Yoshinari Kameda****, **Koh Kakusho*****, **and Michihiko Minoh*****

*Graduate School of Law, Kyoto University
Yoshidahonmachi, Sakyoku, Kyoto 606-8051, Japan
E-Mail: nishigu@mm.media.kyoto-u.ac.jp
**Institute of Engineering Mechanics and Systems, University of Tsukuba
1-1-1 Tennoudai, Tsukuba, Ibaraki 305-8573, Japan
E-Mail: kameda@image.esys.tsukuba.ac.jp
***Academic Center for Computing and Media Studies, Kyoto University
Yoshidanihonmatsucho, Sakyoku, Kyoto 606-8051, Japan
E-Mail: kakusho@media.kyoto-u.ac.jp
E-Mail: minoh@media.kyoto-u.ac.jp

[Received August 11, 2004; accepted October 31, 2004]

This paper propose a method for automatic recording of audience during the lectures based on the results from conventional studies of teaching process improvements. In the presented approach we propose the audience analysis features which are later used for proper camera settings in the lecture hall with the multiple cameras installed. We focus on the analysis of student activities during the lectures in order to select the regions with different features representing the cues related to the estimated lecture attendance levels. The experimental results of the application of the proposed system together with user comments are presented in order to evaluate the validity of our approach.

Keywords: automatic video recording, lecture archives, multiple cameras, observing students, faculty development

1. Preface

Recently the *e-learning* methods are introduced increasingly into education and automatic video recording for distance lectures or lecture archives is being more extensively studied [1–5]. Most of these studies aim to acquire videos for students at distant lecture and for users of the lecture archive to understand the content efficiently.

In addition to the acquisition of videos for students, the use of automatic lecture recording system includes the possible application in order to improve lectures based on later review of archives by teachers to improve their teaching techniques. Lecture observation for teacher's education, such as faculty development (FD), very often includes recording of teacher-students interaction during the classes at universities. The lectures are observed to find possible improvements by analyzing and evaluating the activity of students in relationship to the learning process [6–8]. Many approaches in FD to improve the lectures propose the enhancement of student's attention directly or suggest changes in teaching strategies. Our study concerns the improvements of lectures based on the observation of videos captured during the classes by showing interaction between teachers and students. Our approach helps teachers to find weak points in their performances, which they usually do not notice during their lectures. We propose the utilization of automatic videos archiving system for such purpose.

The implementation of our approach focuses on acquiring of proper student videos as reference to educate the teachers. Conventional studies on lecture observation have shown that such approach is useful to improve the lectures by analyzing the students' responses to presented content by the teachers. This study utilizes the two following features related to the efficient lectures according to FD studies, which we implement in video capturing system. The first feature is based on the common finding that an experienced teacher can determine how well a lecture is understood and whether students pay attention by correlating the following two sets of audience cues. The first set includes active listening, note-taking and inattention, and the second one includes student feedback and satisfaction level. The observation of audience reactions is useful to improve the content and teaching techniques [6]. Automatic lecture archiving enables the teacher later review of student attention at different points during the lecture. We defined this feature as *the audience response range*. The second feature is based on the notion that good teachers proceed while observing the audience at different levels [9] such as individuals, groups, and the audience as a whole. The captured videos must provide such information, and thus should use different focuses to catch these levels. We defined this feature as *the focus on the audience*.

The main goal of this research is the video acquiring of students using automatic lecture recording with multiple

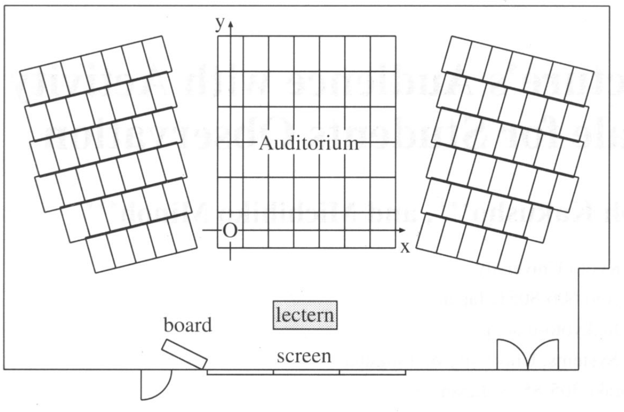


Fig. 1. Example of a face-to-face type of lecture hall (overhead view)

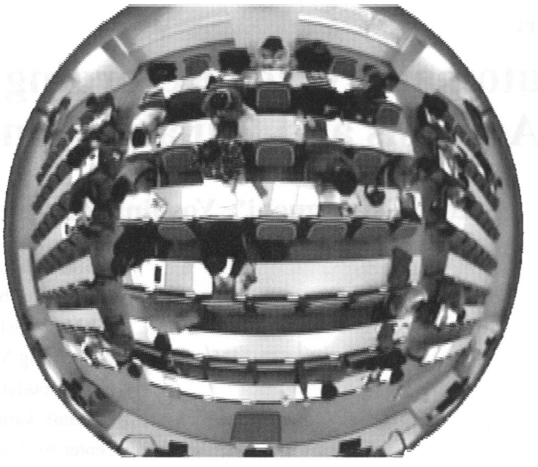


Fig. 2. Fish-eye image of seating which observes the students without occlusion

cameras installed in a lecture hall in order to capture the audience response range and the focus on the audience.

