PAPER

Interpersonal Coevolution of Body Movements in Daily Face-to-Face Communication

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SUMMARY People's body movements in daily face-to-face communication influence each other. For instance, during a heated debate, the participants use more gestures and other body movements, while in a calm discussion they use fewer gestures. This "coevolution" of interpersonal body movements occurs on multiple time scales, like minutes or hours. However, the multi-time-scale coevolution in daily communication is not clear yet. In this paper, we explore the minute-to-minute coevolution of interpersonal body movements in daily communication and investigate the characteristics of this coevolution. We present quantitative data on upper-body movements from thousand test subjects from seven organizations gathered over several months via wearable sensors. The device we employed measured upper-body movements with an accelerometer and the duration of face-to-face communication with an infrared ray sensor on a minute-by-minute basis. We defined a coevolution measure between two people as the number of per-minute changes of their body movement and compared the indices for face-to-face and non-face-to-face situations. We found that on average, the amount of people's body movements changed correspondingly for face-to-face communication and that the average rate of coevolution in the case of face-to-face communication was 3–4% higher than in the case of non-face-to-face situation. These results reveal minute-to-minute coevolution of upper-body movements between people in daily communication. The finding suggests that the coevolution of body movement arises in multiple time scales.

key words: *face-to-face contact, body movement, daily communication, minute-time-scale, coevolution*

1. Introduction

In daily face-to-face communication, people's behavior adjusts to the behavior of their communication partners [1]–[11]. This holds for short conversations measured in min-

utes and long meetings or classroom conversations measured in hours. When communicating, people's body movements interrelate on multiple time scales. When a conversation is turning more heated, the participants' gestures and other body movements often increase at the same time. When listening to a passionate speech or an interesting presentation, the audience usually reacts with body movements such as nodding or laughing. When attending a boring class with little body movement from the teacher himself, students' body movements gradually decrease and in the worst case, the students fall asleep. These examples show that body movements of people affect each other and occur via the interaction with other people on multiple time scales in daily life. In this paper, such mutual engagement of people's movement flows on various time scales is called "interpersonal coevolution." We investigated the interpersonal coevolution of people's body movements on a second-time scale for daily situations. We observed the body movements and face-to-face contact of the test subjects [10], [11] using wearable devices [12]. We gathered data from over one thousand test subjects in real organizations over the course of one to two months. The frequencies of upper-body movements were correlated between people who were in face-to-face contact. This study revealed that in daily communication the body movement of one communication partner affects the body movements of the others on a second scale.

In laboratory settings, various research psychologists had already verified interpersonal coordination of body movements [13]–[16]. The interpersonal coordination of body movements between people is coevolution on millisecond or second scales. The interpersonal coordination can be divided into two categories: behavior matching and interpersonal synchrony [17]. The behavior matching is appearance of similar movements between people on millisecond and second scales. People unconsciously imitate their communication partner's body movements such as gestures, posture, and facial expression [18]–[20], which are called mimicry and mirroring. In contrast to the behavior matching, the similarity of the people's movements is not focused on in the interpersonal synchrony. The interpersonal synchrony is simultaneous appearance of movements between people on millisecond and second scales. For instance, when two people know the sentences of the other in advance, their movements spontaneously synchronize [21].

Some researchers revealed the effect of interpersonal

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coordination of upper-body movement on a smooth communication [13]–[16], [21]–[27]. When there are correlating body movements between therapists and their patients, the patients perceive the quality of therapy as better [27]–[29]. These studies show that the quality of communication is affected by interpersonal coevolution between people on millisecond and second scales.

Recently, computer-mediated communication such as affective computing [30]–[33] and social signal processing [34], [35] have also focused on second-scale interpersonal coordination. For instance, in video conferencing, the body synchrony between an interviewer and an interviewee was inferior compared to face-to-face communication [36]. Some researchers applied the interpersonal coordination to human-robot/avatar interaction to achieve an affective interaction between them. Riek *et al.* developed a robot that can mimic facial gestures of people [37]. Watanabe *et al.* constructed a system to entrain the body movements including speech between people and robots/characters [38], [39]. These studies suggest that the interpersonal coevolution can be applied to support communication between people and between people and robots/characters.

