Ferromagnetic interaction model of activity level in workplace communication

Tomoaki Akitomi, Koji Ara, Jun-ichiro Watanabe, and Kazuo Yano

Hitachi, Ltd, Central Research Laboratory and 1-280, Higashi-koigakubo, Kokubunji-shi, Tokyo 185-8601 Japan

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The nature of human-human interaction, specifically, how people synchronize with each other in multiple-participant conversations, is described by a ferromagnetic interaction model of people's activity levels. We found two microscopic human interaction characteristics from a real-environment face-to-face conversation. The first characteristic is that people quite regularly synchronize their activity level with that of the other participants in a conversation. The second characteristic is that the degree of synchronization increases as the number of participants increases. Based on these microscopic ferromagnetic characteristics, a "conversation activity level" was modeled according to the Ising model. The results of a simulation of activity level based on this model well reproduce macroscopic experimental measurements of activity level. This model will give a new insight into how people interact with each other in a conversation.

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Introduction. Many phenomena, such as the synchronization of a firefly's glow with those of other fireflies, suggest that living animals influence each other more strongly than was originally thought [1]. In the case of people, many synchronization phenomena, such as synchronization of lengths of menstrual periods [2] and applause at a concert [3], exist. In particular, conversation has been found to involve a lot of synchronization phenomena related to postures, gestures [4], words, tone of voice [5], and timing of turn taking [6]. Furthermore, synchronization in a conversation has been attracting attention, because it is related to affiliation between conversational partners [7] and makes a conversation smoother and more successful [8,9]. These research studies, however, were based on a two-participant conversation; so the dynamics of synchronization of a multiparticipant conversation, which often occurs in a real environment condition, has not yet been revealed.

In the present study, to determine the synchronization mechanism in a multiparticipant conversation, the effect of the number of participants on activity-level synchronization was analyzed through data on real-environment face-to-face conversation. As for this analysis, all conversations in a real environment, namely, a company employing 412 people, were measured over three months by using "wearable social badges." The measurement data indicate who met whom, when and where they met, and what their activity levels were. Analyzing these data reveals two basic characteristics of the activity level of human conversation: first, people synchronize with each other; second, the degree of synchronization increases as the number of participants increases. A statistical-physics model including these characteristics was made, and the model was verified by comparing measurement results and simulation results of activity level in a conversation. This comparison indicates that human's complex synchronizing behavior can be described using the framework of statistical physics.

Measurement. Social badges and IR beacons were used to measure the workplace conversations [10]. These devices not only measure the simple amount of face-to-face conversation but also predict a person's state, such as concentrating, when working alone [11]. Each social badge has three functions. First, it measures a person's physical movement (in terms of an "acceleration signal") by using a single three-axis accelerometer. "Zero-crossing counts," defined as the number of times an acceleration signal crosses the zero level within a predefined time, are used to identify individual activity levels such as being quiet, web browsing, keyboard typing, gesturing, and walking. Second, it captures the time involved in face-to-face communication by using six infrared (IR) sensors that can detect when two people wearing badges are facing each other. Third, it captures location data by using the IR sensors to detect when the person wearing the badge is near an IR beacon.

Conversations in a software-development company were measured over three months. All 412 people who work in the main office building cooperated in this experiment and wore social badges. As for their working roles, 231 people work in development teams, and 181 people work in management teams. As for their hierarchical positions, 59 people hold positions higher than managerial level, and 353 people hold positions lower than managerial level. To ensure that conversations are analyzed under the same conditions, it is necessary to identify whether a communication was a formal meeting or an informal chat. Accordingly, 42 IR beacons were set up in all of the 12 meeting spaces in the building, and all conversations occurring in those meeting spaces were analyzed.