The next section discusses the video features for evaluation of the audience response range. Based on this discussion, Section 3 proposes how to select and capture the focus on the audience in videos. Section 4 reports the results of experiments using our technique and Section 5 presents conclusions and future work guidelines.

2. Video Features

2.1. Estimation of Student Location

To record videos for teaching improvement purposes, as described in Section 1, the audience location information, (e.g. where students sit in a lecture hall) is necessary. Conventional automatic recording applications tend to focus mainly on the teacher. The students are recorded only sometimes, as a whole audience using a camera in front of them [4, 10]. Such approach may disturb the view of individual students in an image. This method does not provide the optimal solution to estimate the focus on the audience.

We propose the use of the camera with a fish-eye lens mounted on the ceiling in the lecture hall in order to estimate the focus on the audience robustly and efficiently. The students' seats are usually arranged in a graduated auditorium style (**Fig.1**). This enables the audience to view and listen to the teacher clearly. The ceiling mounted camera with the fish-eye lens can thus capture the videos without occlusion. The example is shown in **Fig.2**.

Figure 3 shows a rectangular area called a *cell* which corresponds to each student's seat, enabling attendees to be grasped at a glance (**Fig.2**). The following discussion assumes that students' seats are arranged in a horizontal 2-dimensional (2D) grid. The x and y axes of 2D coordinates are regarded as rows and columns, e.g. a seat at row x_i and column y_i is represented by (x_i, y_i). The cell corresponding to (x_i, y_i) in the camera image is represented by $C(x_i, y_i)$. x_i and y_i are positive integers including zero. Even if the seats are not arranged in such a way, the same discussion applies if each seating position can be described with adjacent relationship features.

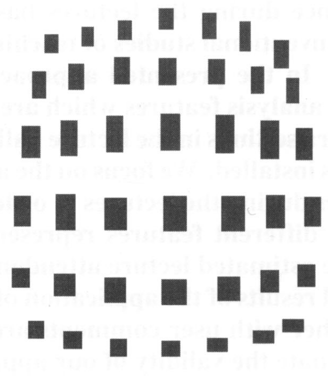


Fig. 3. Cells corresponding to individual seating

For a student occupying the seat (x_i, y_i), we introduce a binary variable $s(x_i, y_i)$, which is *true* or *false*. This variable is used to represent the student's location. The binary value of the above variable is determined based on the background differences $\Delta_b(x_i, y_i)$ inside the cell $C(x_i, y_i)$. $\Delta_b(x_i, y_i)$ is obtained by dividing the number $n_b(x_i, y_i)$ of pixels exceeding the threshold of which an absolute value is in $C(x_i, y_i)$ by the total number $n(x_i, y_i)$ of pixels in $C(x_i, y_i)$. If this value exceeds threshold T_b, a student is present in cell $C(x_i, y_i)$, otherwise the location is marked as empty.

$$s(x_i, y_i) = \begin{cases} true & \text{for } \Delta_b(x_i, y_i) \geq T_b \\ false & \text{otherwise} \end{cases} . \quad (1)$$

2.2. Cluster and Scale

Consider a cluster of students including one or more of them, which becomes the focus on the audience based on the location obtained in Section 2.1. The number of students included in this cluster is defined as *a scale* in our approach. To find the cluster we search for the adjacence of seats which are occupied by students. The chessboard distance (near-eight-distance) $d(x_i, y_i, x_i, y_i)$ is shown in the following expression in order to evaluate adjacence between seat locations (x_i, y_i) and (x_j, y_j).

$$d(x_i, y_i, x_j, y_j) \quad = \quad \max(x_j - x_i, y_j - y_i) \quad . \; . \; . \quad (2)$$

The cluster of students is defined based on the distance d between each student's location hierarchically. First, we define a set $\mathbf{G_1}$ which contains the cells occupied by students as follows (see **Fig.4** with single student example):

$$\mathbf{G_1} \quad = \quad \{(x_i, y_i) | s(x_i, y_i) = true\} \quad . \; . \; . \; . \; . \quad (3)$$

The set $\mathbf{G_1}$ contains l elements g_1^l. Next, we compose the set $\mathbf{G_2}$ which contains the clusters of the neighboring student pairs. The grouping procedure continues up to set $\mathbf{G_k}$ with the constrain of finding the set containing the largest clusters of neighboring students which distance d to the previous cluster g_{k-1}^l is expressed as follows:

$$\min_{(x_i, y_i) \in g_{k-1}^l} d(x_i, y_i, x_j, y_j) = 1 \quad . \; . \; . \; . \; . \; . \; . \; . \quad (4)$$

Finally, the set G is composed from the subsets $\mathbf{G_1}$ to $\mathbf{G_k}$ as follows:

$$\mathbf{G} = \mathbf{G_1} \cup \mathbf{G_2} \cup \ldots \cup \mathbf{G_k} \quad . \; . \; . \; . \; . \; . \; . \; . \quad (5)$$

A cluster grouping procedure example is shown in **Fig.4**. The cells occupied by students are depicted as shaded circles with letters A to F. In this example, there are 12 clusters all together which composed the subsets $\mathbf{G_1}$ to $\mathbf{G_4}$.