Compared to the research of interpersonal coevolution on a second-time scale in various fields, coevolution of body movements occurs on over a second-time scale, while minute-time or hour-time scales are rare. Ono *et al.* investigated the relation between synchronization of body movements and communication context [40]. They revealed that people's nods synchronize when they reach an agreement. Although this study measured the second-scale movements, the authors observed a minute-scale change of the movements relating to an agreement between people. This research suggests the minute-scale coevolution under laboratory setting.

By the lack of knowledge about the over-second-scale coevolution, it seems to be constricted to observe and apply the coevolution in daily life. The time series of body movements on a second scale is usually much less stable or uniform in the real world than in a laboratory setting [11]. That is, in daily situation, it would be difficult to evaluate the quality of people's communication and to support the communication from the viewpoint of second-scale coevolution like many previous studies [13]–[16], [22]–[29], [37]–[39].

Therefore, if the over-second-scale coevolution between people can be seen in daily situation, the evaluation and support of people's communication would be developed. As a first step towards understanding coevolution on over a second scale, this study aims to investigate minute-to-minute coevolution of people's body movements in daily life. Especially, how a person's daily body movements change from minute to minute depending on the people around him or her. We investigate whether the number of body movements changes synchronously among people in daily face-to-face communication, e.g., during a heated discussion or boring classroom presentation, or whether the number of body movements changes in the reverse direction among people.

For this purpose, we analyzed the data of daily upper-body movements of over one hundred test subjects in seven organizations for one or two months, measured using wearable sensors equipped with an accelerometer and an infrared ray sensor. We focused on upper-body movements of people because this is also the focus in the field of daily human behavior on different time scales [10], [11], [41], [42]. We calculated the amount of upper-body movements by the same procedure as in the previous study [12]. The value of minute-by-minute coevolution was determined using the number of movements to investigate the degree of coevolution in daily contact. We compared the coevolution indices between face-to-face and non-face-to-face situations. Finally, we calculated the kurtosis of the coevolution distribution to clear the coevolution structure constructed by people.

2. Materials and Methods

2.1 Test Subjects

We observed organizations from seven corporate sectors. Measurements were taken for 175, 216, 136, 219, 144, 109 and 124 voluntary participants, and 164, 452, 301, 410, 306, 232 and 170 communication pairs (see Table 1). Four of the seven organizations (D to G) belong to the same parent company but operate in different sectors. The types of businesses and divisions included research and development, consulting, sale, and development support. We observed each organization for a few months. The participants' behavior was measured from the time they arrived at work until they left for the day. The ethical committee, general section of Hitachi, Ltd. authorized his measurement. Informed consent in writing was obtained from all participants.

2.2 Measuring Device

Measurements were taken using wearable devices (Business Microscope, Hitachi High-Tech Corp.), which are the size and shape of a business card (see Fig. 1) and can be worn around the neck [10]–[12]. The device was equipped with an accelerometer to measure upper-body movements and an infrared ray sensor to detect face-to-face contact. The temporal resolution of the accelerometer was 50 Hz. From the accelerometer's measurement data, we can calculate the fre-

Table 1 Measured organizations. Organizations observed, by type of business and the numbers of participants, pairs, and days of observation. The Participants and Days columns show the actual/possible frequencies for each organization. The Pairs column shows the number of pairs within face-to-face situation during the observation period.

Organization	Type	Participants	Pairs	Days
A	Product Development Support	219/219	410	57/91
B	Wholesale	212/216	452	48/48
C	Consultant	135/136	301	33/53
D	Research & Product Development	117/175	164	41/63
E	Product Development	144/144	306	57/91
F	Product Development	109/109	232	57/91
G	Product Development	124/124	170	57/91

Fig. 1 The wearable device and the range of the infrared ray sensor. The device was equipped with an accelerometer to measure upper-body movements and an infrared ray sensor to measure the duration of face-to-face interactions. The green and red lines depict the horizontal and vertical range (respectively) of the infrared ray sensor.

quency of upper-body movements (see Sect. 2.4 for more detail), which reflects people's activities such as running (over 4 Hz), excited discussion or rushed walking (3-4 Hz), walking or dynamic gesture (2-3 Hz), talking or typing (1-2 Hz), web browsing or listening (0-1 Hz), or sleeping or no-movement (0 Hz) [12]. The temporal resolution of the infrared ray sensor was 10 s. The sensor's detection field (for detecting other sensors) was 120 degrees horizontally and 60 degrees vertically, with a range of two meters (see Fig. 1).

