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The Role of Body Motion Synchrony in Distance Education

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Abstract
The concept of well-being has spread to communication and education dimensions. In recent year, there has been remarkable progress in research on distance education. The interactive and communication factors have been considered important in distance education. In particular, body motion synchrony well represents the characteristics of social and interpersonal interaction during face-to-face communication process. This article investigated how the spatiotemporal separation as distance education factors affects body motion synchrony during the communication process. As a result, there were significant differences in the synchronization characteristics among three conditions. We suggest that body motion synchrony is useful to evaluate communication factors in distance education. In addition, the detection method of the algorithm can apply to the communication technology on well-being.

Introduction
There has been remarkable progress in research on well-being (Diener et al. 1999; Keyes, Schmotkin, and Ryff 2002; Stratham and Chase 2010; Seligman 2011). Well-being has been derived from two general perspectives: the hedonic approach, which focuses on happiness, positive affect and satisfaction with life (Bradburn 1969; Diener 1984; Kahneman, Diener, and Schwarz 1999; Lyubomirsky and Lepper 1999); and the eudaimonic approach, which focuses on positive psychological functioning and human development (Rogers 1961; Ryff 1989; Waterman 1993). In recent year, research in well-being technology has attracted much attention in recent decades, such as healthcare (Jsselsteijn et al. 2006). In particular, the concept of well-being has spread to communication and education dimensions (Dodge et al. 2012).
Distance education is accomplished by various tools such as computer-, phone- video-based technologies (Beldarrain 2006). These tools for distance education have been grown with development of technologies. The first stage on research in distance education focused on separately learner-side or instructor-side factor and most has focused on student achievement by learning environments (Bekele, and Menchaca 2008). In recent year, success factors in distance education have been studied such as motivation, delivery format, asynchronous and synchronous tools and system functionality, et cetera (Abel 2005; Pituch, and Lee 2006). However, the interactive and communication factors have been considered important in dist ance education (Allen, and Seaman 2004; Dede, Whitehouse, and Brown-L'Bahy 2002). Therefore, some researchers have studied and devised interactive and communication-based education system with new technologies (Carr-Chellman, and Duchastel 2000; Gilbert, Morton, and Rowley 2007; Martz, Jr., and Reddy 2005; Ostlund 2008; van der Kleij, Paashuis, and Schraagen 2005; van der Kleij et al 2009; Morris 2004).
Instructor-learner communication is an essential factor in class. Communication is a process that two or more people interact information through verbal and nonverbal channels. In distance education, the learners and instructors would be spatially or temporally separated because distance education is devised for those who are not able to attend to face-to-face courses. If they are spatiotemporally apart, the communication factors (such as verbal and nonverbal interaction and social interaction) would largely decrease. Therefore, it is important to investigate how the spatiotemporal separation affects communication characteristics in distance education.
Body motion synchrony well represents the characteristics of social and interpersonal interaction during face-to-face communication process. For example, some researchers reported that postures and body motions between familiar partners are frequently synchronized (Jones 1993). Furthermore, strong body motion synchrony between clients and their psychotherapy counselors has been found for highly evaluated counselor's groups (Bernieri et al 1996).

In particular, many researchers reported that body motion synchrony, especially head nods, includes positive emotions and relationships in interpersonal communication (Komori, and Nagaoka 2010; Kita, and Ide 2007). Therefore, body motion synchrony would be able to be very useful indicator to evaluate the aspect of communication.

This article explores how the spatiotemporal separation affects body motion synchrony during the communication process. We examined three types of lecture task experiments, which consist of the face-to-face education condition, the real-time distance education condition and the non-real-time distance education condition. The face-to-face education condition shows that participants conducted a lecture task without spatiotemporal separation. The real-time distance education condition indicates that participants performed the lecture task spatially separated but in real time. In the non-real-time distance education condition, participants conducted the lecture task with spatiotemporal separation. To detect body motion synchrony, we used the previously reported detection method (Kwon et al, 2015) called phase difference analysis and compared the synchronization characteristics in the three conditions (Kwon et al, 2015).