The above cluster grouping procedure enables later proper camera zoom setting since all groups of neighboring students are marked properly because they are adjacent in the clusters. The number of students in the cluster represents the scale captured in the recorded video.

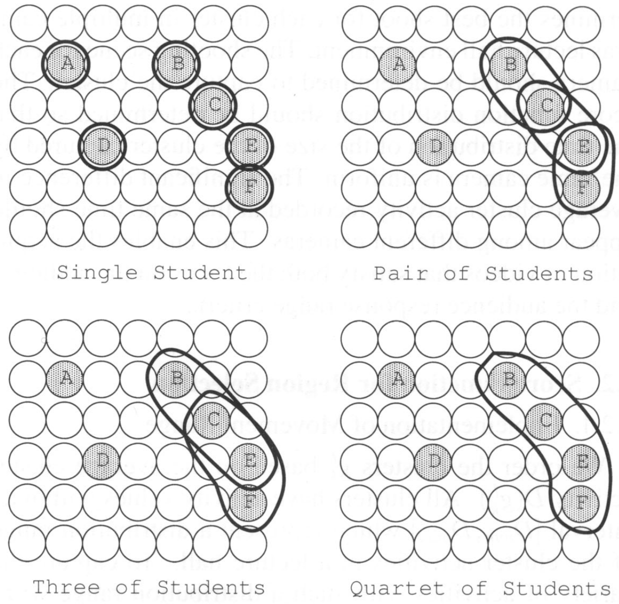


Fig. 4. Cluster example

2.3. Size of Cluster Movement

It is necessary to acquire information on the activity of the individual students when acquiring the video for lecture improvement. The amount of movement derived from differences between the consecutive video frames is used as one of the features of human activity in motion recognition methods. Our approach also incorporates such technique and evaluates the activity for each cluster using inter-frame differences. Inter-frame differences for a single cell $C(x_i, y_i)$ are represented by $\Delta_f(x_i, y_i)$. $\Delta_f(x_i, y_i)$ is obtained by dividing the absolute value of the difference between the number of pixels $n_f(x_i, y_i)$ exceeding the threshold in consecutive frames by the total number of pixels $\hat{n}(x_i, y_i)$ in the cell. The value $\Delta_f(x_i, y_i)$ is used to calculate the average activity $D(g_k^l)$ inside of each cluster g_k^l obtained in Section 2.2. The average cluster activity $D(g_k^l)$ is obtained as follows:

$$D(g_k^l) \quad = \quad \frac{1}{k} \sum_{(x_i, y_i) \in g_k^l} \Delta_f(x_i, y_i) \quad . \; . \; . \; . \; . \; . \quad (6)$$

3. Selection of a Region

3.1. The Focus on the Audience and Audience Response Range

We consider the acquisition of videos with the focus on the audience and audience response range using the multiple cameras installed in a lecture hall incorporating the methods described in Section 2. The focus on the audience includes the concept that the attendees are captured a single individuals in some cases or group of students in certain students situations. It means that there is no selection bias about the number of students captured in video frame throughout the video recorded by each camera. To implement this recording concept, it is necessary to select a cluster, in which the distribution of students' number in time is uniform. This enables to obtain the proper audience response range from video recorded throughout a lecture. This means recording in which multiple cameras capture as many possible audience responses as possible. The above assumption enables us to select the clusters as regions with the different average cluster activity recorded by multiple cameras at the same time.

To implement the cluster selection satisfying the above requirements, we propose the score function which determines the best shoot for each cluster in multiple cameras lecture hall environment. The shooting scene for each camera should be determined to capture the cluster. The score function distribution should be determined so that the time distribution of the size of the cluster captured by the same camera is uniform. The significant difference in average cluster activity recorded at the same time should appear among different cameras. This enables the acquisition of videos that satisfy both the focus on the audience and the audience response range criteria.

3.2. Score Function for Region Selection

3.2.1. Implementation of Movement Range

We order the clusters g_k^l based on the average cluster activity $D(g_k^l)$. All clusters have activity values within an interval $[D_{min}, D_{max}]$ which represent a distribution range of the cluster activities in a lecture hall. To capture the variety of activities with such a distribution range without failure by multiple cameras, interval $[D_{min}, D_{max}]$ is equally spaced by the number of cameras in order to determine a score function for selecting regions. Let's assume that the number of cameras to be c and the score function for the mth camera which can capture the selected cluster g_k^l is $P_m(g_k^l)$. This score function is represented by the following expression, where α_k^m is a positive integer defined in Section 3.2.2:

$$P_m(g_k^l) = \begin{cases} \alpha_k^m, & \text{for } D(g_k^l) \in [D_0, D_1] \\ 0, & \text{otherwise} \end{cases} . \quad (7)$$

where

$$\begin{aligned} D_0 &= D_{min} + \frac{m-1}{c}(D_{max} - D_{min}) \\ D_1 &= D_{min} + \frac{m}{c}(D_{max} - D_{min}). \end{aligned}$$

