An Efficient Interaction Pattern Discovery For Human Meetings

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Abstract **- Meetings are an important communication and coordination activity of teams: status is discussed, new decisions are made, alternatives are considered, details are explained, information is presented, and new ideas are generated. As such, meetings contain a large amount of rich project information that is often not formally documented. Capturing all of this informal meeting information has been a topic of research in several communities over the past decade. In this work, data mining techniques are used to detect and analyze the frequent interaction patterns to discover various types of knowledge on human interactions. An interaction tree based pattern mining algorithms was proposed to analyze tree structures and extract interaction flow patterns for meetings. In this work tree based mining algorithm proposed for human interaction flow, where the human interaction flow in a discussion session is represented as a tree. Proposed system extend an interactive tree based pattern mining algorithm in two ways. First, it is proposed a mining method to extract frequent patterns of human interaction to support several categories of meeting. Second, it is explored modified embedded tree mining for hidden interaction pattern discovery. Modified Embedded subtree mining is the generalization of induced subtrees, which not allow direct parent child branches, also considers ancestor-descendant branches. The experimental results show the discovered patterns can be utilized to evaluate a meeting discussion (debate) is efficient and compare the results of different algorithms of interaction flow.**

Keywords **- Tree based mining, Frequent interaction subtree mining, Frequent interaction mining and Modified Embedded subtree mining.**

I. INTRODUCTION

In the social dynamics, such as human interaction is the one of the important for understanding how a human's behavior or human activities under the meeting and determining whether the meeting was well organized or not is the one of the main issues in the meetings. Several methods have been used to find the interaction of the flow in the meeting in each human. To further understand the human and interference of the human interactions in meetings, here it needs to discover higher level semantic knowledge such as which interactions flow often occur in a discussion ,what interaction flow discussion usually follows, and relationships between the exist among interactions. This knowledge will help to describe important patterns of interaction. Meetings constitute the natural and important cases in the people interaction, becomes challenging problem for several conditions and a relatively well-defined dictionary of relevant events. The previous work of the paper investigates to discover patterns can be utilized to evaluate whether a meeting discussion is efficient and to compare two meeting discussions using interaction flow as a key feature. Capturing all of this informal meeting information has been a topic of research in several communities over the past decade. Data mining is a powerful method of discovering new knowledge. A mining method to extract frequent patterns of human interaction based on the captured content of face-to-face meetings. Human interaction flow in the meetings is defined as proposing a new idea expressing a positive opinion, negative opinion and giving comments. The mining results can be used for indexing meeting semantics; also existing meeting capture systems could use this technique as a smarter indexing tool to search and access particular semantics of the meetings. Interaction tree pattern mining algorithms to analyze tree structures and extract interaction flow patterns.

The Previous work of the tree based mining method discovers the human interactionin the only one data set or various categories of the data set not considered.

An interaction flow that appears frequently reveals relationships between different types of interactions. It is valuable to capture various categories of meetings and planned to develop several applications based on the discovered patterns in human meetings. So i propose my work with the meetings (debate). It is extract from previous work with the two ways in first method it is proposed the mining method that extracts frequent patterns of human interaction and insecond, it is proposed a work with the embedded subtree mining.

II. DATAMINING

Data mining, which is a powerful method of discovering new knowledge, has been widely adopted in many fields, such as Bioinformatics, marketing, and security. Knowledge discovery in databases process, or KDD is relatively young and interdisciplinary field of computer science is the process of discovering new patterns from large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics and database systems. The goal of data mining is to extract knowledge from a data set in a human-understandable structure. Data mining is the entire process of applying computer-based methodology, including new techniques for knowledge discovery, from data. Databases, Text Documents, Computer Simulations, and Social Networks are the Sources of Data for Mining.

A. Datamining In The Human Interaction

In this study, it is to investigate the data mining techniques to detect and analyze frequent interaction patterns; I hope to discover various types of new knowledge on interactions. Human interaction flow in a meeting discussion session is represented as a tree. Motivated by tree-based mining algorithms are used to analyze tree structures and extract interaction flow patterns in human. An interaction flow that appears frequently reveals relationships between different types of interactions.

B. Tree Based Mining

Association based rule mining is the fundamental method to find frequent itemsets in databases. The problem of mining association rules over transactional databases in the larger database. Mining frequent tree patterns have many useful applications in XML mining, Bioinformatics, network routing. A tree is used to represent an interaction flow in a session. It is an acyclic connected graph. Trees are also rooted, directed, and labeled. There would be some differences in the frequent interaction patterns for different meeting styles. I explore embedded tree mining for hidden interaction pattern discovery and proposed a modified embedded subtree based mining method to extract frequent patterns items of human interaction based mine on the captured content of face-to-face meetings. Human interaction flow in a discussion session is represented as a tree. Embedded subtree mining algorithms are designed to analyze the structures of the trees and to extract interaction flow patterns.

III. PROBLEM DEFINITION

Discovering semantic knowledge is significant for understanding and interpreting how people interact in a meeting discussion. As such, meetings contain a large amount of rich project information that is often not formally documented. Capturing all of this informal meeting information has been a topic of research in several communities over the past decade.