Methods

Experimental Designs

As described in detail previously (Kwon et al, 2015), lecture task was used in three experiments. Three groups of pairs of participants performed a lecture task in the face-to-face, real-time distance and non-real-time distance education conditions separately. In the face-to-face education condition, an instructor explained a content to a learner in face-to-face situation. Then, head nodding motion was focused on as a specific indicator of body motion synchrony because nodding motion plays an important role as a form of feedback in human communication. An acceleration sensor was attached to participant' forehead directly and analyzed their head nodding motion. Throughout the experiments, phase differences were calculated from the time-series data on the acceleration of head nodding motion between a pair of participants. Then, the phase difference distribution was extracted for analyzing the head nod synchronization. In the real-time distance education condition, a pair of participants conducted the lecture task remotely via television in different rooms in which two participants know mutually the existence of each other. The lecture task was conducted in real time. In the non-real-time distance education condition, a pair of participants also performed the lecture task via television remotely in different rooms. Specifically, we informed instructor of the existence of learner. However, we did not informed learner of the existence of instructor and we instructed the learner that the lecture is recorded video to eliminate the real-time characteristic. The head nod synchronization was detected from the phase difference distribution in the real-time and non-real-time distance education conditions.

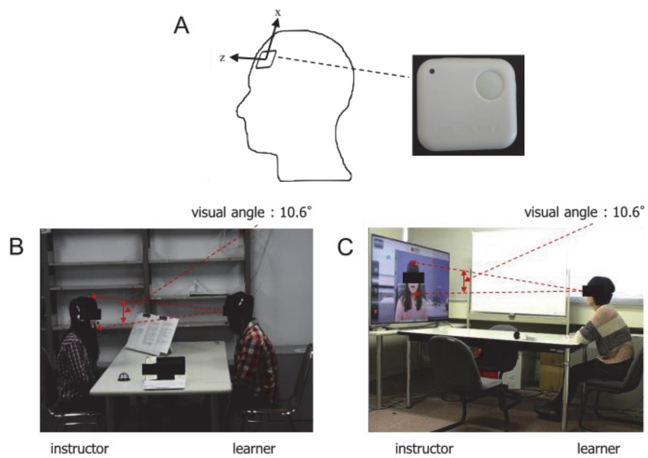

Table 1. Participant's information and selection criteria.

Number	- 24 pairs of participants (32 males and 16 females, all in their 20s)
Selection criteria	- Same gender - Age by less than five years - Native speakers of Japanese

Figure 1. Schematic illustration of the face-to-face education, real-time and non-real-time distance education conditions. (A) The position of a three-axis acceleration sensor. (B) The experimental situation in the face-to-face education condition, and (C) The experimental situation in the real-time distance education and non-real-time distance education conditions.

Participants

Twenty-four participants took part in the three experiments and a pair of participants performed the lecture task in each condition, separately. Specifically, one teacher conducted the lecture three times in each condition and different learners participated in each condition. The partners were of the same sex and native speakers of Japanese. All participants had normal hearing and normal or corrected-to-normal visual acuity, and were naive as to the purpose of the experiment. Participants were paid to take part in the experiments, and written informed consent was obtained. These experiments were approved by the ethics committee of the Tokyo Institute of Technology.

Apparatus

Table 2. Details of apparatus for the experiments.

Apparatus	Details
Three-axis acceleration sensor	Size: 4.5 cm × 4.0 cm Sampling frequency: 100 Hz Model: WAA-006, Wireless Technologies, Japan
PC for data recording	Model: Latitude E5400, Dell, TX, USA
Video cameras	Model: Xacti, Sanyo, Japan, HDR-CX270, Sony, Japan
Television	Size: 60-inch LED display Pixel resolution: 1920 × 1080 Model: UN60ES8000F, Samsung, Korea

Experimental Procedures

As described in the study by Kwon et al (2015), the article for the lecture was "cold reading," which is about the communication technique as a less well-known topic. The article was three A4 pages and 2,759 Japanese characters in length. In face-to-face education condition, the instructor was asked to read and fully understand the article before the experiment. The instructors summarized the article freely in his/her own words for 5 to 10 minutes. The instructors then practiced their lecture and the experimenter confirmed the instructor's lecture. In face-to-face education condition, the instructor and the learner sat face to face across a table at a distance of 1.2 meters. The article was placed on a book stand in front of the instructor, who described the article to the learner in approximately 5 to 10 minutes in Japanese. A small three-axis acceleration sensor was attached to the forehead of each participant to measure time-series data on the acceleration of head nodding motion. The data were transmitted and recorded on a PC via Bluetooth. Furthermore, three video cameras recorded the experimental situation of the instructors and learners.