The example of ordering of the clusters according to the average cluster activity is presented in **Fig.5**. The horizontal axis indicates the cluster arrangement and the vertical one the average cluster activity values as described in Section 2.3. In this example, three cameras were used and the interval $\{D_{min}, D_{max}\}$ was divided into three ranges. Every camera installed in the lecture hall should select a cluster within defined above interval. In this example, the score function is determined so that cameras #0, #1, and #2 may have a positive selection score for the 25 clusters within an interval of $[D_{min}, D_{min} + 1/3(D_{max} - D_{min})]$. The 24 clusters within an interval of $[D_{min} + 1/3(D_{max} - D_{min})$, and the three clusters within an interval of $D_{min} + 2/3(D_{max} - D_{min})]$, respectively. Such ordering causes each camera to capture the cluster with preselected amount of activity range.

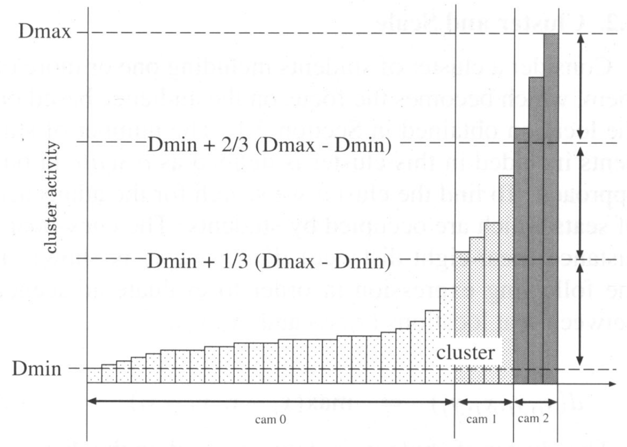


Fig. 5. Example of audience response range implementation

3.2.2. Implementation of the Focus on the Audience

After selection of one cluster with average cluster activity within an interval allocated by the score function described above for each camera, the time distribution of the level of a cluster selected as a region must be uniform to satisfy the focus on the audience. In other words, the number of students in a recorded student cluster must be selected without selection bias throughout recording.

It is, thus, necessary to determine the score function $P_m(g_k^l)$ so that the selection of clusters becomes uniform inside the region possible to capture by each camera as described in Section 3.2.1

In order to define this score function distribution, the clusters selected for the mth camera are classified based on the focus of the audience.

Figure 6 shows clusters allocated to a single camera and there are six clusters including one student, four clusters including two students and two clusters including three students. Assuming the number of degree of focus as $\sigma(m)$ and the number of clusters with a focus of k as $\nu_m(k)$, α_k^m of expression (7) which is responsible for selection of camera for cluster is defined as follows:

$$\alpha_k^m = \frac{1}{\sigma(m) * \nu_m(k)} \quad \ldots\ldots\ldots \quad (8)$$

Figure 6 shows an example where for $\sigma(m) = 3$, $\nu_m(1) = 6$ and the score function value is $P_m(g_1^l) = 1/18$, for $\nu_m(2) = 4$ the score function value is $P_m(g_2^l) = 1/12$ and for $\nu_m(3) = 2$ the score function value is $P_m(g_3^l) = 1/6$, respectively. The score for clusters with a focus of $k = 1, 2, 3$ is $1/3$.

4. Experiments

The proper implementation of defined score function in the above sections let us properly capture the ongoing students' activity during the lecture with regard to propose measures such as the focus on the audience and the audience response range. The experiments conducted in a real lecture hall at our university let us determine what kind of videos can be recorded for teaching improvement purposes.

Figure 7 shows the lecture hall used for this experiments. The layout of the room is the same as the drawing