If an accelerometer reacted at least once, the data for that sensor were used in the analysis. However, days for which the number of reacting sensors was less than 10% of the average daily number of reacting sensors for the whole measurement period, were considered outlier days such as holidays, and the data for these days were dropped from the analysis. If a sensor did not react for more than 20 minutes, we assumed that it was not worn and dropped the data for that period from the analysis.

2.3 Body Movements

The oscillation of upper-body movements accompanied by nodding and other gestures was measured as upper-body movements by the accelerometer [10]–[12]. Figure 2 shows the method of calculating the frequencies of the minute-by-minute upper-body movements. First, the norm, defined as the sum of squares of triaxial accelerations, was calculated. Next, the number of points for which the curve of the norm crossed the per-minute average of the norms (red points in Fig. 2) was calculated. Finally, the per-second average of the crossing number was defined as the frequency of upper-body movement for that minute. This frequency in each minute is called the amount of upper-body movement in this paper.

Note that the acceleration data were measured for 2 s every 10 s. Because of the limited memory capacity of the device, it recorded the acceleration data only during the first 2 s of each 10-s period. Therefore, the upper-body move-

Fig. 2 The method of calculation of the upper-body movements per seconds in every minute. (a) The time series for the norm of the triaxial accelerations. The green bars indicate the per-minute averages of the norms of the triaxial accelerations. The red points depict the crossing points of the norms with the per-minute averages. Note that the curves of the norm (solid black line) expand in the horizontal direction. That is, the real changes of the norm were more rapid than those shown. (b) The time series for the upper-body movements. First, the number of points for which the curve of the norm crossed the per-minute averages of the norms was calculated every minute. The per-second average of the point numbers was defined as the upper-body movement for that minute.

ments were calculated using the norm for 12 of the 60 s. This means that the calculated values for the upper-body movement also decreased by that amount.

2.4 Face-to-Face Contact Events

Each device had a unique ID, and each participant always wore the same sensor with the same ID. Through these IDs, the face-to-face contact between two individuals was identified [10]–[12]. When participants i and j were detected by a wearable device within the communication range of the infrared sensor during a one-minute time block, the device recorded a “1” at that block. If the score “1” was logged, we recognized that the participants i and j had been in face-to-face contact. If i and j contacted the participant h at the same time and i and j were over 2 m apart, the device recorded a score for the time of i and j .

2.5 Coevolution Value for Upper-Body Movements

2.5.1 Coevolution Value in Face-to-Face Situations

The coevolution value of an upper-body movement during a face-to-face situation is defined as follows:

$$CE_F(i, j) = \frac{\sum_{t \in T_F(i, j)} g(\Delta x_i(t) \cdot \Delta x_j(t))}{|t \in T_F(i, j)|}, \quad (1)$$

where $CE_F(i, j)$ is the coevolution value in face-to-face situations, $\Delta x_i(t)$ is the difference in the amount of upper-body movement for participant i between time t and time $t + 1$, and

$T_F(i, j)$ is the elapsed time during which participants i and j are face-to-face, with both of their amounts of upper-body movement being non-zero. The denominator in Eq. (1) represents the total duration of face-to-face situations between i and j . The term $g(*)$ is a function that returns +1 for a positive argument and -1 for a negative argument. That is, when the upper-body movement for both members of a pair increases or decreases at the same time, $g(*)$ is +1. When the upper-body movement increased for one member of a pair and decreased for the other member at the same time, $g(*)$ is -1. $CE_F(i, j)$ is the sum of all $g(*)$ for the elapsed time $T_F(i, j)$ when i and j are face-to-face, which is normalized. That is, $CE_F(i, j)$ represents the time-averaged degree of coincidence (or non-coincidence) between the pair's changes in upper-body movement during all face-to-face situation.

