Journal of International Information Management

Volume 7 | Issue 1 Article 6

1998

A group decision support system idea consolidation tool

Chittibabu Govindarajulu
University of Texas-Pan America

Milan Aiken
University of Mississippi

Weigi Li
University of Mississippi

A group decision support system idea consolidation tool

Chittibabu Govindarajulu
University of Texas - Pan American

Milan Aiken
Weigi Li
University of Mississippi

ABSTRACT

Manual consolidation of ideas generated in a Group Decision Support System meeting can be a lengthy, inaccurate, and dissatisfying process. The objective of this paper is to demonstrate how an automatic idea consolidation program can reduce the time needed by group members to aggregate comments, inaccuracies of these comment groupings, and dissatisfaction with the comment consolidation process. A case study comparing the program's results with those of two human subjects shows a time savings of 98.8%. Although the computer's comment groupings were not identical with those of the subjects, they were logically consistent.

INTRODUCTION

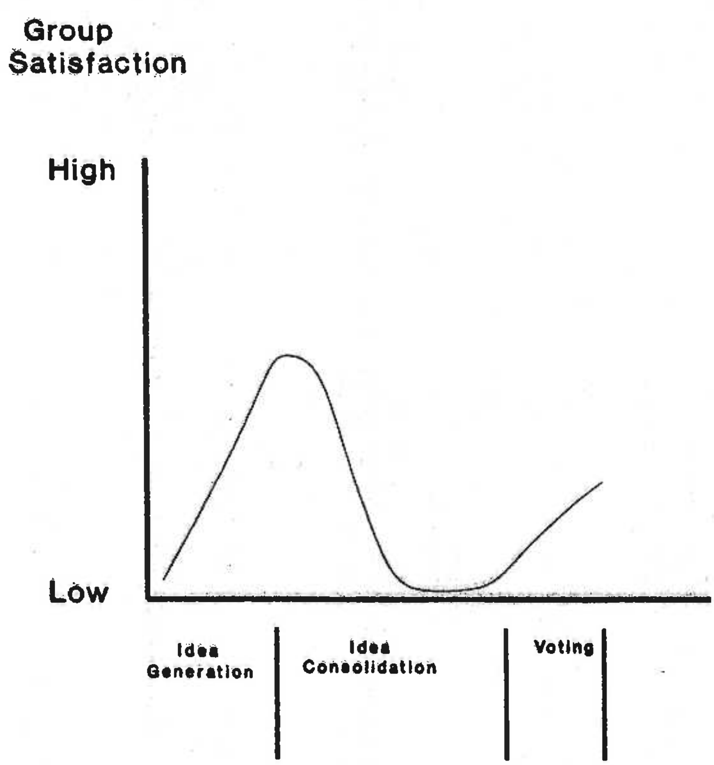
In recent years, Group Decision Support Systems (GDSSs) have played an important role in supporting managerial decision making. GDSSs (also called Group Support Systems or Electronic Meeting Systems) automate a group meeting and can help groups to arrive at a better decision faster (Dennis, George, Jessup, Nunamaker, & Vogel, 1988; Nunamaker, Dennis, Valacich, Vogel, & George, 1992). However, these systems can be improved further. For example, the second stage of a GDSS meeting typically involves manually consolidating comments generated during the first stage (Plexsys, 1988). This manual consolidation is conducted in about 72% of GDSS meetings and lasts nearly three times longer than generating the ideas in the first place (83.6 minutes versus 32.2 minutes) Aiken & Carlisle, 1992, p. 375). In addition, manual idea consolidation is inaccurate (redundant comments are placed in some groups while relevant comments are left out of other groups). As a result of this lengthy and tedious process, groups are extremely dissatisfied with the process (Chen, Hsu, Orwig, Hoopes, & Nunamaker, 1994). Clearly, this idea consolidation process needs to be improved.

In this paper, we describe a completely automated idea consolidation program which reduces the amount of time needed to group comments while improving the accuracy and subsequent group satisfaction. A large amount of time is spent in electronic meetings simply organizing the output; automatic idea consolidation programs may alleviate this bottleneck (Aiken & Carlisle, 1992). A simple case study is included which illustrates its effectiveness and efficiency.