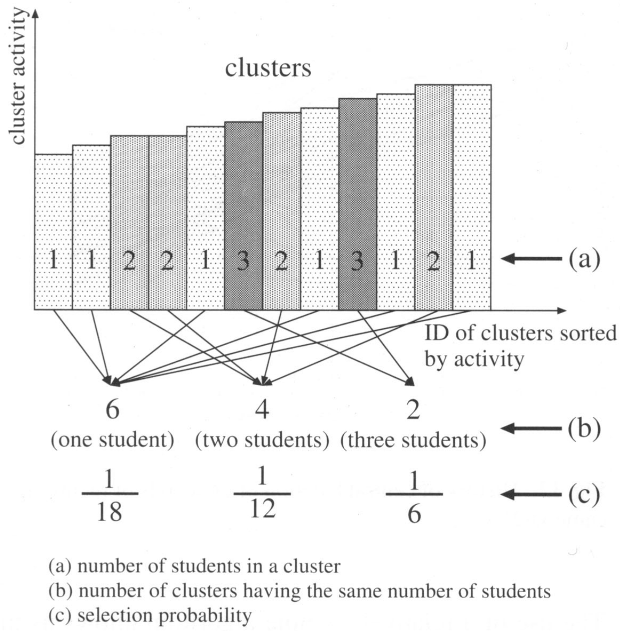


Fig. 6. Example of implementing the focus on the audience

Fig. 7. Full view of lecture hall used for experiments

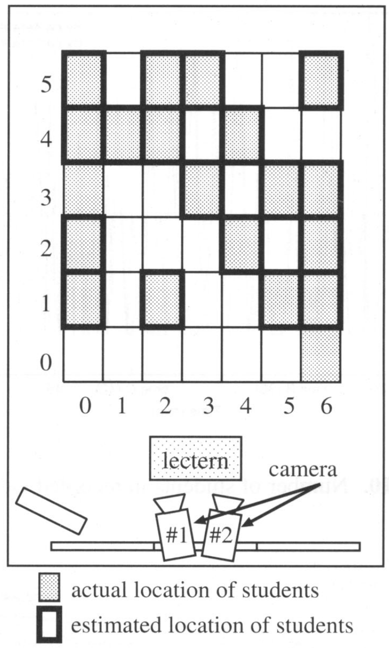


Fig. 8. Results of estimated student locations

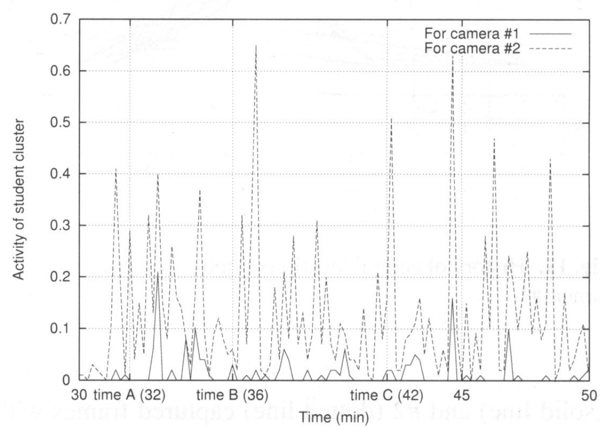


Fig. 9. Size of selected cluster movement

in **Fig.1**.

Two cameras were installed there as shown in **Fig.8**. The lecture recording time was set for 90 minutes which is a general lecture's time interval.

4.1. Camera Operation

We applied the proposed method for the central seating area of the lecture hall in **Fig.8**. The students were seating in locations indicated by shading in **Fig.8**. The presence of seating students was detected using the proposed method as described in Section 2.1 and indicated on **Fig.8** with bold line squares. We found that the locations were detected almost accurately. Based on the proposed method, we selected shooting regions for each camera and later recorded them.

Figure 9 shows the variations of the amount of average cluster activity during 20 minutes and about 30 minutes after the start of the lecture. The horizontal axis is the elapsed time (in minutes) from the start of the lecture, while the vertical axis is the amount of the average cluster activity. There are shown two plots of variations of the average cluster activity captured by two cameras. Camera #1 captured the clusters with students characterized by small activity values (solid line in **Fig.9**). The camera #2 captured the higher activity clusters, respectively (dotted line). The above procedures shows that using our method we can capture the audience during the lecture according to preselected audience response ranges.

Figure 10 shows the captured changes in the number of students recorded in videos in a selected cluster during 20 minutes of a lecture. The horizontal axis is the elapsed time (in minutes) from the start of the lecture and the vertical axis is the number of recorded students. Cameras