Table 3. Rules for instructor and learner in face-to-face learning condition

Common rules
- Neither instructor nor learner could change posture significantly. - Neither instructor nor learner could touch the sensor during the experiment.
Instructor's rules
- Instructors speak in a loud and clear voice - Instructors look the learner in the eye while speaking - The instructor was not allowed to show the manuscript to the learner.
Learner's rules
- They listen carefully to the instructor's description - They learn the lecture's content - They were not allowed to ask questions - They were only allowed to use back-channel signals, including head nods and short utterances such as "un," "hai" and "ee," which are equivalent to "mmhm," "uh huh" and "yeah" in English (Kita, and Ide 2007; Maynard 1987)

In the real-time distance education condition, the same procedure was used as the face-to-face education condition, except for the following settings. We informed the instructor and learner of the existence of each other. The instructor and learner sat in separate rooms, and the lecture was given via television. The instructor sat in front of a video camera and described the same article as in the face-to-face education condition. The volume of the instructor's voice via television was adjusted to the actual range of the volume of the instructor's real voice. During the experiment, the instructor was asked to look at the camera while speaking, as if speaking face-to-face with the learner. A video camera in the instructor's room recorded and transmitted the instructor's description (audiovisual information) to a television in the learner's room. The video camera and television were connected by an HDMI cable. The learner sat in front of the television at a distance of 1.8 meters, and the visual angle of the instructor's face was 10.6° (see Figure 1C). The learner was instructed to look the instructor in the eye, to listen carefully to the instructor's description, and to learn the content. Only back-channel signals such as head nod and short utterances were permitted, and the constraints for the experiment were the same as in the face-to-face education condition. In the non-real-time distance education condition, the same procedure was used as the real-time distance education condition, but we did not informed learner of the existence of instructor and we instructed the learner that the lecture is recorded video.

Data Analysis

Algorithm for detection of phase difference

The original algorithm reported by Kwon et al, (2015) is as follows. During head movements, time-series data on the acceleration of three axes were recorded per 10 ms interval. As Figure 1(A), a head movement was defined as a movement in the vertical and longitudinal directions. The time-series data of the norm of the accelerations in the vertical and longitudinal directions (x, z) were calculated as

$$a(t_i) = \sqrt{a_x^2(t_i) + a_z^2(t_i)} \quad \text{for } i = 0, 1, 2, \ldots \quad (1)$$

The interval between t_i and t_{i+1} is 10 ms. As the vertical amplitude of head nodding motion are differed between individuals, $a(t_i)$ was normalized by

$$a'(t_i) = \frac{a(t_i) - \bar{a}}{\sigma_a} \quad . \quad (2)$$

Here, $\bar{a}$ and σ_a are calculated as

$$\bar{a} = \sum_{t_i \in T} \frac{a(t_i)}{|T|}, \quad (3)$$

$$\sigma_a = \sqrt{\frac{\sum_{t_i \in T}\left(\bar{a} - a(t_i)\right)^2}{|T| - 1}}, \quad (4)$$

where T indicates the overall measurement period in each pair. The time-series data $a'(t_i)$ were smoothed with a moving average of 100 ms to reduce fluctuations as follows

$$\overline{a'}(t_i) = \frac{1}{11}\sum_{l=i}^{i+10} a'(t_l) \quad \text{for i =0, 1, 2, ….} \quad (5)$$

When head nods occurred, the local maximum values, hereafter called peaks, existed in time-series data $\overline{a'}(t_i)$. The peak acceleration was therefore defined as the $\overline{a'}(t_i)$ with the following inequality:

$$\overline{a'}(t_i) - \overline{a'}(t_{i\pm1}) > 0 \cdot \quad (6)$$

To extract only reliable signals of head nods, a threshold amplitude for $\overline{a'}(t_i)$ of 2.0 or more was used. It was confirmed visually that peaks of 2.0 or more actually corresponded to head nodding motion using the video data. Thus, the following conditions was imposed on $\overline{a'}(t_i)$:

$$\overline{a'}(t_i) - 2.0 \geq 0 \cdot (7)$$

After detecting peaks in the acceleration of head nodding motion by learner and instructor, the minimum temporal difference ($t_j - t_i$) was calculated from the time (t_i) of a peak in acceleration of the instructor's head nods to that (t_j) of the learner. The range of the phase difference was limited to 1.0 s because it has been reported that the maximal temporal difference for nonverbal synchronization is 1.0 s (Komori, and Nagaoka 2010). Therefore, the following restriction was imposed, in addition to conditions (6) to (7), on the definition of synchronization:

$$-1.0s \leq t_j - t_i \leq 1.0s. \quad (8)$$

In distance learning condition, there was a delay in the transfer of the audiovisual data from the video camera to the television. The learners perceived the delayed information of the instructors and reacted to it as if it were in real time. Therefore, the delay time was measured by calculating the temporal difference between the time depicted on the stopwatch on the computer screen and the one on the television screen. The mean delay time for 50 trials was approximately 160 ± 13 ms (Mean ± SD). Therefore, the instructor's acceleration data was adjusted to the learner's acceleration data with a time delay of 160 ms in data processing.

