# Understanding Effects of Feedback on Group Collaboration

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### Abstract

Small group collaboration is vital for any type of organization to function successfully. Feedback on group dynamics has been proven to help with the performance of collaboration. We use sociometric sensors to detect group dynamics and use the data to give real-time feedback to people. We are especially interested in the effect of feedback on distributed collaboration. The goal is to bridge the gap in distributed groups by detecting and communicating social signals. We conducted an initial experiment to test the effects of feedback on brainstorming and problem solving tasks. The results show that real-time feedback changes speaking time and interactivity level of groups. Also in groups with one or more dominant people, the feedback effectively reduced the dynamical difference between co-located and distributed collaboration as well as the behavioral difference between dominant and non-dominant people. Interestingly, feedback had a different effect depending on the type of meeting and types of personality. We intend to continue this direction of research by personalizing the visualization by automatically detecting type of meeting and personality. Moreover we propose to demonstrate the correlation of group dynamics with higher level characteristics such as performance, interest and creativity.

## Introduction

Small group collaboration is an essential factor for success in workplaces. The study of organization behavior has researched methods to improve the effectiveness of group collaboration. Group dynamics have been one of their focus as it is a key factor affecting the performance and satisfaction of the group (Shaw 1976). Shaw defines group dynamics as the activities, processes, operations, changes, interdependencies, and interrelationships that transpire in social groups. Feedback on group dynamics has been proven to help participants modify their behaviors, which may lead to higher satisfaction and performance (Smith and Kight 1959). However there have not been methods to measure group dynamics in real-time. Traditional methods rely on video coding or post-questionnaires which require a large delay in providing feedback and measuring its effect.



Figure 1: A small group collaborating on a task while wearing sociometric sensors. Real-time feedback is provided through individual mobile phones on the table.

Furthermore, groups have radically different dynamical characteristics when they collaborate while distributed. Distributed collaboration has become an indispensable form of communication in today's global society. Yet Hinds and Bailey have demonstrated that distributed collaboration may have very different dynamics compared to co-located collaboration, and that these differences often lead to poorer performance (Hinds and Bailey 2003). The obstacles of distributed collaboration call for a stronger need of feedback on group dynamics.

In this position paper we propose using sociometric sensors to provide feedback on group dynamics and once again using the sensors to understand the change in the group's behavior. We present the work of an early experiment with a sample application and present intended directions of research.

## Related Work

There have been recent efforts to detect group dynamics automatically. Choudhury and Pentland used duration and frequency of meeting to define the group link structure in real world settings (Choudhury and Pentland 2003). Jayagopi et al. uses video and audio sensors to automatically estimate the dominance structure of the group (Jayagopiet al. 2009). We build on these work with a focus on fine scale interaction detection using non-invasive wearable sensors, all done in real-time. We further apply these detection techniques to show feedback to encourage change in group behavior.

Scholars across many disciplines have studied the effect of feedback using different approaches. Bergstrom and Karahalios used audio volume to show the interaction history of the participants on table tops (Bergstrom and Karahalios 2007), while DiMicco et al. detected participants' speaking time and visualized the information on a large shared display. These systems have demonstrated the potential benefits of feedback on group dynamics (DiMicco et al. 2007). However, these systems only capture one aspect of speech, which is a limited representation of the group's social interaction. Furthermore, public displays are not optimal because they are not always available for ad-hoc meetings, and they cannot provide personalized information to users.

Many researchers have tried to overcome the limitations of distributed collaboration by augmenting communication with additional channels such as voice, chat and video (Pedersen et al. 1993; Streitz et al. 1994; Tang et al. 2001). However Mark et al. discovered that even with rich communication channels participants still pay less attention to the group dynamics when distributed compared to when the group was co-located (Mark, Grudin, and Poltrock 1999). One of the solutions suggested by Mark et al. was to include an extra member whose explicit role was to facilitate the meeting reacting on the flow of group dynamics. However, when human resources are precious, employing an additional member is usually not a viable option. Hence an automated real-time facilitation may be an affordable alternative option.