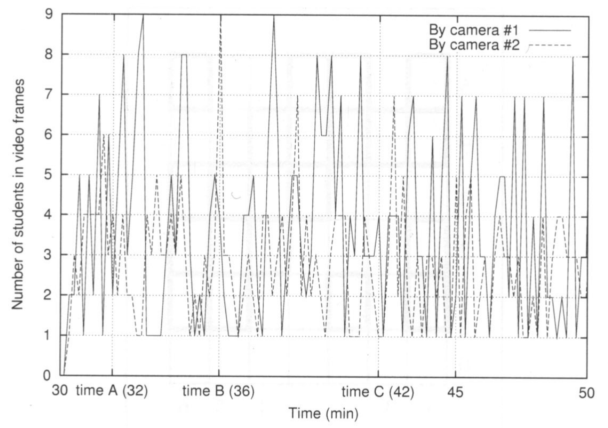


Fig. 10. Number of students in recorded videos

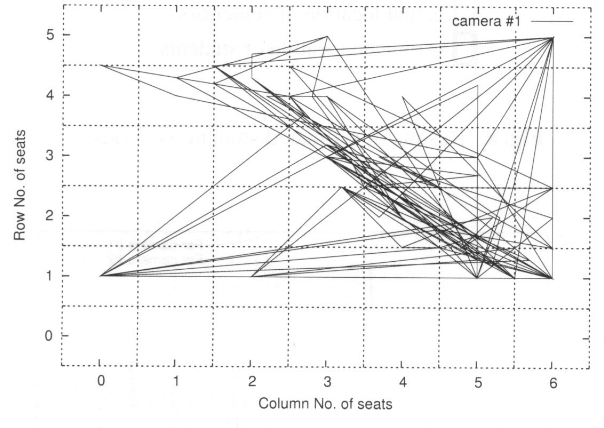


Fig. 11. History of central location of optic axis of recording camera#1

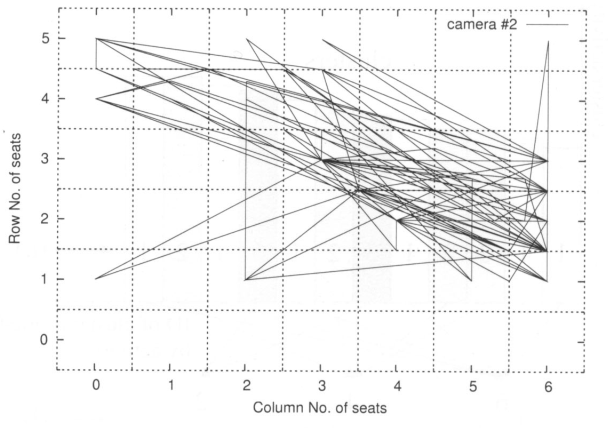


Fig. 12. History of central location of optic axis of recording camera#2

#1 (solid line) and #2 (dotted line) captured frames with a small and large number of students, respectively. The focus on the audience was also estimated.

Figures 11 and **12** present the locations' history at which two cameras were setting their optic axes. The rectangulars enclosed within thick dotted lines correspond to the seats in **Fig.8**. Cameras recorded an area based on the location of the seat in which students were presumed to be present. However, our method does not deal with individuals equally, so there is selection bias during recording. There might be a few students who are infrequently recorded.

Figure 13 shows an example of a selected cluster. The time slots A, B, and C in **Fig.13** correspond to the same time slots in **Figs.9** and **10**. The value indicated for each seating location is the activity of each student at that time. Since two cameras are used, two clusters are selected each time. Thus, two clusters are enclosed with solid and dotted lines to show the activity in each cluster. The cluster indicated by dotted line was selected by camera #1 and the cluster indicated by solid line was selected by camera #2.

The use of a relatively simple algorithm allows us the real-time automatic recording. Each camera selects a cluster as its region with frequency of a maximum 10Hz or more. The clusters are selected at intervals of about ten seconds during actual recording.

Figure 14 shows shots of cluster frames recorded by two cameras. For example, camera #1 captured a student apparently not attending the lecture actively at time slot A with little movement. Camera #2 captured more active student looking at a teacher or moving his arms. Videos recorded by each camera at different times captured different numbers of students and reflected the focus on the audience.

4.2. Evaluation for Teaching Improvement

As discussed in Section 1, the automatically recorded lectures and stored in lecture archives may be a valuable support for teachers to enhance their teaching skills. The teachers may access the archives to watch the videos and search for possible mistakes they do. We applied the proposed system to four lectures and determined whether teachers could evaluate their performances. Our intension was to check whether the videos acquired by the proposed system would be useful in *automatic recording of lectures for teaching improvement*.

For the evaluation of our system we chose four lectures and two videos were recorded for each. We asked the four professors responsible for these lectures to review the videos for 10 minutes, that is, one 5 minutes video segment starting 10 minutes after the beginning of the lecture and one 5 minutes video segment starting 60 minutes after the beginning of the lecture, together with the recorded audio. We obtained the following responses from the professors based on the following 6 points questionnaire:

- **Question 1.** Could you see in the video the facial expression of students which you didn't see during the lecture?
- **Question 2.** Could you see the facial expressions and responses of students while explaining complex

Question	Lecture				Average
	A Economics	B Physics	C Information	D Law	
1	4	5	5	5	4.75
2	4	5	2	5	4.00
3	4	4	4	4	4.00
4	4	5	5	5	4.75
5	4	4	4	4	4.00
6	4	5	5	5	4.75

Table 1. Result of questionnaire

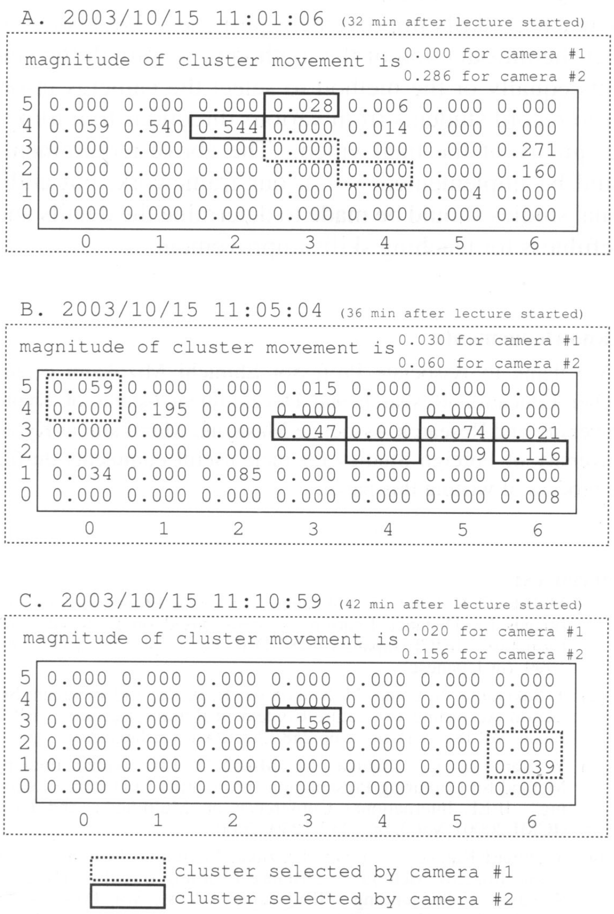


Fig. 13. Example of selected clusters

Fig. 14. Recording based on selected cluster

ideas?