A positive value of $CE_F(i, j)$ means that the changes of upper-body movements of i and j during their face-to-face situation were synchronized with each other. A negative value of $CE_F(i, j)$ means that the changes of upper-body movements were not synchronized. If a pair changed all their upper-body movements during a face-to-face situation together, $CE_F(i, j)$ would be +1. In contrast, if the pair's upper-body movements always involved opposite changes, $CE_F(i, j)$ would be -1.

The coevolution value does not indicate the similarity of the degree of movement between people. This value represents the similarity of changes in direction (up or down) of the degree of movement. This means that even if the amounts of body movements are close between people, the coevolution value is not always high. In addition, this value does not assess the characteristics of the group, only those of each pair.

2.5.2 Coevolution Value in Non-Face-to-Face Situations

For those pairs who were in a face-to-face situation at least once during the observation period, the coevolution value for non-face-to-face situations was defined in a similar manner: Non-face-to-face situation means that the pair was in a place where both infrared ray sensors did not detect the partner's sensor.

$$CE_{NF}(i, j) = \frac{\sum_{t \in T_{NF}(i, j)} g(\Delta x_i(t) \cdot \Delta x_j(t))}{|t \in T_{NF}(i, j)|}, \quad (2)$$

where $CE_{NF}(i, j)$ is the coevolution value for non-face-to-face situations and $T_{NF}(i, j)$ is the elapsed time during which participants i and j were not face-to-face. The other variables are defined in the same way as for a face-to-face situation. That is, $CE_{NF}(i, j)$ represents the time-averaged degree of coincidence (or non-coincidence) between the pair's changes in upper-body movement during all non-face-to-face situations.

3. Results

The time-series data in Fig. 3 show a sample of the upper-body movement for each minute for a pair of participants

Fig. 3 Sample time series data for upper-body movements. These sample data show upper-body movements for a pair of participants from Organization C. The green area shows a period when the pair was not face-to-face, and the red area shows when they were face-to-face. The upper color bar indicates when their upper-body movements changed correspondingly (yellow) or oppositely (blue).

from Organization C. The red area indicates a period of a face-to-face situation, whereas the green area indicates a period when the pair was not face-to-face. When the amount of upper-body movement for each of the pair increased or decreased at the same time, we call this “corresponding coevolution.” When the amount of upper-body movement increased for one person and decreased for the other person, we call this “opposite coevolution.”

We found that in face-to-face situations, people tended to coevolve in a corresponding manner, but that in non-face-to-face situations, there was no such tendency. Figure 4 shows histograms of the coevolution values for each pair of participants in face-to-face and non-face-to-face situations, for each organization. The coevolution value refers to the rate of corresponding and opposite coevolution in face-to-face (or non-face-to-face) situations. If a pair is always in corresponding coevolution, the value of the coevolution is +1. In contrast, if a pair is always in opposite coevolution, the value is -1. If a pair showed equal amounts of corresponding and opposite coevolution, the coevolution value would be 0.

For non-face-to-face situations (green bars in Fig. 4) the peak of the distribution is near zero for all organizations. This result indicates that in non-face-to-face situations people did not coevolve their body movements correspondingly or oppositely from minute to minute. In face-to-face situations (red bars in Fig. 4) the peak of the distribution is positive. This result shows that in this situation people had the tendency to coevolve correspondingly with each other in minute scale.

The between-pair-averaged coevolution values for each of the seven organizations (A to G) for the whole period are shown in Fig. 5 and Table 2. We conducted a paired t -test, and the result showed significant differences for the coevolution values between face-to-face and non-face-to-face situations ($t_6 = 20.88$, $P = 0.000002$). The effect size was large ($r = 0.99$). The two-sided 95% confidence interval

Fig. 4 Histograms of coevaluation values for each pair of participants. Panels (A) to (G) show the histograms for each of the organizations (respectively) as identified in Table 1. The red and green bars show the histograms for face-to-face and non-face-to-face situations, respectively. The vertical axis is the rate of the pair to all the pair number in each organization.