To model the activity level of conversation, the state of face-to-face conversation must first be defined in terms of both individual state and group state. In a conversation, the activity level of each individual is in a certain state. For example, someone in a communication who is gesturing, speaking, or nodding strongly would be at a high-activity level, and someone just sitting and not reacting would be at a low-activity level. Although the activity level is actually in a continually changing state, hereafter, it is simply discriminated as either of two levels, "active" or "nonactive," for the sake of simplicity. Group activity level (L_{ga}) expresses the state in which the communication itself is active or not. To model this state, it is assumed that the group state is a summation of each participant's state. L_{ga} is defined as

$$L_{ga} = n_a/N, \tag{1}$$

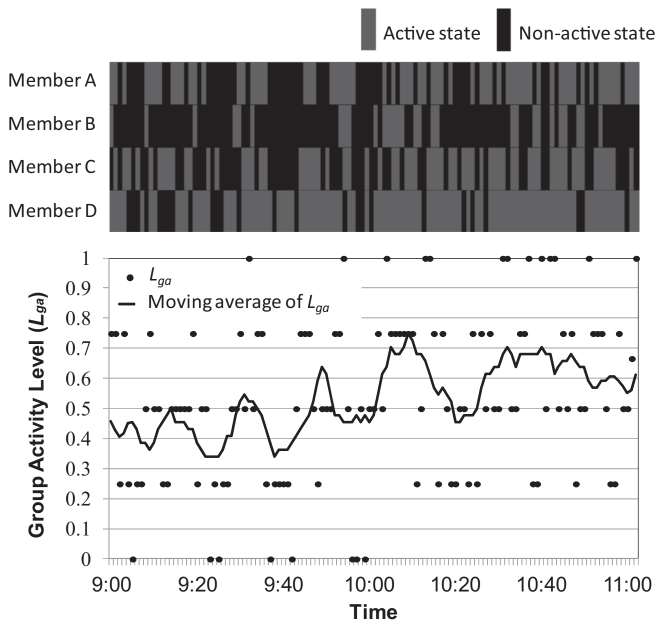

FIG. 1. Each member's active state (top) and L_{ga} (group activity level) (bottom). Each member's active state looks somewhat random; however, the moving average of L_{ga} shows the oscillation of activity level of the conversation.

where n_a means the number of the participants who are active, and N means the total number of participants. L_{ga} ranges from "0" to "1," where "1" is the maximum activity level (i.e., all participants are active) and "0" is the minimum activity level (i.e., nobody in the communication is active). Activity level, defined above, was calculated from sensor data in the following way. The activity state of each individual was classified as either active or nonactive every minute according to the zero-crossing count, which was calculated every 10 seconds (Z_{10s}). The maximum Z_{10s} over 1 minute ($Z_{\max}$) is used to determine whether the participant is active or not. An example of an individual's activity state and L_{ga} in a meeting is shown in Fig. 1.

To determine if people microscopically synchronize in a multi-participant conversation, the "transition probability" of the active state (namely, the probability that activity level will change) was focused on. If people synchronize their active state with other participants' states, a participant's transition probability should follow the other participants' states. For example, if the number of active-state participants out of all the other participants increases, a participant's transition probability for nonactive to active ($P_{na\to a}$) should increase, and that for active to nonactive ($P_{a\to na}$) should decrease. To visualize this effect of synchronization, the relation between $P_{na\to a}/P_{a\to na}$ and the number of other active-state participants for each size of a conversation (i.e., number of participants) is plotted in Fig. 2. It is clear from this graph that regardless of the size of a conversation, $P_{na\to a}/P_{a\to na}$ increases exponentially as the number of active-state participants increases. In other words, no matter how big or small the size of the conversation is, people always synchronize their activity level with that of others.