- **Question 3.** Could you observe all the students?
- **Question 4.** Could you observe the behavior of students in detail?
- **Question 5.** Do you think that proposed shootings algorithm let you capture individual students, groups and the whole audience comfortably?
- **Question 6.** Could you obtain information unavailable to you during your lecture?

- **Evaluation 5.** Absolutely
- **Evaluation 4.** Satisfactory
- **Evaluation 3.** Not sure
- **Evaluation 2.** Not satisfactory
- **Evaluation 1.** Absolutely not

The results of the questionnaire are shown in **Table 1**. The average value of 4 or higher was given to all questions. The answers for questions 2, 3, and 5 were evaluated as low. Regarding question 2, in this experiment we asked teachers to watch videos and listen to audio, but since the proposed method did not record students based on their movement types, their facial expressions, activity and the presence of responses to presented material. For questions 3 and 5, "all students" were interpreted as the whole audience present in the lecture hall. Additionally, our method does not capture the whole audience all the time so the students' captured locations could be not uniform. This may cause that some students in the audience might be captured very seldom. These factors could cause the low evaluation.

We also obtained the free comments from the professors which were as follows: Teacher A did not perceive not attending students during his lecture. Teacher B could not remember particular students, but he could remember the audience as a whole. Our videos enabled him to observe the attitude and let him look at individuals or groups. Such videos, according to him, would be useful for his future lectures evaluation. Teacher C could gain a lot from presented videos since he could see some of the students whom he could not perceive during his actual lecture and additionally, he noticed some of the students listening to him eagerly without giving active responses. Teacher D had the impression that there were significant differences in attending a lecture depending on individuals.

We found from this description that each teacher has discovered new information that could be not perceived during a lecture based the analysis of the amount of the student activity or the degree of attention.

5. Conclusions

The intension of our research was to develop an automatic lecture recording system which could have to improve teaching skills such as used in FD. We focused on the practical implementation of the technique for acquiring the videos useful from the FD point of view. We propose the use of multiple cameras installed in a lecture hall in order to record the defined in this paper audience response range and the focus on the audience. Our approach is based on the conventional FD studies which involve the observational behavior analysis for teaching skills improving purposes. The proposed method captures the activity of students in different group sizes using multiple cameras and lets each camera to select regions covering the clusters of students with different sizes for further recording. Our approach was implemented with determination of the score function for selecting the regions for capturing, based on information about the location and activity of students obtained from the camera with a fisheye lens installed on the ceiling in the lecture hall. Our method was applied to the actual lectures at university and it was confirmed that videos recorded according to the defined score function provided the audience reaction range and the focus on the audience satisfactory. It was also confirmed by questionnaires to teachers that they could gain new information about their own lecture styles.

Our future work will include an attempt to introduce a more detailed motion feature extraction from videos for evaluating the audience activity in addition to the proposed in this paper the average cluster activity. An attempt has been made to recognize activity from motion features. Incorporation of such more advance features should lead to more precise estimation of the focus on the audience and the audience response range. The image resolution problem will always remain for large lecture halls even with application of high resolution cameras. We will attempt to enhance the motion recognition methods from lower resolution videos. The another issue would be the consideration of additional constrains for choosing captured regions of the lecture hall. In our research we considered only the two constrains which are the audience response range and the focus on the audience, which according to FD findings are the most important features for teachers skills improvement purposes. We also consider the introduction of the method to record all the students equally or the method to select the cameras in order to record students from various directions to improve the quality of the final video. The above requirements could be implemented within our framework, but additional studies should be made to determine the details and usefulness for teaching skills improvement.

Acknowledgements

We thank to Associate Professor Shinichi Mizokami of the Higher Education Research and Development Center of Kyoto University and Research Associate Masayuki Murakami at Kyoto University of Foreign Studies for their useful comments during the process of writing this paper.

References:

[1] M. Onishi, M. Izumi, K. Fukunaga,"Automatic Production of Video Images for Distance Learning System Based on Distributed Information." IEICE Japan, vol.J82-D-II, no.10, pp.1590-1597, Oct. 1999. (in Japanese)

[2] T. Sakiyama, N. Ohno, M. Mukunoki, K. Ikeda,"Video Stream Selection According to Lecture Context in Remote Lecture", IEICE Japan, Vol.J84-D-II, no.2, pp.248-257, 2001. (in Japanese)

[3] Y. Kameda, K. Ishizuka, M. Minoh,"A Live Video Imaging Method for Capturing Presentation Information In Distance Learning", IEEE International Conference on Multimedia and Expo (ICME2000), Vol.3, pp.1237-1240, 2000.