BACKGROUND

GDSS meetings often involve three stages: (1) generating comments, (2) consolidating comments into categories, and (3) voting. During these meetings, participants are generally satisfied with all the stages except the for the idea consolidation stage, as shown in Figure 1 (adapted from Aiken, Paolillo, Shirani, & Vanjani, 1995). These stages are described in more detail below:

Figure 1. Satisfaction in a GDSS Meeting (Manual Idea Consolidation)



1. *Comment generation stage:* In this stage, participants write comments about the problem the group is attempting to solve. Group members have high involvement in this stage as they strongly believe that their contributions will help solve the problem. In addition, they have an opportunity to state what they really think (anonymously) and are able to read what others are thinking. This naturally leads to increases in participants' satisfaction levels.
2. *Comment consolidation stage:* During this stage satisfaction begins to decline. This is mainly due to the time consuming process which involves going through all the comments, filtering duplications and removing redundancies. A significant amount of time (from 25% to 40% of the meeting) is consumed by idea consolidation. Also, as grouping of comments is highly subjective, it may be difficult for group members to arrive at a consensus list of groups. Ideas may be consolidated by the entire group, a subset of the group, or staff members (e.g., the group facilitator). If the group or subset of the group consolidates the ideas, there is likely to be considerable disagreement about how they should be grouped, and the group members are likely to resent doing "clerical" work. If the facilitator groups the comments, the group members take a break for an hour or so, but they may not agree with the facilitator's choices for comment grouping.
3. *Voting:* In this stage, group members may rank the categories generated in the second stage by their importance to the problem. Group members once again feel they are solving the problem at hand and hence satisfaction begins to rise again.

AN ARTIFICIAL INTELLIGENCE APPROACH

Because GDSS comments are composed of sentences or sentence fragments written in natural language, an artificial intelligence (AI) approach may improve group productivity in the idea consolidation stage.

AI researchers have successfully used techniques such as augmented transition networks (ATN) and semantic grammar to "understand" natural language in other fields. Natural language has two main structures: syntactic and semantic. While it is relatively easy to identify syntactic structures, semantic analysis is extremely difficult as the relationships between different words are numerous. Augmented transition networks (ATNs) (Woods, 1972) have proved useful in understanding syntactic structures. Though this has been found useful in restricted domains, it is not useful for GDSS session comments because comments may not have syntactic similarities and in certain cases no syntactic structure. This is possible to a certain extent by the use of the Semantic Grammar technique (Burton, 1976). However, this technique is domain dependent and hence, not suitable for GDSS session comments as these comments are domain independent (i.e., many different vocabularies may be used [scientific, business, political, . . .).

Though it is difficult to "understand" natural language by the use of the above techniques, researchers have used automatic indexing techniques (which are domain independent) successfully (Salton, 1983). Automatic indexing consists of word identification (to break up the comments for further processing), dictionary lookup (checking for misspelled words), function word removal (eliminating words which do not substantially contribute to the meaning of the comment, e.g., this, what, a, etc.), stemming of content words (removal of suffixes and prefixes to reach the root of a word), and term-phrase formation (combining adjacent words to form phrases). The final step is cluster analysis in which comments with similar keywords are put into the same category.

