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Interpersonal Entrainment of Body Sway in Everyday Face-to-face Communication

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Abstract— **This study investigates whether people entrain their body sway in everyday face-to-face communication. Interpersonal entrainment has been observed under experimental conditions, but not in daily life. We used wearable sensors to measure individual body vibration and face-to-face interactions in daily life. The observation included at least 100 participants from each of seen organization over a period of two to three months. We carried out measurements over a period of two to three months for each organization. It was found that the body vibration frequencies of two participants become more closer in face-to-face situations than in non-face-to-face situations. This result suggests that interpersonal entrainment of body sway occurs in everyday face-to-face communication.**

I. INTRODUCTION

In face-to-face communication, the swaying of people's bodies becomes entrained with each other [1]–[17]. Nonverbal communication, such as the entrainment of body sway, relates to the quality of communication [7], [8], [12], [16], [17]. For example, interpersonal entrainment affects the impression of the communication partner [7] and the smoothness of communication [8], [16]. An accurate measurement and understanding of nonverbal communication in daily life could be expected to indicate how to encourage more efficient everyday communication between people.

A. Previous Studies on Interpersonal Entrainment

For several decades, the entrainment of body sway has been recognized as a rhythmic behavior in social interaction [1]–[17]. For example, Condon and Ogston [5] reported that listeners move in time with the rhythms of a speaker's speech. They analyzed this synchrony by hand scoring videotapes of a listener's body sway with reference to the rhythmic properties of a speaker; that is, the measures were based on subjective procedures.

Recently, measurements have been made more objectively and more quantitatively. In one example, Shockley *et al.* [14] measured two participants' body sway while conversing to solve a puzzle. They conducted cross-recurrence quantification and proposed that the method provides objective evidence of interpersonal coordination. In a recent interesting report, Schmidt *et al.* [15] investigated the coherence of body sway quantitatively as two participants swapped jokes in an experimental setting. They found that body vibrations of high amplitudes cohered with face-to-face communication. These findings indicate that interpersonal entrainment is based on large body sway such as the motion of the human torso.

As stated above, an increasing number of studies have employed more quantitative measures. However, these observations were performed under experimental conditions, not in daily life. From the viewpoint of supporting smooth everyday communication, it is necessary to make observations of daily situations.

B. Life-Log Technology

Recent developments in sensor technologies and the miniaturization of computers have enabled the recording of many types of human activity [18]–[29]. These human activity records are called life logs. Through the use of life-log technology, universal patterns of human activity have been found [18]–[21], [25], [27]. Universal patterns are important and beneficial for the prediction of the risk such as an epidemic spreading possiblity [23], [25].

Furthermore, the diversity of the nature of human activity obtained through life-log technology has been related to the individual's personality [21], [22]. Nakamura *et al.* [21] recorded physical activity data of humans using accelerometers over multiple days, and showed a difference in the activity patterns of healthy individuals and patients with a major depressive disorder. That is, there is the possibility of quantitatively diagnosing depressive illness. Life-log technology has since been applied to social interactions [21], [23]–[29]. Cattuto *et al.* [25] revealed that the duration of human interaction follows a heavy-tailed distribution. This suggests that people do not decide randomly whether to meet others, and there is a pattern of interaction dynamics.

In these previous studies using life-log technology, many types of data have been recorded, not in simulations or under experimental conditions, but in daily life. Hence, results have

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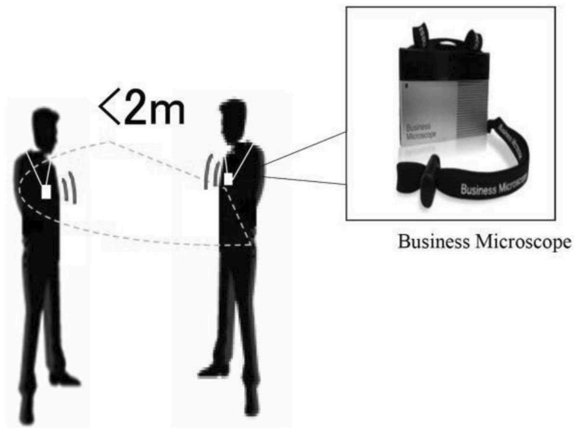

Fig. 1. A wearable sensor (Business Microscope). A participant wears the sensor on the upper torso [28], [29].

been obtained for real social systems. However, little study has focused on the interpersonal physical interaction.