[4] Yoshinari Kameda, Kentaro, Ishizuka, Michihiko MInoh, "A Realtime Imaging Method for Distance Learning Based on Dynamic Situation Understanding", IPSJ Japan CVIM, Vol.2000, No.33, No.121-11, pp.81-88, 2000. (in Japanese)

[5] Masaki ONISHI, Takehiko KAGEBAYASHI, Kunio FUKUNAGA,"Production of Videoconferencing Images by Computer Controlled Camera Based on Integration of Audiovisual Information"IEICE Japan. vol.J85-D-II, no.3pp.537-542, 2002. (in Japanese)

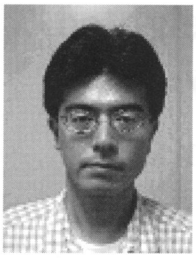
[6] Research Center for Higher Education, Kyoto University ed., "A fieldwork of an lecture in Universities,", Tamagawa University Press, 2001. (in Japanese)

[7] Research Center for Higher Education, Kyoto University ed., "Aiming of an open lecture in Universities,", Tamagawa University Press, 1997. (in Japanese)

[8] Hideko Itoh, Yusaku Otsuka eds., "A guidebook of an improvement of a lecture in Universities"", Yuhikaku publishing, Japan, 1999. (in Japanese)

[9] Steven G.Krants, "How to Teach Mathematics," the American Mathematical Society. 1993.

[10] Makoto Takano, Shunsuke Kodama, Kaori Toyoki, Takeshi Shirai, Shinji Shimojo, Hideo Miyahara, "Distance Learning Support System for Teacher to Aggregate Audience Reaction", IPSJ Japan, 2000 Symposium on Multimedia, Distributed, Cooperative and Mobile Systems (DICOMO 2000), pp.463-468. June 2000. (in Japanese)



Name:
Satoshi Nishiguchi

Affiliation:
Research Associate, Graduate School of Law, Kyoto University

Address:
Yoshidahonmachi, Sakyoku, Kyoto 606-8501, Japan

Brief Biographical History:
2000- Research Associate, Kyoto University

Main Works:
• "Automatic Video Shooting Method for Fixed Move Pattern Using Template-Video", The Journal of IIEEJ, Vol.31 No.5 pp.806-814, 2002.

Membership in Learned Societies:
• The Institute of Electronics, Information and Communication Engineers (IEICE)
• The Japanese Society for Artificial Intelligence (JSAI)
• The Institute of Electrical Engineers of Japan (IEEJ)

Name:
Yoshinari Kameda

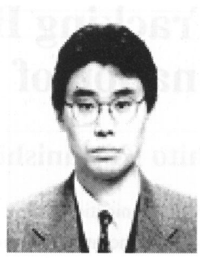
Affiliation:
Assistant professor, Institute of Engineering Mechanics and Systems, University of Tsukuba

Address:
3F309, University of Tsukuba, 1-1-1 Tennoudai, Tsukuba, Ibaraki 305-8573, Japan

Brief Biographical History:
1996-2003 Assistant professor, Kyoto University
2001-2002 Visiting Scientist, Massachusetts Institute of Technology
2003- Assistant professor, University of Tsukuba

Main Works:
• "High Speed 3D Reconstruction by Spatio-Temporal Division of Video Image Processing," The Transactions of the IEICE D, J83-D, No.7, pp.1422-1428, 2000.
• "CARMUL: Concurrent Automatic Recording for Multimedia Lecture," IEEE International Conference on Multimedia and Expo (ICME2003), Vol.1, pp.129-132, 2003.

Membership in Learned Societies:
• The Institute of Electronics, Information and Communication Engineers (IEICE)
• Information Processing Society of Japan (IPSJ)
• The Institute of Electrical and Electronics Engineers (IEEE)



Name:
Koh Kakusho

Affiliation:
Associate Professor, Academic Center for Computing and Media Studies, Kyoto University

Address:
Yoshidanihonmatsucho, Sakyoku, Kyoto 606-8501, Japan

Brief Biographical History:
1992- Visiting Scholar, Stanford University
1994- Research Associate, Osaka University
1997- Associate Professor, Kyoto University

Main Works:
• "Adjusting the difference between 3D Spaces in VR Systems and Human Perception through Region Manipulation," Proceeding of the IEEE Virtual Reality 2000 pp.99-106, 2000.

Membership in Learned Societies:
• The Institute of Electrical and Electronics Engineers (IEEE)
• Association for Computing Machinery (ACM)
• Information Processing Society of Japan (IPSJ)

Name:
Michihiko Minoh

Affiliation:
Professor, Academic Center for Computing and Media Studies, Kyoto University

Address:
Yoshidanihonmatsucho, Sakyoku, Kyoto 606-8501, Japan

Brief Biographical History:
1983- Research Associate, Kyoto University
1987-1988 Visiting Researcher, University of Massachusetts
1989- Assosiate Professor, Kyoto University
1995- Professor, Kyoto University

Main Works:
• "Shape Modeling for String-like Deformable Regions in Manipulation by Observing Real Regions," The journal of IPSJ, Vol.43 No.12 pp.3632-3642, 2002.

Membership in Learned Societies:
• The Institute of Electrical and Electronics Engineers (IEEE)
• Association for Computing Machinery (ACM)
• The Institute of Electronics, Information and Communication Engineers (IEICE)