AUTOMATIC IDEA CONSOLIDATION

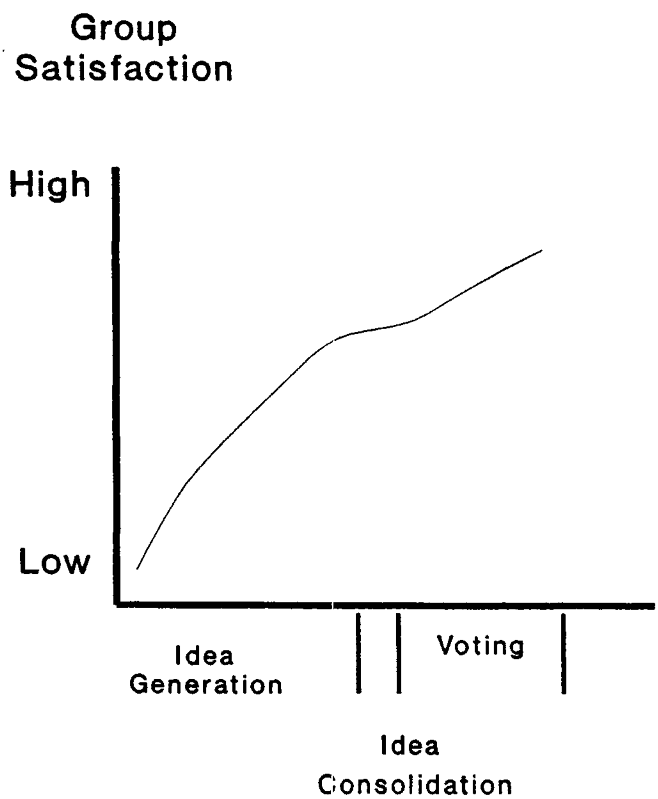
The proposal for automatically consolidating comments was first made in 1990 as part of a comprehensive design for integrating artificially-intelligent agents into a GDSS (Aiken, Liu Sheng, & Vogel, 1991), and the first prototype was developed in 1991 using stemming and cluster analysis described above (Aiken & Carlisle, 1992). In the study using this system, comments from eight GDSS meetings were grouped into categories in approximately 5% of the time required by the group participants using the manual process. In addition, the system was more accurate in categorizing the comments than were the group members. The idea consolidation tool took on average 1.12 minutes with 100% recall and 100% precision of groupings while the manual process took on average 42.5 minutes with 82.6% recall and 72.1% precision on average (Aiken & Carlisle, 1992).

An additional study was conducted to investigate how group members' satisfaction changed over the course of a GDSS meeting (Aiken, Paolillo, Shirani, & Vanjani, 1995). As expected, group members using the manual process were extremely dissatisfied during the GDSS meeting (as shown in Figure 1), and group members using the automatic idea consolidation program had very little chance to become dissatisfied (the consolidation took less than one minute), as shown in Figure 2. By using the idea consolidation program, the meeting time was reduced by approximately 40%.

Chen, Hsu, Orwig, Hoopes, & Nunamaker (1994) developed another automatic idea consolidation program later which contained many conceptual similarities with the earlier program. Both tools use word identification, function word removal, content word identification, and cluster analysis. However, the Chen, et al. tool used an artificial neural network (a Hopfield Net) in addition for classifying the comments. These similarities and differences are described in more detail below. For brevity, the Aiken & Carlisle tool is referred to henceforth as *Tool A,* and the Chen, et al. tool is referred to as *Tool B.*

1. *Word identification:* Both tools break up the comments into individual words ignoring punctuation and case.
2. *Function word removal:* Tool B used a list of 1000 "stop words" such as on, in, at, etc., and "pure" verbs such as articulate, teach, etc. Tool A retains only the content words by removing the function words (stop words).

Figure 2. Satisfaction in a GDSS Meeting (Automatic Idea Consolidation)



3. *Stemming the content words:* Both tools use stemming algorithms based on suffix removal. Tool B used a 28,000 word dictionary with flags indicating legal suffixed forms to remove the suffixes whereas Tool A used Lovin's (1968) suffix removal algorithm.

4. *Clustering:* Tool B, after identifying content words, combines adjacent words to form phrases (a maximum of three words is combined). After this, term frequency and document frequencies are computed. After this step, weights are combined and fed into the Hopfield Net for cluster identification. Tool A uses term frequency and the number of unique keywords in each comment to form the keyword matrix. A proprietary clustering algorithm using this keyword matrix identifies the comment categories.

Tool B uses phrases in addition to single words. One might expect that this will lead to better idea consolidation when compared to Tool A which uses only single keywords, not phrases. However, even with an additional sophisticated process like Hopfield Net, Tool B's performance is poor when compared to Tool A. As shown in Table 1, Tool A was able to process comments about 49.3 times faster, after adjusting for differences in CPU speed.

Table 1. A Comparison of Performance Measures

	Tool A (Aiken & Carlisle, 1992)	**Tool B (Chen, Hsu, Orwig, Hoopes, & Nunamaker, 1994)**
System Used	IBM PC/AT running at about 3 MIPS	DEC Station 5000/120 running at about 25 MIPS
Mean consolidation time	1.11 minutes	7 minutes
Comments consolidated per minute	276.4	46.7
Comments per minute (after adjusting for differences in CPU speed)	2302	46.7
	49.3* faster	

In terms of accuracy, Tool A achieved 100% recall and 100% precision in comment grouping. In the study, recall was defined as the percentage of relevant comments put into a group, and precision was defined as the percentage of irrelevant comments excluded from the group. Recall was reduced if comments were placed in multiple categories; precision was reduced if comments were not placed in any category (they were forgotten). Using this simple definition, the human subjects achieved a recall of 82.6% and a precision of 73.1%.