C. Purpose and Approach

The purpose of this study is to quantitatively detect the interpersonal entrainment of body sway in everyday face-to-face communication. We focused on the dissimilarity of frequencies of body vibration between people as the degree of interpersonal entrainment of body sway. If interpersonal entrainment of body sway occurs in face-to-face situations, two people's body vibration frequencies can become more similar in face-to-face situations than in non-face-to-face situations. Note that *non-face-to-face situations* are all situations except a face-to-face meeting, where two people are in different places and engaging in different activities.

Over a period of two to three months, we measured individual body vibrations and face-to-face proximities in seven business organizations having more than 100 employees each through the use of wearable sensors. We then calculated the dissimilarity of two participants' body vibration frequencies in both face-to-face situations and non-face-to-face situations for each organization. Finally, we investigated the difference between face-to-face and non-face-to-face dissimilarities of two participants' body vibration frequencies.

II. METHOD

A. Measurement

The measurement device used was a sensor with an accelerometer and an infrared transceiver worn on the upper torso (Fig. 1 [28], [29]). The frequency of body vibration was measured by the accelerometer and face-to-face interaction was detected by the infrared transceiver.

We evaluated body vibration quantitatively every minute by averaging zero-cross counts per second in a time series, which we obtained from a time series of the acceleration vector's magnitude by reducing the offset. This value, which expresses body vibration quantitatively by the minute, is defined as the body vibration frequency $x_i(t)$[Hz], where i is a participant's label and t expresses a time stamp. The more frequent is the body vibration of the human torso, the higher is $x_i(t)$, since zero-cross counts increase in time series of the acceleration vector's magnitude. According to the report by Ara *et al.* [28], for instance, when $x_i(t)$ is 0 to 2 Hz, participant i is sleeping, browsing the Internet or typing, and when $x_i(t)$ is more than 2 Hz, the participant is walking, running or is in excited discussion.

The index of face-to-face proximities was defined using records of communication between infrared transceivers. The range within which infrared transceivers can communicate is 2 m (within a horizontal angle of 120 degrees and a vertical angle of 60 degrees to the front). The devices exchange their IDs within this range every minute. These ID records indicate who met whom in each time interval.

The measurement data were managed and provided by the World Signal Center, Hitachi, Ltd.

B. Analysis

First, the body vibration dissimilarity, $y_{ij}(t)$, between participants i and j at each time t was defined by

$$y_{ij}(t) = \left| \frac{x_i(t) - x_j(t)}{x_i(t) + x_j(t)} \right| \times 100. \quad (1)$$

The range of $y_{ij}(t)$ is 0 to 100 percent. The lower is $y_{ij}(t)$, the more similar are two participants' body vibrations.

Next, we calculated $\overline{y_{ij}^F}$ as a time average of $y_{ij}(t)$:

$$\overline{y_{ij}^F} = \frac{\sum_{t \in T_{ij}^F} y_{ij}(t)}{|T_{ij}^F|}, \quad (2)$$

where T_{ij}^F is a set that has time labels for when i and j were meeting. $|T_{ij}^F|$ is the total time that participants i and j met each other during the measurement period.

Finally, as the mean of $\overline{y_{ij}^F}$ for each organization, Y^F was calculated:

$$Y^F = \frac{\sum_{(i,j) \in E} \overline{y_{ij}^F}}{|E|}, \quad (3)$$

where E is a set that has pair labels for analysis. For the analysis conditions, see the following section.