To address these various limitations, we use Sociometric badges (Olguin Olguin et al. 2009) to verify the effects of real-time feedback on group dynamics. The badge collects unbiased and richer data by sensing body movement, proximity to other badges, and speech characteristics such as speaking speed and tone of voice. Not only can we provide feedback of this data in real-time but we can also measure its effect in real-time.

## How to Provide Feedback

We introduce a system implemented to detect group dynamics and provide feedback according to the group's goal. The feedback is visualized on the mobile phone of each participant.

### Measuring Group Dynamics

The Sociometric badge (figure 2) is an electronic sensing device that collects and analyzes social behavioral data. It is intended to be worn around one's neck allowing voice capture and IR transmission and reception (Olguin Olguin et al. 2009). Its current capabilities include:

- Extracting speech features in real-time to measure non-linguistic social signals: The badge does not record any speech content, but is capable of identifying social signals such as enthusiasm, interest level, persuasiveness and nervous energy (Pentland 2008) of the user. Turn taking or short affirming phrases reveal social dynamics that can be measured through synchronization of multiple badges.

Figure 2: Sociometric badges can capture group dynamics in real-time. It is intended to be worn around one's neck.

- Measuring body movement using a single 3-axis accelerometer: This can detect individual activities such as gesturing, walking, and sitting as well as social interactions such as body movement mimicry or rhythmic patterns.
- Detecting proximity data using a 2.4 GHz radio or Bluetooth to understand the relational distance and position of multiple wearers: This function can be used to detect the distribution of group members.
- Capturing and identifying face-to-face interaction using an IR sensor: By detecting the face-to-face alignment of individuals we are able to detect encounters as well as postural direction.
- Real-time sending and receiving of information over 2.4GHz radio to and from different users and base stations for real-time communication: The data transfer between individuals can be both on a one-to-one level or initiated by a central server to obtain data from the whole network.
- Performing indoor user localization by measuring received signal strength from fixed based stations.
- Communicating with Bluetooth enabled devices such as mobile phones or Bluetooth headsets: Coupling with other commercial devices allow flexibility in output channels.

### Feedback Visualization

We visualize sociometric data to provide feedback on their group dynamics. We have chosen to use a mobile phone display as a platform. For it to be a persuasive interface, encouraging change in group behavior, visualization should be designed to guide the direction of change. In this paper we present a sample visualization called Meeting Mediator (Kim et al. 2008). Meeting Mediator (MM) was designed for meetings where interactivity and balance in participation is encouraged.

For MM to work, each participant wears a Sociometric badge which is paired with a mobile phone via Bluetooth. The four badges communicate their wearer's speaking and movement status to each other over the 2.4GHz radio. Each of the four participants is represented as colored squares in

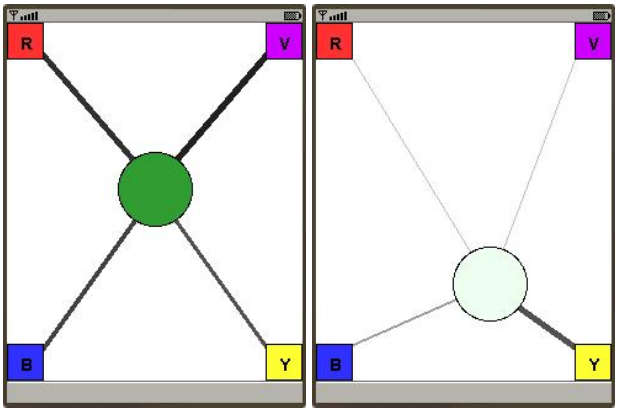


Figure 3: Sample visualization of group dynamics. Visualization on the phone emphasizes balance and interactivity in group collaborations: balanced and highly-interactive (left) or un-balanced and less-interactive (right). Circle color denotes group interactivity level, circle position denotes balance in participation, and line thickness denotes speaking time.

the corners of the screen (figure 3). In the user study, the square colors were identical to the color of each participant's badge and seat. The color of the central circle gradually shifts between white and green to encourage interactivity, with green corresponding to a higher interactivity level. Balance in participation is displayed through the location of the circle: the analogy is such that the more a participant talks, the stronger they are pulling the circle closer to their corner. We further promote balanced speech by displaying each member's speaking time through the thickness of the line connecting the central circle with each member's corner. The visualization is updated every 5 seconds and can be re-initialized every time a new meeting session starts. The data is accumulated throughout the meeting, showing the accumulated group dynamics from the start of the meeting to the current time.