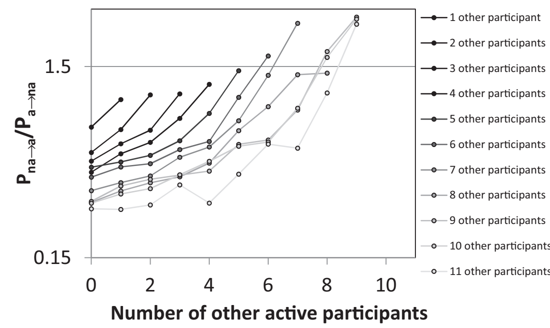

FIG. 2. Single logarithmic graph, showing the relation between $P_{na\to a}/P_{a\to na}$ and the number of other active-state participants. To ensure calculation reliability, the points in the graph that were calculated from samples of less than 10 transitions were excluded. In addition, the larger the size of a conversation is, the fewer times a conversation occurs. The size of the target for analysis of communication was limited to 12 people, under which more than 70% of the points could be calculated from samples of more than 10 transitions.

To quantify this synchronization effect, a "synchronization index" ($=I_s$) is defined as

$$I_s = \frac{\Delta \log(P_{na\to a}/P_{a\to na})}{\Delta r_a}, \tag{2}$$

where r_a is the ratio of active participants out of all the other participants. To make the relation of $P_{na\to a}/P_{a\to na}$ and r_a linear, the logarithm of $P_{na\to a}/P_{a\to na}$ was taken. I_s is the gradient of $\Delta \log_(P_{na\to a}/P_{a\to na})$ over r_a and indicates how strongly a participant is influenced by the surrounding conditions. Linearity of $\Delta \log(P_{na\to a}/P_{a\to na})$ and r_a is listed in Table I. According to the table, a significantly high correlation coefficient for each size of a conversation confirms that people regularly synchronize with others in a conversation and that I_s is a good index for expressing the synchronization of a human conversation.

To determine the effect of size of a conversation on synchronization in a multiple-participant conversation, the correlation between size of a conversation and I_s was calculated (see Fig. 3). The coefficient of the correlation was significant

TABLE I. Linearity of $\Delta \log(P_{na\to a}/P_{a\to na})$ and r_a. N_o means number of other participants in a conversation. R means correlation coefficient, and p means significance probability.

N_o	R	p
1	–	–
2	0.99	0.07
3	0.97	0.03
4	0.98	0.00
5	0.93	0.01
6	0.92	0.00
7	0.94	0.00
8	0.97	0.00
9	0.93	0.00
10	0.94	0.00
11	0.88	0.00

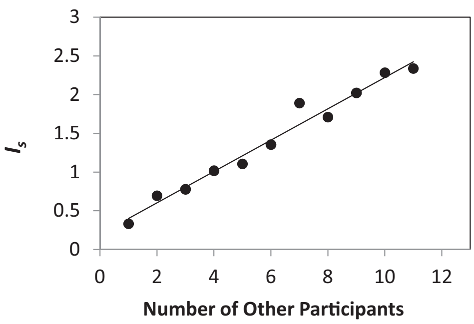

FIG. 3. Synchronization Index (I_s) versus number of other participants in a conversation.

($R = 0.99$, $p < 1.0 \times 10^{-7}$) and confirmed that the degree of synchronization in a conversation gets higher as the number of other participants increases.

Ferromagnetic model. To develop a model describing human-human synchronization in a multiple-participant conversation, a framework based on statistical physics, which has proved to be useful to model social dynamics [12] such as opinion dynamics [13,14], crowd behavior [15], and stress dynamics [16], was applied. To make a model of a multiple-participant conversation based on statistical physics, a full-mesh network structure was chosen. This network structure was chosen on the supposition that every participant in the same conversation at least somewhat influences the other participants. Based on this network structure, an Ising model of a conversation activity level is proposed as the following Hamiltonian:

$$\mathcal{H}_i = -J s_i \sum_{\langle j \rangle} s_j - H s_i. \tag{3}$$

Here s_i is the active state of each participant, taking a value of either "-1" (nonactive state) or "1" (active state), h is the coefficient of external effects (such as location), and J is the coefficient of synchronization. In this model, a participant is modeled as an atom, the active state of the participant as the spin of the atom, the external effect as an external magnetic force, and the randomness of the participant's transition of active state as temperature.