In the same way as for face-to-face situations, in the case of non-face-to-face situations, $\overline{y_{ij}^{NF}}$ and y^{NF} were calculated according to

$$\overline{y_{ij}^{NF}} = \frac{\sum_{t \in T_{ij}^{NF}} y_{ij}(t)}{|T_{ij}^{NF}|}, \quad (4)$$

$$Y^{NF} = \frac{\sum_{(i,j) \in E} \overline{y_{ij}^{NF}}}{|E|}. \quad (5)$$

Y^F and Y^{NF} were respectively defined as the degrees of body vibration dissimilarity in face-to-face and non-face-to-face situations for each organization. We compared these values quantitatively.

TABLE I
SUMMARY OF ORGANIZATIONS

Organization	A	B	C	D	E	F	G
Type	R&D	Wholesale	Consultant	Development support	Development	Development	Development
Participants	117	212	135	219	144	109	124
Days	41	48	33	57	57	57	57

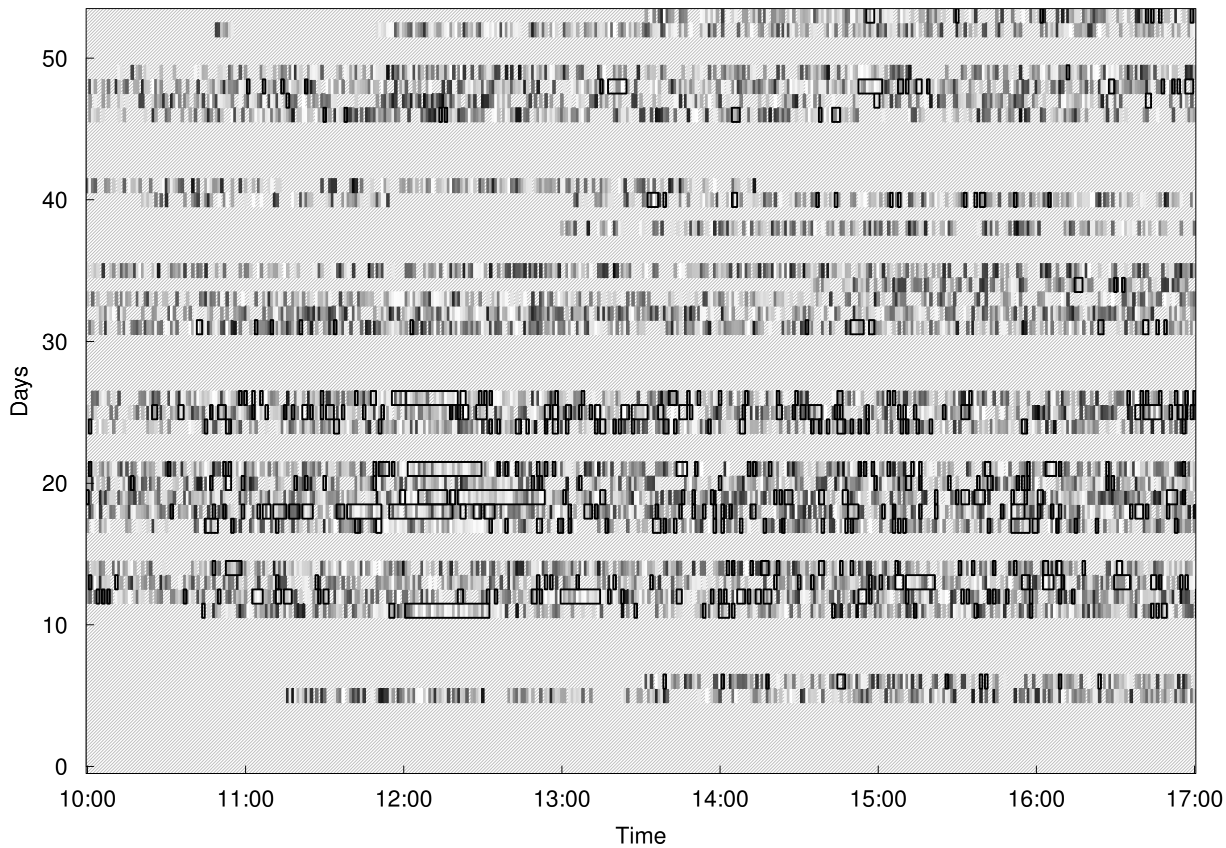

Fig. 2. A sample of the body vibration dissimilarity time series for a pair of participants visualized by gray-scaling. The vertical axis gives the measurement date. The horizontal axis gives a time stamp from 00:00 on each measurement date. Note that the range in the figure is from 10:00 to 17:00 for 53 days. Note that the grayscale indicates $y_{ij}(t)$. Light gray indicates a low value of $y_{ij}(t)$, which means that two people's body vibration frequencies are similar. Dark gray indicates a high value of $y_{ij}(t)$ and dissimilar vibration frequencies. Shading means that one or both participants, i and j, did not wear the equipment. A black frame indicates the time that participants i and j met.

C. Data

We carried out measurements and analysis for seven organizations. The organizations are summarized in Table 1. *Type* expresses the category of business of the organization. *Participants* is the number of people who were analyzed. *Days* is the total duration for analysis. Organizations A, B and C are different companies. Organizations D, E, F and G are different divisions of the same company.

We distributed this equipment to over one hundred of people in each organization. They put on the equipment when arriving at work and took off the equipment when leaving. The data for any individual who had no record for the period of measurement were excluded. We further excluded days on which there were data for less than 10 percent of the total number of participants for analysis. Furthermore, pairs whose total meeting time was less than the following threshold were dropped from the analysis in this study. The threshold was defined as 1/1440 of the whole time period of the measurement for each organization.

III. RESULTS

A. A sample time series of body vibration dissimilarity

Figure 2 visualizes one pair's $y_{ij}(t)$ for organization C. This pair's total meeting time was 1,128 minutes. The figure has the following features. We confirm that the cells in black frames (face-to-face situations) were likely to be