Analysis of body motion synchrony

As previously described in detail (Kwon et al, 2015), body movement synchronization was analyzed by the phase difference distribution during the whole lecture time. Body movement synchronization is characterized by using statistical indicators of the phase difference distribution over the entire lecture time. Specifically, the four statistical measurements was defined as density, mean phase difference, standard deviation (SD) and kurtosis. In addition, the synchronization was characterized by these four statistical measurements and Table 4 shows the details.

Table 4. Relationship between statistical indicators in the phase difference distribution and synchronization characteristics

Statistical indicator	Synchronization characteristic
Density - Frequency per minute within each pair	Synchronization activity
Mean phase difference - Indicator which indicates whose the body movement of the instructor or the learner leads the synchronization	Synchronization direction
SD - Spread of the phase difference distribution	Synchronization strength
Kurtosis - Degree of convergence to the mean phase difference in the phase difference distribution	

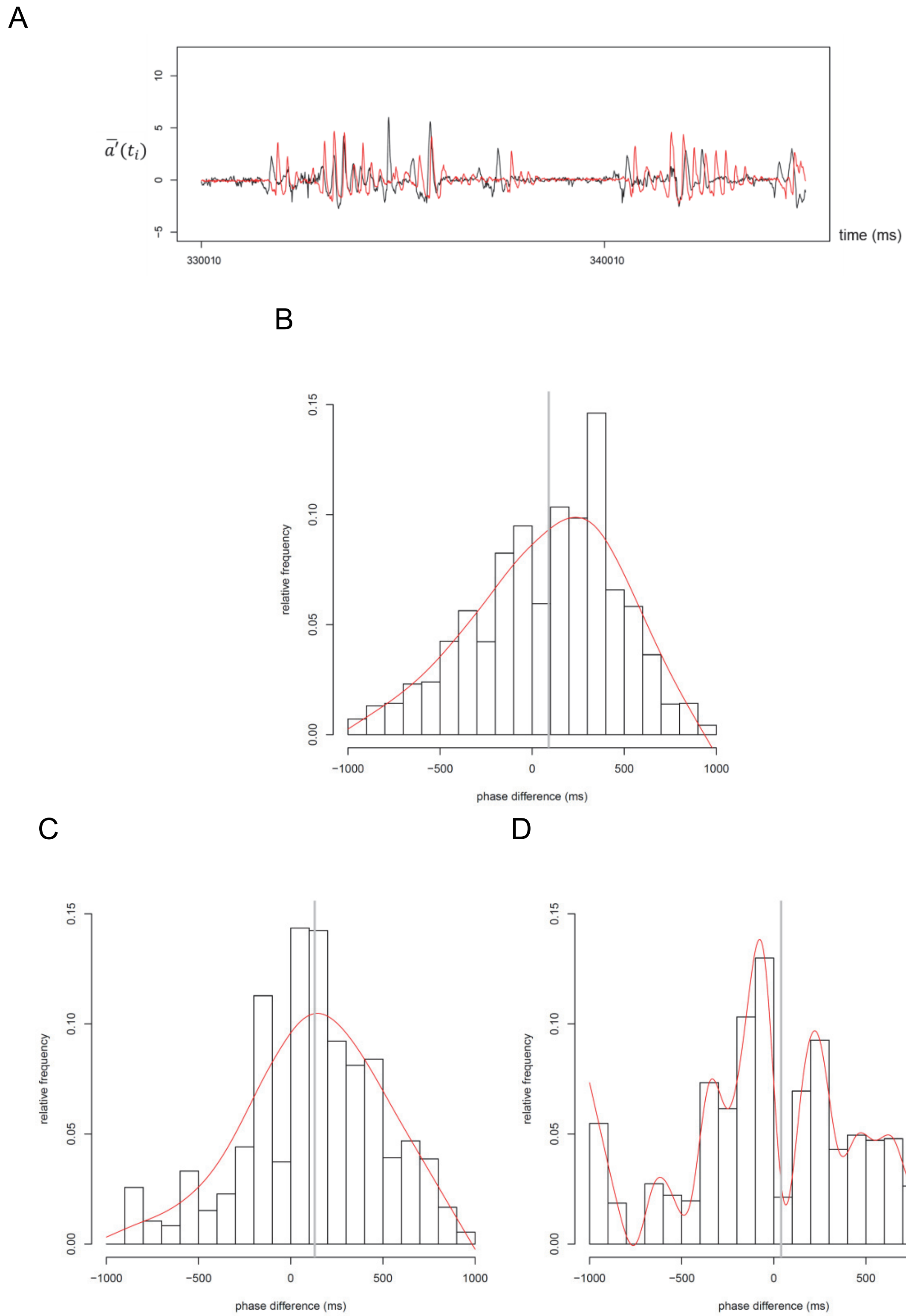

Fig. 2. (A) Typical example of time series data for head nod synchronization in the face-to-face learning condition. The black line indicates the teacher's acceleration data, and the red line shows the learner's acceleration data Total results from the face-to-face education condition (B), the real-time distance education condition (C) and the non-real-time distance education condition (D). Distribution of the mean relative frequency of head nod synchronization across all pairs. A smoothing spline curve (red line) is fitted to the mean relative frequency of head nod synchronization across all pairs and the vertical gray line shows the mean phase difference.

Results

Head nod synchronization was detected using the phase difference distribution and the relative distribution of the phase difference of all instructor–learner pairs was plotted. Figure 2B shows the total results of all instructor–learner pairs from the face-to-face education condition. Total results are obtained by the overall means of the relative frequency of phase differences in each class (intervals of 100 ms) across all pairs. In Figure 2A, the horizontal axis