Simulation. To determine the macroscopic characteristic of the Hamiltonian and verify its appropriateness, the proposed model was simulated by applying the Metropolis method [17]. In this method, the Monte Carlo step, in which the selected participants' energy is calculated with flipped active state and that state is adopted according to the probability given by Eq. (4) from time step t_i to t_{i+1}, is repeated a fixed number of times to minimize the energy. The participants to be calculated in a flipped active state are selected randomly in each step, according to a Gaussian distribution with a mean probability of 0.5:

$$P_{s(t_i)\to s(t_{i+1})} = \begin{cases} \frac{e^{-\Delta E/T}}{Z} & \text{if} \quad \Delta E > 0 \\ 1 & \text{if} \quad \Delta E \leqslant 0 \end{cases}. \tag{4}$$

The difference between the energy of a state before and after a spin flips is denoted as ΔE, temperature is T, and Z is a normalization constant. To conduct this simulation, parameters H, J, and T have to be determined on the basis of the measured transition probability. The way to estimate H, J, and T is described as follows. J is set as $J = 1$ because the number of degrees of freedom of the Ising system is two, and one of either H, J, or T has to be set.

From Eq. (4) it is clear that, the ratio of transition probability under different conditions (namely, r_a and N_o) is described as

$$\frac{P_{(na\to a, r_a, N)}}{P_{(a\to na, r_a, N)}} = e^{\frac{-(E_{(a,ra,N)} - E_{(na,ra,N)})}{T}}. \tag{5}$$

This ratio of transition probability is useful, because even though either $\Delta E_{na\to a}$ or $\Delta E_{a\to na}$ being negative and $P_{na\to a}$ or $P_{a\to na}$ being 1, the ratio could be described in an equation as Eq. (5) without dividing into cases. $\log(P_{na\to a}/P_{a\to na})$ could be assumed to have a linear relationship with r_a according to the measurement results listed in Table I. On the basis of Eq. (3), Eq. (5), and the measurement result that $\log(P_{na\to a}/P_{a\to na})$ and r_a have a linear relationship, $\log(P_{na\to a}/P_{a\to na})$ is given as

$$\log\left(\frac{P_{(na\to a, r_a, N_o)}}{P_{(a\to na, r_a, N_o)}}\right) = I_s(N_o) r_a + B(N_o), \tag{6}$$

$$I_s(N_o) = \frac{4}{T} N_o, \tag{7}$$

$$B(N_o) = -\frac{2}{T} N_o + \frac{2H}{T}. \tag{8}$$

The procedure to estimate parameters T and H consists of two steps. First, both $I_s(N_o)$ and $B(N_o)$ were estimated by the method of least squares using measurement data varying in terms of r_a. $I_s(N_o)$ and $B(N_o)$ shown in the Fig. 4 "experiment," which were estimated from experiment data, suggest the linearity of $I_s(N_o)$ versus N_o ($R = 0.99$, $p < 1.0 \times 10^{-7}$) and $B(N_o)$ versus N_o ($R = -0.98, p < 1.0 \times 10^{-7}$). The result also suggests that T and H are independent of N_o and can be treated as constant values. Second, T was estimated from Eq. (7) and $I_s(N_o)$, and H was estimated from Eq. (8) and $B(N_o)$.

Performing the two steps described above gave $\{H,J,T\}$ as $\{-3.20, 1.0, 17.5\}$. Parameter H being negative means that external effects lower a participant's activity level. This result is consistent with those of former studies, suggesting that formal communications, such as those occurring in meeting places, tend to be one-way and not active [18]. The present experiment focused on conversations occurring in meeting

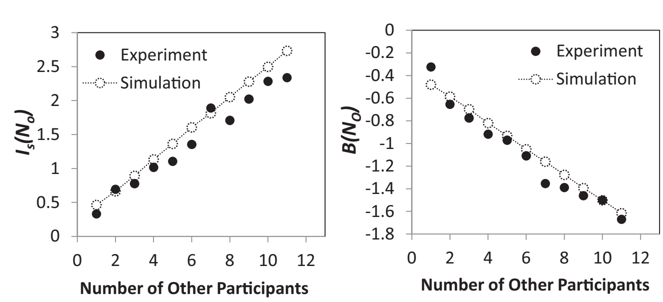

FIG. 4. Experimentally measured and simulated results $I_s(N_o)$ (left) and $B(N_o)$ (right) versus number of other participants in a conversation.