Tool B achieved a recall of 32.25% and precision of 32.5% on average, worse than the human subjects in the experiment. In the study, recall and precision were defined in terms of how relevant human facilitators thought the computer's grouping categories were.

A possible reason for the poor precision and recall rates of Tool B may be due to the use of a threshold value of 4. In other words, if a word occurs less than four times in the comment set, then it is ignored. This might have led to high information loss. Tool B uses this threshold value to minimize the time for idea consolidation. Lower threshold values led to an objectionable delay in processing; more than 15 minutes (over twice as long a usual and longer than the meeting members' break time). An additional reason for Tool B's poor performance may be due to the use of a neural network. Neural networks are computationally intensive and take many iterations to converge (Tam, 1994).

However, comparisons of accuracy between the two tools are difficult due to the differences in subjects, topics, measures, and other variables in the studies. Further research in an experimental setting will be necessary before a clear claim of superiority of one tool over the other may be established.

A CASE STUDY

To illustrate the effectiveness and efficiency of Tool A's idea consolidation algorithm, a case study was conducted. Two subjects (Subject A and Subject B) were presented four files of seven comments each (shown in the *Appendix*) and were asked to group the comments into logically-related categories using a word processor. The comments were meant to reflect those found in actual meetings, although they were kept fairly simple. The comments in file #4 are almost trivial, but some nonsensical comments are occasionally found in meetings.

The amount of time the subjects took was also recorded. In addition, the idea consolidation program grouped the comments. A comparison of the two subjects' and the computer's groupings and times are shown in Table 2.

Table 2. Case Study Comparisons

	Computer		Subject A		Subject B		Mean
	Groups	Time	Groups	Time	Groups	Time	Subject Time
File #1	(1,2,3, 4,5,6,7)	1	(1,2,) (5,6,7) (4) (3)	240	(1,2) (3,7) (4) (5,6)	140	190
File #2	(3,4) (1,2,5, 6,7)	1	(1,2) (3,4) (5,6,7)	85	(1,2) (3,4) (5,6) (7)	25	55
File #3	(1,5,6) (3,4) (2,7)	1	(1) (3,4) (5,6) (2,7)	80	(1) (3,4) (5,6) (2,7)	45	62.5
File #4	(1,2) (3,4,5) (6,7)	1	(1,2) (3,4,5) (6,7)	50	(1,2) (3,4,5) (6,7)	20	35
Mean time:		1		113.75		57.5	85.625
Minimum time:		1		50		20	35
Maximum time:		1		240		140	190

Time in seconds.

Groups are indicated by listing comment numbers in parentheses (e.g., (1,3) indicates that comments #1 and #3 were put into a single group).

The amount of time taken by the two subjects varied from a minimum of 20 seconds to a maximum of 240 seconds to group seven comments. The mean time taken was 85.6 seconds or about 12 seconds for each comment. Large variations are evident between the two subjects and among the four files of comments, illustrating the differences in content difficulty and individual's skills. In comparison, the computer took only 1 second, a time savings of 98.8%, which compares favorably with the time savings found in an earlier study. A mean time savings of 97.6% was found in a comparison of the program with subjects looking at eight sets of comments from GDSS meetings (Aiken & Carlisle, 1992, p. 379).

The computer generated the same groupings as the subjects for only file #4. The two subjects had the same groupings for file #3 and file #4. However, as the complexity and the number of comments increases, subjects can be expected to disagree over the groupings more often. Although different, we believe that all of the groupings made sense. No comments were left out, and there were no redundant comments (comments placed in more than one group). These problems occur frequently in manual groupings involving several people and hundreds of comments, accounting for the very low recall (82.6%) and precision (73.1%) of these GDSS meetings (Aiken & Carlisle, 1992).

In general, the subjects tended to generate more groups than did the computer. In the most extreme case (file #1), the computer put all seven comments into one group, but the subjects made four or five groups. The earlier study found that subjects made on average 2.8 times more groups than did the computer (Aiken & Carlisle, 1992, p. 379).