Fig. 5 The coevaluation value averaged among pairs for each organization. Organizations A to G on the horizontal axis correspond to the organizations as identified in Table 1. The red and green bars show the averages for face-to-face and non-face-to-face situations, respectively. The error bars represent the standard deviations among pairs.

for the difference between the average coevaluation values in face-to-face and non-face-to-face situations was between 0.060 and 0.079. This means that the amount of corre-

Table 2 Means and kurtoses of coevaluation for face-to-face and non-face-to-face situations in each organization. s.d. indicates standard deviation of coevaluation.

Organization	mean $\pm$ s.d.		kurtosis	
	face-to-face	non-face-to-face	face-to-face	non-face-to-face
A	0.091 ± 0.130	0.008 ± 0.014	0.33	2.62
B	0.069 ± 0.114	0.006 ± 0.011	0.35	0.89
C	0.086 ± 0.146	0.009 ± 0.016	0.72	1.90
D	0.069 ± 0.096	0.005 ± 0.009	0.46	0.78
E	0.079 ± 0.109	0.005 ± 0.007	0.52	0.54
F	0.075 ± 0.092	0.004 ± 0.010	0.29	2.34
G	0.058 ± 0.114	0.005 ± 0.008	0.33	0.73

sponding coevaluation in face-to-face situations was 3% to 4% higher than in non-face-to-face situations because the coevaluation values ranged from -1 to 1 .

We calculated kurtosis of each situation in each organization to investigate the shape of the distribution. The results are shown in Fig. 6 and Table 2. When the kurtosis was positive, we had a fat-tailed distribution compared to a normal distribution. For each situation in all organizations, the kurtosis was positive. The paired t test showed that there were significant differences between face-to-face and non-face-to-face ($t_6 = -2.873$, $P = 0.028$) situations. The effect

Fig. 6 The red and green bars show the kurtosis of each organization for face-to-face and non-face-to-face situations

size was large ($r = 0.76$). The two-sided 95% confidence intervals for the kurtoses of face-to-face and non-face-to-face are between 0.29 and 0.57 and between 0.60 and 2.20, respectively.

4. Discussion

The present study aimed to reveal minute-to-minute coevolution of body movements between people in daily face-to-face communication. We calculated the number of upper-body movements and face-to-face contact from data collected with wearable sensors. We defined the coevolution value between two individuals and compared the values of indices between face-to-face and non-face-to-face situations. The corresponding coevolution in face-to-face contact was on average higher than for non-face-to-face situations. The coevolution was near zero in non-face-to-face situations, and the coevolution value in face-to-face situations for the corresponding direction was 3% to 4% higher than that in non-face-to-face situations. The kurtoses were positive for both face-to-face and non-face-to-face situations in all organizations. Additionally, the kurtosis was higher in non-face-to-face situations than in face-to-face situations.

The result of averaged coevolution shows that the upper-body movements of people tend to coevolve correspondingly from minute to minute when they are face-to-face in daily life. That is, in a face-to-face situation, people synchronously increase or decrease their upper-body movements. Our previous study found that if people are in a face-to-face situation, their number of body movements tends to be similar [11]. Our result suggests that we do not achieve similarity of upper-body movements by closing the gap of the amount of body movements between people. In addition to the similarity of the number of body movements, people also synchronize the change direction (increase/decrease) of their body movements on a minute time scale.

The minute-scale coevolution of upper-body movements in this research may relate to the second-scale coevolution of various body movements. Research revealed that in laboratory settings, the body movement of one communi-

cation partner encourages the body movement of the other communication partner. If this encouragement also occurs in daily face-to-face communication, the minute-to-minute coevolution we observed would be partially caused by an accumulation of encouragement. In that case, the average corresponding coevolution values reported here could represent the smoothness of communication.

Note that on average, the coevolution of all pairs increased to the corresponding direction in face-to-face situations, whereas the coevolution value of some pairs increased to the opposite direction in all organizations. This result shows that some people often increase (decrease) their upper-body movement when the partner in a face-to-face communication decreases (increases) the upper-body movement. This opposite coevolution does not necessarily represent a “bad communication” such as a less smooth communication. This coevolution might depict different temporal cooperation from corresponding coevolution. For example, this opposite coevolution is partially caused by switching the roles of speaker and listener. One way to clarify the relation of coevolution in daily face-to-face communication and the quality of the communication is to reveal the relation of different time scale coevolution.