## Meeting Mediator Experiment

We introduce the findings from an experiment on the effects of MM on group behavior. The results are shown as an example of the effects of feedback detected by Sociometric badges. More detailed results of the experiment can be found in (Kim et al. 2008).

### Experimental Setup

To verify the effects of MM, we performed a between-subject experiment comparing 18 groups with MM feedback on their mobile phones (experimental condition) to 18 groups without mobile phones (control condition). Each team performed two scored tasks. In one task, which we call the co-located case, all four participants were co-located having all audio and video communication available. In the other task, which we call the distributed case, the group was divided into pairs and a conference call setting was simulated by having a curtain between the two pairs. The sequence of co-located and distributed case was counter balanced to eliminate learning effects.

For each setting groups participated in a brainstorming phase and a problem solving phase each lasting approximately 10 minutes. Following the tasks, subjects filled out a questionnaire comprised of questions regarding their own personality, the group dynamics and each individual's performance for each phase, and if applicable, the utility of the MM system.

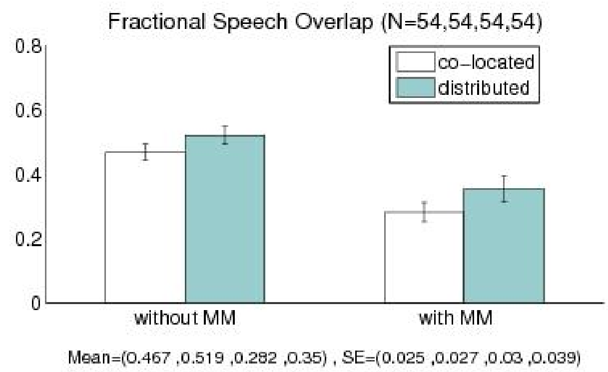


Figure 4: MM reduces overlapping speech time. Mean = (49.2% of total time without MM, 31.8% of total time with MM), F(1,106)=17.8, $p<.001$. In both cases, there is more speech overlap in the distributed case

### Effects of Feedback on Group Dynamics

**MM reduces the amount of overlapping speaking time** MM had a very strong effect on speaking dynamics. The primary effect was a dramatic reduction in overlapping conversations. This is in line with our qualitative observation that groups without MM tended to divide into subgroups and have separate conversations instead of working as one team. The average overlap speaking time is significantly lower for subjects with MM (mean=31.8% of the total time) than subjects without MM (mean=49.2% of total time, F(1,106)=17.8, $p<.0001$, Fig. 4). Therefore when subjects were provided with visual feedback through MM they were more likely to collaborate with their teammates as one group with less overlap in speech.

**MM encourages interactivity** Further analysis of speech gives us new insights into the group interactivity level. Subjects with MM have significantly shorter speech segment lengths (mean = 7.4sec) compared to those without MM (mean =10.3sec, F(1,106)=16.8, $p<.0001$, Fig. 5). This relationship is maintained in both brainstorming and problem-solving phases. Since shorter speech segment lengths indicate more frequent changes in speaking turns, we verify that MM encouraged higher level of interactivity.