CONCLUSION

GDSS meeting participants historically have spent a large amount of time manually grouping comments generated during electronic meetings. These manual groupings are often inaccurate (relevant information is omitted or irrelevant information is included), and the grouping process is extremely dissatisfying. An automatic idea consolidation program may dramatically increase the speed of comment grouping, and by reducing or eliminating entirely the manual process, also increase group satisfaction during the meeting.

This paper has described how an idea consolidation program can be used in an electronic meeting. A case study comparing the computer's results with two subjects showed that the computer was approximately 86 times faster than the subjects and generated fewer groupings. The groupings of the computer and the subjects were identical in only one case, fairly similar in two cases, and fairly dissimilar in only one case. However, we believe the computer's groupings were logical, and subjects also may disagree on groupings. Accuracy measures were beyond the scope of this case study, but have been addressed in other research (e.g., Aiken & Carlisle, 1992). This study focused primarily on how people and the software group comments, but makes no claim as to which is superior (a subjective decision). The case study has also focused on time savings available through use of the idea consolidation software.

Further studies will investigate the similarities and dissimilarities of computer and subject groupings and will determine subjects' satisfaction with the computer's results.

REFERENCES

Aiken, M. & Carlisle, J. (1992). An automated idea consolidation tool for computer support cooperative work. *Information and Management, 23,* 373-382.

Aiken, M., Liu Sheng, O., & Vogel, D. (1991, January). Integrating expert systems with group decision support systems. *ACM Transactions on Information Systems, 9*(1), 75-95.

Aiken, M., Paolillo, J., Shirani, A., & Vanjani, M. (1995, Fall). Group efficiency, effectiveness, and satisfaction using a group decision support system idea consolidation tool. *International Business School Computing Quarterly.*

Burton, R. (1976). *Semantic grammar: A technique for efficient language understanding in limited domains.* Ph.D. dissertation, Computer Science Department, University of California, Irvine, CA.

Chen, H., Hsu, P., Orwig, R., Hoopes, I., & Nunamaker, J. (1994, October). Automatic concept classification of text from electronic meetings. *Communications of the ACM, 37*(10), 56-73.

Dennis, A., George, J., Jessup, L., Nunamaker, J., & Vogel, D. (1988, December). Information technology to support electronic meetings. *MIS Quarterly, 12*(4), 591-624.

Lovin, J. (1968). Development of a stemming algorithm. *Mechanical Translation and Computational Linguistics, 11*(1,2), 11-31.

Nunamaker, J., Dennis, A., Valacich, J., Vogel, D., & George, J. (1991, July). Electronic meeting systems to support group work. *Communications of the ACM, 34*(7), 30-39.

PLEXSYS User Guide. (1988). Department of Management Information Systems, University of Arizona.

Salton, G. (1989). *Automatic text processing.* Reading, MA: Addison-Wesley.

Tam, K. (1994). Neural networks for decision support. *Decision Support Systems, 11,* 389-392.

Woods, W. (1972). An experimental parsing system for transition network grammars. In *Natural Language Processing.* New York, NY: Algorithmic Press.

APPENDIX: Comment Transcripts

Comment File #1

1. We need to improve our profits.
2. We should improve profits and sales.
3. What about earnings and cash flow?
4. The product needs to be improved first.
5. Maybe we should reduce our overhead.
6. Reducing overhead will improve earnings.
7. What were our earnings last year?

Comment File #2

1. We need to improve our profits.
2. We should improve profits and sales.
3. Let's talk about manpower.
4. Manpower is not the issue.
5. Maybe we should reduce our overhead.
6. Reducing overhead will improve earnings.
7. What were our earnings last year?

Comment File #3

1. We need to improve our profits.
2. What is for lunch today?
3. Let's talk about manpower.
4. Manpower is not the issue.
5. Maybe we should reduce our overhead.
6. Reducing overhead will improve earnings.
7. It is not time for lunch.

Comment File #4

1. This is my first comment. This is neat.
2. This is another comment. It is neat. Group with first.
3. I think computers are good.
4. Computers and printers are good.
5. Computers can help you.
6. Let's go on a trip to Florida.
7. Where is Florida?