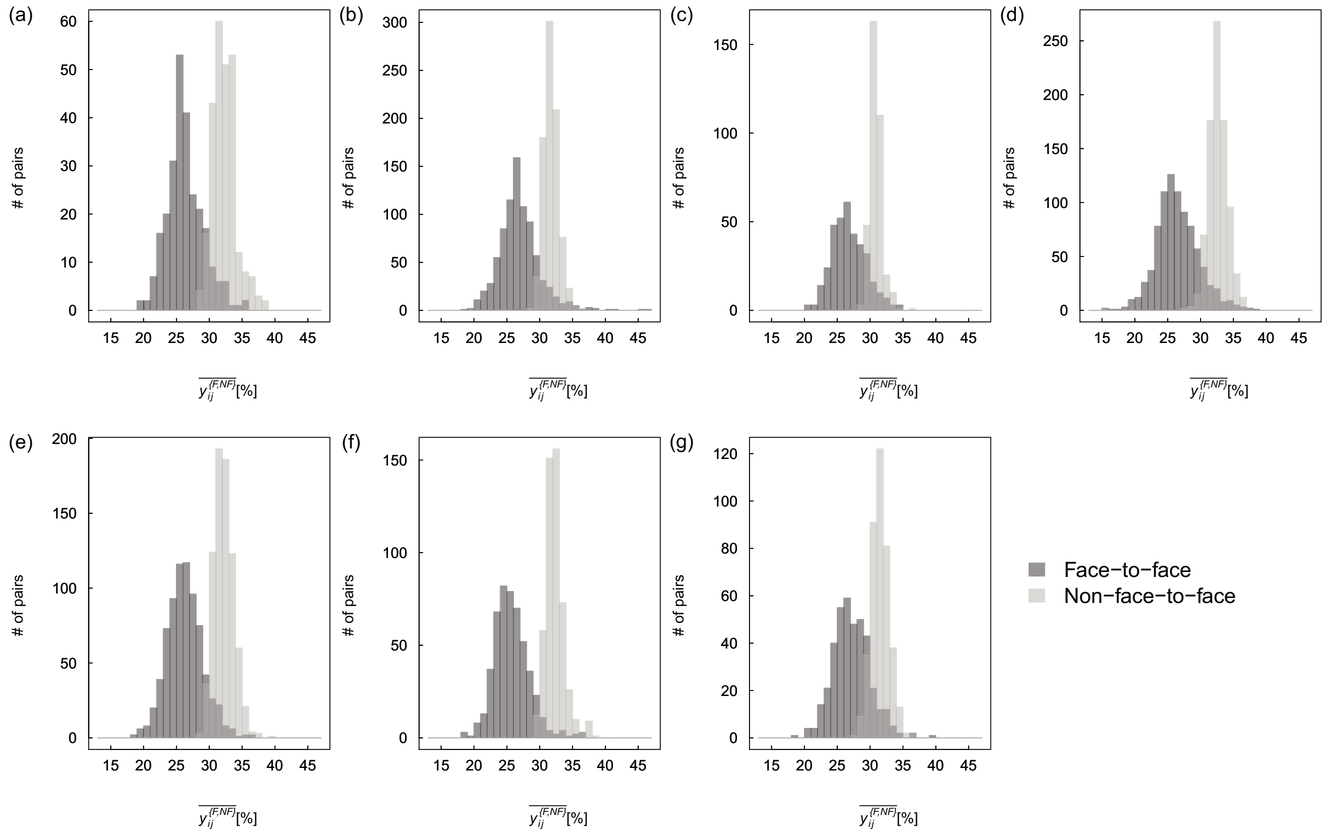

Fig. 3. Histograms of y_{ij}^{F} and y_{ij}^{NF} for each organization. In this figure, subpanels (a), (b), (c), (d), (e), (f) and (g) correspond to the results of histograms for organizations A, B, C, D, E, F and G, respectively. The dark-gray histogram presents the distribution of $\overline{y_{ij}^{F}}$ and the light-gray histogram presents that of $\overline{y_{ij}^{NF}}$.

white; that is, $y_{ij}(t)$ in the face-to-face situation tends to be lower than that in the non-face-to-face situation. This means that the difference between two participants' body vibration frequencies in face-to-face situations is likely to be small.

B. Comparing body vibration dissimilarity in face-to-face situations and non-face-to-face situations

Figure 3 shows the distributions of $\overline{y_{ij}^{F}}$ and $\overline{y_{ij}^{NF}}$ for each organization. For all organizations, the distribution of $\overline{y_{ij}^{F}}$ is lower than that for $\overline{y_{ij}^{NF}}$. Thereby, Y^F was likely to be lower than Y^{NF}. That is, two participants' body vibration frequencies in face-to-face situations tended to be more similar compared with those in non-face-to-face situations.

To clarify this tendency, we applied statistical tests to the difference between Y^F and Y^{NF}. To check the normality of $Y^F - Y^{NF}$, we performed a one-sample Kolmogorov–Smirnov test. Since this test gave $D = 0.168$ ($p = 0.970$), we assumed the normality of $Y^F - Y^{NF}$. Therefore, from the result of a paired difference test between Y^F and Y^{NF}, Y^F is significantly lower than Y^{NF} ($t(6) = -14.870$, $p \ll 0.001$) (Fig. 4). Furthermore, we found a huge effect size in this test ($d = 11.0$), which suggests that there is a very large difference between Y^F and Y^{NF}.