**MM influences distributed collaboration to be more like co-located collaboration** When designing MM, we hypothesized that MM will make distributed collaboration more like co-located collaboration. For groups with one or

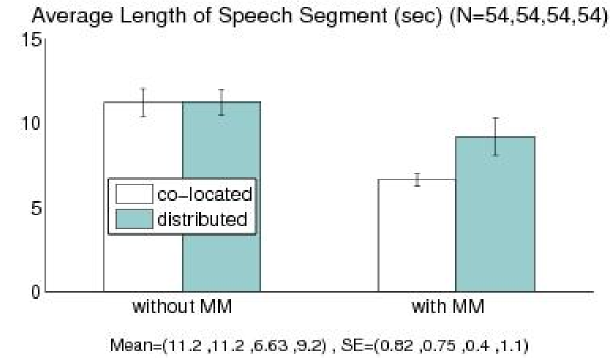


Figure 5: MM encourages more interactions (shorter speech segment lengths). Mean = (10.3sec without MM, 7.4sec with MM), F(1,106)=16.8, $p<.0001$. This effect is stronger in the co-located case.

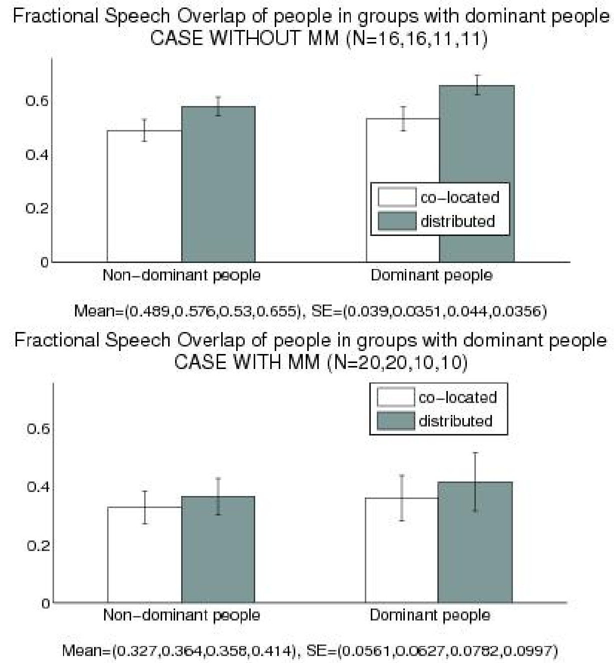


Figure 6: People in groups with a dominant person have more speech overlap when they are in distributed settings. When MM is introduced speaking times are not significantly different.

more dominant people, we found that MM reduces the difference between co-located and distributed collaboration.

In groups with one or more dominant person, people have more speech overlap when groups are distributed and this effect is significant for dominant people (Mean = 48.9%, 57.6%, t(15)=-2.06, p=.06 for non-dominant people and Mean = 53.0%, 65.5%, t(10)=-3.15, $p<.05$ for dominant people, Fig. 6-top). This may be because in distributed settings it is more difficult to signal people to let them know that they are being intrusive or impolite.

However, when MM is present the signal may be reintroduced through the visual feedback on the mobile phones. Thus with MM, there is no significant difference between the co-located case and the distributed case (Mean = 32.7%, 36.4% for non-dominant people and Mean = 35.8%, 41.4% for dominant people, Fig. 6-bottom). Confirming our hypothesis, MM has made the distributed scenario more like the co-located scenario by enhancing social signals. As mentioned earlier, this hypothesis does not hold for groups without a dominant person–a possible explanation is that non-dominant people are equally polite regardless of distribution.

### Effects of Feedback on Dominance

**MM reduces the difference between dominant people and non-dominant people** In the problem-solving phase, the overlapping speaking time of non-dominant people was lower than dominant people (Mean = 58.1%, 71.6%, t(25)=-2.47, $p<.05$ when co-located, mean = 76.4%, 77.0%, t(25)=-0.08, p=.94 when distributed, Fig. 7-top). However when MM is introduced, all participants' overlap speaking time is lowered reducing the difference between dominant and non-dominant people to be no longer significant (Mean = 44.0%, 49.6%, t(28)=-0.50, p=.62 when co-located, mean = 52.3%, 51.7%, t(28)=-0.06, p=.96 when distributed, Fig. 7-bottom). This can be understood as MM spreading out the energy of the dominant person, allowing every participant to be more energetic and involved in the communication.