indicates the phase difference, and the vertical axis represents the relative frequency of phase differences in each class. Negative values on the horizontal axis show that the head nod of learner occurred before the instructor's head nod, whereas positive values represent the reverse. In the face-to-face education condition, the mean density across pairs was 6.8 nods/min (SD = 1.9 nods/min). The overall mean (across pairs) of the mean phase differences was 90 ms, and the mean of the SDs across pairs was 360 ms. The mean kurtosis across pairs was 1.0 (SD = 3.7).

Figure 2C shows the total results from the real-time distance education condition. The mean density was 3.2 nods/min (SD = 1.2 nods/min). The overall mean (across pairs) of the mean phase differences was 130 ms, and the mean of the SDs across pairs was 370 ms. The mean kurtosis across pairs was -0.4 (SD = 0.7).

Figure 2D shows the total results from the non-real-time distance education condition. The mean density was 2.4 nods/min (SD = 1.3 nods/min). The overall mean (across pairs) of the mean phase differences was 40 ms, and the mean of the SDs across pairs was 500 ms. The mean kurtosis across pairs was -1.0 (SD = 0.5).

A one-way factorial analysis of variance (ANOVA) of the densities showed a significant main effect for the communication characteristic ($F(2, 15) = 19.53$, $p < 0.001$). Multiple comparisons with Bonferroni correction showed significant differences between the face-to-face and the real-time distance education conditions ($p < 0.05$) and between the face-to-face education and the non-real-time distance education conditions ($p < 0.05$). Moreover, a one-way factorial ANOVA of the SDs revealed a significant main effect of the communication characteristic ($F(2, 15) = 5.831$, $p < 0.05$). In addition, multiple comparisons with Bonferroni correction confirmed that there was a significant difference the face-to-face education and the non-real-time distance education conditions ($p < 0.05$) and between the real-time distance education and the non-real-time distance education conditions ($p < 0.05$). However, one-way factorial ANOVAs of the mean phase differences and kurtoses revealed that there was no significant main effect of the communication characteristic (mean phase difference: $F(2, 15) = 0.496$, $p = 0.49$; kurtosis: $F(2, 15) = 2.10$, $p = 0.17$).