IV. DISCUSSION

As shown in Fig. 4, Y^F was lower than Y^{NF}. This means that the body vibration dissimilarity in face-to-face situations was lower than in non-face-to-face situations for any organizations. Simultaneously, it was found that each organization was likely to have an equal difference of the body vibration dissimilarity between in face-to-face situations and in non-face-to-face situations. Schmidt *et al.* clarified that there was large-amplitude body vibration coherence between two participants in face-to-face interaction [15]. Accordingly, it is suggested that the similar frequencies of two people's body vibrations are due to interpersonal entrainment. Furthermore, we found a huge effect size between face-to-face and non-face-to-face situations. That is, it appears that we can sufficiently observe the interpersonal entrainment of body sway in face-to-face situations regardless of circumstances or conditions such as the telling of jokes [15] or neonate–mother interaction [9].

The result obtained in this paper suggests that it is possible to quantify the face-to-face interpersonal entrainment of body sway in everyday life. Additionally, these observations may reveal the possibility of evaluating the quality of communication. A recent report showed that when teachers gave

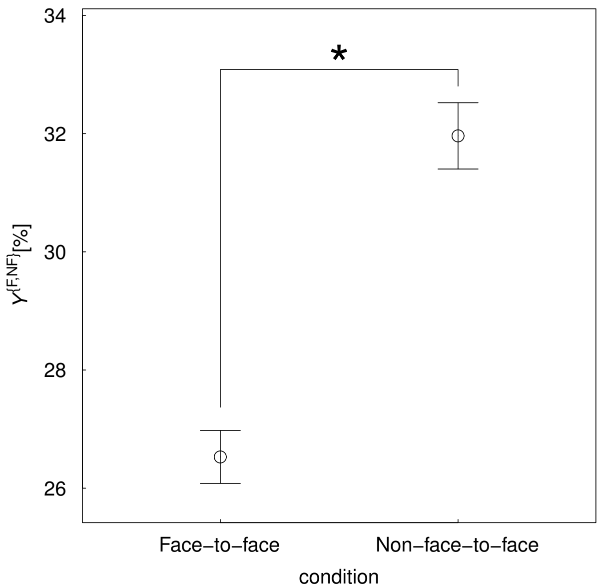

Fig. 4. Averages of Y^F and $Y^N F$. In the face-to-face condition, the circle expresses the mean value of Y^F and $Y^N F$ of seven organizations and error bar the standard deviation; the same is given for the non-face-to-face condition. * = $p \ll 0.01$.

a lecture to students, the degree of students' interest in the lecture could be evaluated by embodied entrainment between the teacher and students [17]. Therefore, we expect that the technology can be used to assess the smoothness of information exchange in daily life. Thereby, it seems we can research the relationship between smoothness of communication and productivity in a business organization.

V. CONCLUSIONS AND FUTURE WORK

A. Conclusions

This study investigated embodied entrainment in everyday face-to-face communication. Individual body vibration and interpersonal interactions were measured over several months at seven companies that had more than 100 employees. We calculated the body vibration dissimilarity between two participants in both face-to-face and non-face-to-face situations. It was revealed that the frequency of body vibration is significantly more similar in face-to-face situations than in non-face-to-face situations. That is, bodies synchronize with each other in usual face-to-face communication irrespective of the circumstances and conditions. Therefore, the observation of the quality of human mass communication are expected in the future.

B. Future Work

Our ultimate goal is to create technology that supports human communication in daily life through face-to-face interpersonal entrainment phenomena. In this study, we showed that interpersonal entrainment can be observed in everyday face-to-face communication using life-log technology [28], [29]. However, to evaluate whether social communication is effective on the basis of interpersonal entrainment, it is necessary to reveal the diversity of features of interpersonal entrainment. Hence, we will investigate the relationship between the degree of interpersonal entrainment and an individual's characteristics, such as employment position, sex, mental health and network centrality.

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