Similar results were found in speech energy. The average variation in speech energy of non-dominant people was lower than dominant people (Mean = 346c Pa, 523c Pa, t(25)=-2.60, $p<.05$ when co-located, mean = 538c Pa, 698c Pa, t(25)=-1.24, p=.23 when distributed, $c = constant$). However when MM is introduced, the energy variation of the non-dominant people increases, reducing the difference between dominant and non-dominant people to be no longer significant (Mean = 511c Pa, 558c Pa, t(28)=-2.60, p=.69 when co-located, mean = 555c Pa, 623c Pa, t(28)=-0.51, p=.62 when distributed, $c = constant$). This we also attribute to MM's ability to strengthen the mood contagion effect.

## Future Research Directions

Based on the findings from the MM experiment, we propose new directions for using sociometric feedback to influence group collaboration.

### Automatic Detection of Meeting Types

The MM experiment verified that the same feedback may have a different effect depending on the type of meetings. For example, MM had an effect of reducing the difference between dominant people and non-dominant people only in problem solving meetings and not in brainstorming meetings. Exaggeration of speech expressions may have been more necessary in the problem-solving phase in which the goal is to persuade others in order to bring about a favorable consensus.

Hence we propose providing different types of feedback depending on the goal of the meeting. In order to do so, we

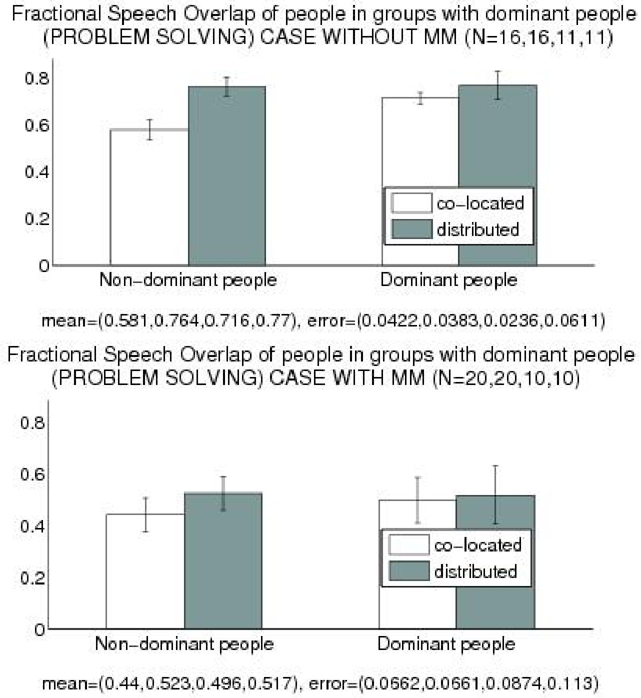


Figure 7: In the problem-solving phase, the fractional overlap speaking time of dominant and non-dominant people are significantly different. When MM is introduced, the difference between dominant and non-dominant people is no longer significant.

first need to construct a prediction model for different types of meeting. Our predictions will allow customized feedback for maximal effect. We would like to distinguish most common meeting types which includes staff meetings; task force meetings; information sharing; brainstorming; and ceremonial meetings (Romano and Nunamaker 2002).

Another distinguishing factor of meetings is distribution. We verified that distribution strongly influences the group dynamics and the effects of feedback. We would like to continue research of distributed collaboration by expanding on various types of distribution. The MM experiment only focused on the group separated into two parties with equal number of participants. We hypothesize as the group gets divided into larger number of parties and the group sizes are not identical, we will see different effects on dynamics and feedback.

## Personalized Feedback

Sociometric sensors can detect personalities from interaction patterns. In the MM experiment, we were able to find significant characteristics of dominant people by correlating the survey data with sociometric data. Dominant people speak more than people who are not (Mean=54.5%, 67.2%, F(1,52)=4.54, $p<.05$). And dominant people have more variance in volume when they speak (mean = $350c$ Pa, $512c$ Pa, F(1,52)=6.07, $p<.05$, $c = constant$). Using these characteristics we can automatically detect the dominant people in groups. We believe that we will be able to detect additional personal characteristics such as energy orientation or judgment style.