Discussion

Changes in body motion synchrony by spatiotemporal separation

In this study, we investigated how the spatiotemporal separation affects body motion synchrony during the communication process in education. We examined three types of lecture task experiments, which consist of the face-to-face education, real-time and non-real-time distance education conditions. From the results, although the mean phase differences did not differ significantly between the three conditions, there were significant differences in the densities and the SDs in head nod synchrony between the three conditions. Specifically, the densities in the face-to-face education condition was significantly higher than those in the real-time and non-real-time distance education conditions. In addition, the SDs in the face-to-face and real-time education conditions were significantly smaller than those in the non-real-time distance education condition, but there is no significant difference between SDs in the face-to-face education and real-time distance education conditions. We discuss this finding to clarify the communication characteristics by spatiotemporal separation.

There was significant difference in the synchronization activity between face-to-face education and distance education settings. Three factors lead to such differences between two learning situations. The first factor is perceptual interaction between instructor and learner (Bernieri 1988; Schmidt, Carello, and Turvey 1990). The two experiments differed in the visual modality, because the instructors could see the learners' back-channel signals in the face-to-face learning experiment, but this information was not available to the instructors in the distance learning experiment. Thus, the absence of visual feedback in the distance learning condition led to a synchronization characteristics compared with those of the face-to-face learning condition. The second factor is the spatial separation in distance learning situation (Morris 2004; Jones 1993). Although face-to-face education between partners occurs in the same room, distance education is carried out in different rooms. This shared space in the face-to-face learning condition may contribute to the differences in body movement synchronization between face-to-face and distance learning conditions. The third factor is the lack of authenticity in distance learning condition (van der Kleij, Paashuis, and Schraagen 2005; van der Kleij et al 2009). Distance education have been developed to approximate face-to-face education, but the reality created by such interactions still falls short of face-to-face communication. Therefore, the lack of authenticity in distance education may have an effect on body movement synchronization.

Usefulness of the algorithm

In this study, we consider whether body movement synchronization is useful to evaluate communication factors in distance education. From the results, body movement synchronization was detected in face-to-face and distance learning settings using the phase difference detection. Although there were significant differences in the synchronization characteristics between three conditions body movement synchronization can be detected in distance learning situation using the algorithm. We discuss the usefulness of the detection method to evaluate interactive and communication characteristics through the measure of body movement synchronization in distance education.

The findings showed a narrower and precise temporal window for body movement synchronization compared with a previous study (Komori, and Nagaoka 2010). With regard to nonverbal synchronization, Komori (2010) reported that the time lag between the amplitude of the body movements of a counselor and a client occurred within a range of ± 1000 ms. In particular, there was a tendency for the counselors' body movements to be delayed by 500 ms compared with those of clients (Komori, and Nagaoka 2010). However, in this study, the mean phase difference was 110 and 80 ms, and the SD was 320 and 430 ms in face-to-face and distance learning conditions, respectively. This means that body movement synchronization was detected not only in face-to-face learning setting but also in distance learning setting using the algorithm. Thus, this method based on a measure of phase difference in the peak amplitudes between body movements can be useful to detect the accurate temporal properties of body movement synchronization.

Application of our findings

The detection method can apply to the communication technology in distance education system. In particular, the algorithm using the phase difference can be utilized to build a system for visualizing body movement synchronization in real time during distance learning. Figure 4 shows the typical example for application of the algorithm. For example, it is possible to detect acceleration data by web camera or glasses camera and to calculate the phase difference using the algorithm. Then, the interpersonal synchronization of body movements between instructor and learner is fed back into the education system and we are able to evaluate communication characteristics between instructor and learner. Furthermore, the algorithm can be used to evaluate interactive characteristics of collective communication using a tablet or smartphone in ubiquitous smart spaces including distance learning.

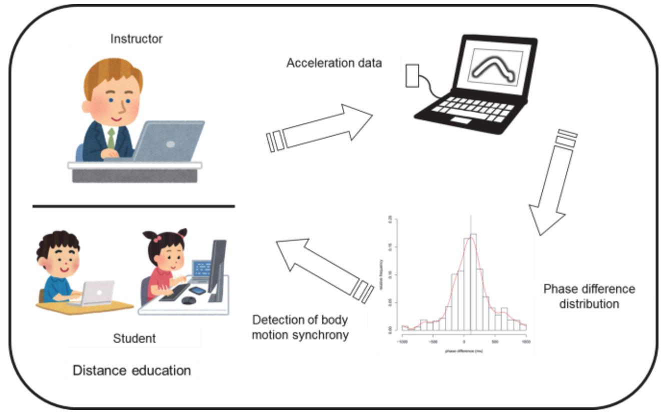

Fig. 4. The typical example for application of the algorithm.

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