In the present study, the change in corresponding coevolution value was about 3% to 4% across all organizations. That is, although the coevolution values varied between pairs, and the business type and the number of participants and pairs were different for the different organizations, the average values were consistent among the seven organizations. This might mean that the corresponding coevolution value is constant for face-to-face situations in real-world organizations. However, it should be noted that all measurements in the present study were performed in Japanese companies and that many participants were office workers. Therefore, cultural and job-related differences might affect coevolution values. In addition, we could not obtain personal data of the participants, such as age, gender, or educational background, which might also affect coevolution values. Further investigation taking personal data, culture, and job style into account will reveal the details of daily coevolution between people.

The kurtoses were positive in all distributions, which means that all coevolution distributions are fat-tailed compared to a normal distribution. Furthermore, non-face-to-face kurtosis was higher than face-to-face kurtosis in each organization. If people move randomly or independently to other people in non-face-to-face situations, the coevolution distribution would be close to a normal distribution. The higher positive kurtosis in the present study suggests a coevolution structure even for the non-face-to-face situations. In addition, the difference of kurtoses for face-to-face and non-face-to-face situations reveals that face-to-face contact changes the coevolution structure.

The positive kurtosis in non-face-to-face situations might be because of non-face-to-face contacts between people such as phone communication. Additionally, coincidences of task schedules between people might affect the

results. For example, if people began to walk to join a meeting at the same time or if people arrived at and/or left from their office at the same time, the coevolution would be observed, even if they were not in face-to-face situations. These coincidences might also cause the slightly positive averages of the coevolution values in non-face-to-face situations (Fig. 5). The reason of coevolution in non-face-to-face situations should be investigated in future works.

Nakamura *et al.* investigated daily body movements of healthy people and patients with a major depression using accelerometers [41], [42]. They found a universal distribution of periods of high and low body movements. The universal distributions ranged from a few minutes to a few hours. The distribution parameter was different between the healthy people and the patients. The authors discussed this difference from the viewpoint of different social interaction patterns between the two groups. These results had suggested the existence of coevolution over a few minutes/hours and relations between minute-scale and hour-scale coevolution. In fact, the present study revealed an in-minute coevolution between the upper-body movements and the non-random structure of coevolution in daily life. The methods and results of the present study would reveal a longer time-scale coevolution, and the observation of more people for an extended period could reveal the relation between multi-scale coevolution.

Finally, we discuss limitations of our present study and future work. For this study, we used low-level sensor data. Although our study suggests a coevolution of nods in laboratory settings [40], it is yet unclear which upper-body movements, such as nods, hand gestures, and trunk movements, coevolve in a real world setting. A detailed measurement of body movements might reveal the daily coevolution more clearly. As a first step in determining the coevolution in a real world setting, we started to measure minute-to-minute coevolution. However, a human's cognitive or affective state might change and be observed in the coevolution of body movements on a time scale that is longer than the one used in this study, such as a few minutes. To understand human coevolution in more detail, we need to consider longer time scales.

5. Conclusion

Using wearable sensors with accelerometer and infrared ray sensor, we observed minute-to-minute coevolution of upper-body movements between people in daily life. We collected data of over thousand people in seven organizations during a few months and found the amount of people's body movements changes correspondingly in face-to-face situations compared to non-face-to-face situations. The corresponding coevolution value was 3% to 4% higher for face-to-face situations than for non-face-to-face situations for all organizations that we investigated. The results revealed the minute-to-minute coevolution in daily face-to-face communication. In addition, the coevolution distributions for both face-to-face and non-face-to-face situations are fat-

tailed compared to a normal distribution. Furthermore, the tail of non-face-to-face distribution was fatter than that of face-to-face situations. These results suggest that even in non-face-to-face situations, in-minute coevolution does not have a random structure and that face-to-face contact alters the structure.

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