MM experiment also verified that personality types have a significant influence on group dynamics. We conclude that feedback should be adjusted depending on the personality type of each member and also the combination of personality types in the group. In future work, we plan to provide personalized feedback to each individual instead of showing the same overall group status to all participants. This will allow us to fine tune the direction of influence on group dynamics.

## Inference of Higher Level Characteristics

We believe that group dynamics can reveal higher level characteristics of groups. We plan to continue research to infer more meaningful output of groups using sociometric data.

**Performance** Many organizational scientists have verified the impact of feedback on performance. One obvious objective of our MM experiment was to find correlations among feedback, group dynamics and performance. We were interested in answering question such as: Does higher level of interactivity mean better performance? Is one person dominating always bad?

However, we were only able to find significant correlations between MM and group dynamics but not between MM and performance. In the brainstorming session, though there were changes in the interactivity level of the group, there were no significant changes in the number of ideas generated (Mean = 10.7 without MM, 8.11 with MM, F(1,106)=3.01, p=.08). This may be interpreted through Wilson's work, where he found that if the given task was easy, more collaboration lead to worse performance (Wilson and Miller 2004). Similarly, in the problem-solving phase we did not discover any significant effects with the use of MM (Mean = 4.84 for groups without MM, and 5.2 for groups with MM , F(1,106)=1.49, p=.23). Our qualitative observations revealed that in some groups the dominant person would take over the conversation, limiting participation of others, while in other groups the dominant person acted as a facilitator (Mark, Grudin, and Poltrock 1999) who brings out ideas of all participants leading to better performance.

We plan to do another study to correctly reveal the black box between feedback and performance. Moreover we would like to expand the time scope of our observations. The MM experiment has only focused on collaborations through meetings where all members are present. We would like to study longer term collaborations which happen throughout working hours.

**Interest** In a study of couples shopping for furniture, we verified that the interest level of groups can be predicted through their interaction patterns (Kim et al. 2009). Interest had a positive correlation with the duration of time they were engaged with an item (r=0.41, $p<.0001$). However interest had a negative correlation with ratio of the two participant's speaking time (r=-0.23, $p<.05$). The negative correlation of speaking time ratio and interest indicates that, when a couple is interested in an item they speak for a similar amount of time. We believe that low speaking time ratio mirrors shared enthusiasm in items, which led to higher probability of purchase. Similar results were found in speech segment length ratio. The ratio of the average speech segment length is negatively correlated with interest (r=-0.20, p<.05). This means that as couples were more interested in an item, their average length of speech were more similar. A real-time prediction model of interest was constructed using a decision tree with a prediction accuracy reaching 79.8% and a sensitivity of 63%.

These results demonstrate that we can predict when participants will make positive decision about the item of interest. We plan to generalize these results to better understand group dynamics and aid the process of groups coming to a consensus.

**Creativity** Human creativity is a vital part of human activity. We would like to use our sociometric system to create a framework for creativity in group collaboration. Real-time sensing and inference algorithms will be adapted to guide individual and team experiences. Ultimately, we hope to develop adaptive reflective technologies that stimulate collaborative activity, reduce time pressure and interruption, mitigate detrimental effects of negative affect, and increase individual and team creative activity and outcomes.

## Conclusion

We have measured the effects of feedback on group dynamics through sociometric sensors. The results of a controlled study show that real-time feedback reduces overlapping speaking time and increases interactivity of the group. Also in groups with one or more dominant people, the feedback helped groups distributed show behavior more similar to that of co-located groups. It also helped reduce the behavioral difference between dominant and non-dominant people in groups.

We plan to incorporate into future studies our findings of the effect of task type, dominance structure, and distribution on group dynamics. Using the ability to automatically detect these group characteristics, we can provide personalized feedback to maximize group performance and satisfaction.

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