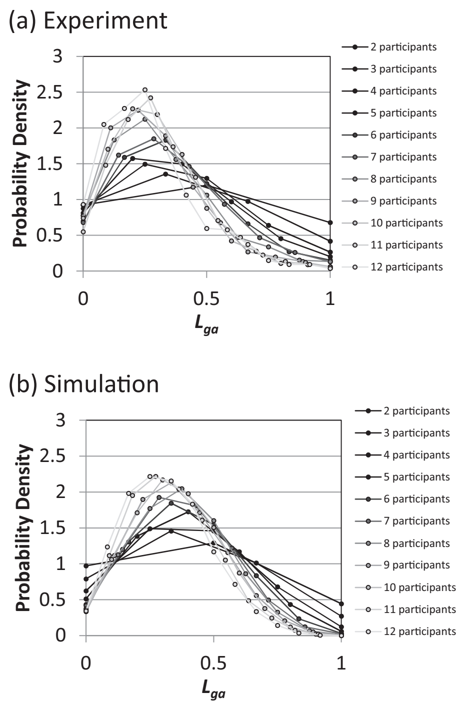

FIG. 5. Probability density of L_{ga} (i.e., group activity level) of (a) experimental measurement data and (b) simulation results.

places, so the result that external effects lower a participant's activity level is persuasive.

The simulation of activity level in a conversation was conducted with the estimated parameters $\{H,J,T\}$. In the simulation, the active-state calculation was iterated 10 000 times. To confirm that the estimated parameters could reproduce the microscopic measurement result, $I_s(N_o)$ and $B(N_o)$ were calculated. The simulation data plotted in the Fig. 4 "simulation" show that the estimated parameters $\{H,J,T\}$ well reproduce the measurement results, namely, $I_s(N_o)$ and $B(N_o)$, especially the important microscopic characteristic that the degree of synchronization gets higher as the number of other participants increases.

The simulated probability density of L_{ga} was then compared with that of measurement, which is a macroscopic characteristic of activity level in a conversation. The probability density of L_{ga}, which was calculated from both simulation and measurement results, is plotted in Fig. 5. The experimental measurements shows that the distribution of probability density of L_{ga} gets high kurtosis and average L_{ga} decreases as the number of participants increases. This result is caused by the synchronization effect. When the number of participants is low, such as two, I_s is low, and participants are not affected by the other participants so much. As a result, the probability density of L_{ga} is almost uniform, regardless of external effects. However, when the number of participants increases, I_s increases, and the participants strongly synchronize their active states with those of the others'. In that situation, L_{ga} gets lower, even if the external effect lowering participants' activity levels stays constant, because the synchronization effect strengthens the external effect. The simulation results shown in Fig. 5(b) show the same trend as the measurement results, thereby verifying the appropriateness of the simulation model.

Summary. A ferromagnetic human-human interaction model, namely, a model describing how people synchronize with each other in a multiple-participant conversation, was proposed. This model is based on two microscopic characteristics of activity level in a conversation, which were found in a real-environment face-to-face conversation. The first characteristic is that the activity level of a participant in a conversation regularly synchronizes with the other participants. The second characteristic is that the degree of synchronization increases as the number of participants increase. The results of a conversation activity-level simulation based on the proposed model reproduce not only the microscopic synchronizing characteristics, but also the macroscopic group activity level trends, which were also found in a real-environment face-to-face conversation. We hope this finding, that is, a person's synchronizing interaction can be modeled precisely with a framework based on statistical physics, will trigger additional research for human-behavioral science.

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