The most common way to capture meeting information is through note-taking. However, fully writing down the content of a meeting is a difficult task, and can result in an inability to both take notes and participate in the meeting. The existing tree-based mining method for discovering frequent patterns of human interaction in meeting discussions at the same meeting.

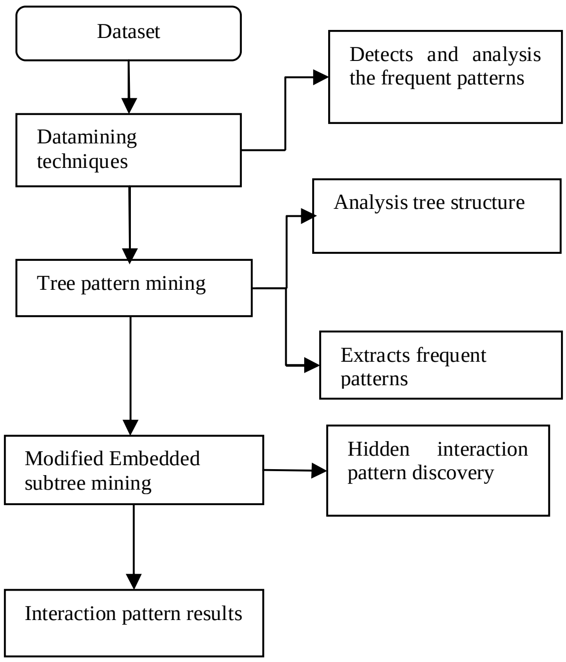

Fig. 1. Architecture diagram

The previous not capture the meeting of the debate, so here enhance my approach with it and planned for various categories.

IV. RELATED WORK

Human interaction is one of the most important characteristics of group social dynamics in meetings. In this paper, proposed an approach to capture the human reaction, recognition of human interaction and visualization of human interactions. Unlike physical interactions such as, turn-taking and addressing the human interactions are incorporated with semantics. Before it is adopted to a collaborative approach for capturing interactions by employing multiple sensors, such as microphones, motion sensors and video cameras. The collaborative based systems [1] mainly focus on detecting physical interactions between participants without any relations with topics. Hence they cannot clearly determine participant’s attitude or role in a topic discussion. Every increasing volume of recorded meeting data is driving the need for the implementation of tools to efficiently access and quickly retrieves important pieces.

TREEMINER [2] is a novel algorithm to discover all frequent subtrees in a tree-plant, using a new data structure called scope-list. In this system TREEMINER with a pattern matching tree mining algorithm (PATTERN MATCHER) were contrasted by the author. After performing these steps, several experiments were conducted test the performance of system and scalability of these methods and find that pattern matching approach performs better than another system; it also has good scale up properties. It also presents an application of tree mining to analyze real web logs for usage patterns.In earlier work Chopper [3] and XSpanner systematically develop the two algorithm pattern growth methods for mining frequent tree patterns. Experimental results shows that the newly developed algorithms out-performs TreeMinerV. Moreover XSpanner is significantly faster than Chopper in several cases. The method for frequent tree pattern mining is efficient and scalable when the patterns are not too complex. Even though there are many complex patterns in the data set.

Modeling and tracking a person's focal point of interest is useful for many applications. For multimodal person computer interaction, the user's focal point of concentration can be used to decide his/her message objective. IT is tends to address the problem of tracking the visual focal point of interest to participants in a meeting; a key aspect [4] of interactive meetings is the present speaker, who is, by definition, changing frequently. Thus, conventional meeting viewing interfaces for such meetings encompass an automatic speaker's view, which all the time shows the current speaker. Previous work has also identified that the speaker's view should be coupled with a fixed context view, which shows an overview of all of the attendees. Research indicates that for viewing recorded meetings, the combination of an automatic speaker and fixed context views does not provide sufficient information. It also found that they desire control of the context views. Based on these issues, i abstract out two high-level requirements for meeting viewing interfaces, which are not fully addressed by current meeting viewing systems: Requirement 1: The interface should correctly convey to the user who an attendee is looking at.Requirement 2: The context view should allow the user to focus on any attendee or any part of the meeting room.

The recording equipment [4] has a large impact on the rest of the system. For example, if a single, regular camera captures the meeting, the video presented in the interface is simply the one captured by the camera. Similarly at the other way if a high-resolution, wide-angle camera is used, then the video can be processed to extract separate video streams of all of the attendees, which can be presented as thumbnails in the interface. In fact, most of the systems require substantial infrastructure or hardware setup, such as an Omni-directional camera, specially positioned IP camera and microphones. It is carefully designed for rooms.

A smart meeting system which record and analyze the generated audio for future viewing, the above mentioned topic becomes a great challenge in recent years. A successful smart meeting system relies on various technologies, ranging from devices and algorithms. This system [5] presents a survey of existing research and technologies, including smart meeting system, meeting capture ,semantic processing, , meeting recognition, and evaluation methods. This article also describes various issues of all possible ways to extend the capabilities of current smart meeting systems. Improves the productivity of a team by automating Capture of the meeting. Displaying of that information accurately and effectively to the end user through a client application.

An omni directional camera [6] is used to capture the scene around a meeting table. Here real time face tracker is used to detect and track participants in the panoramic image .Moreover, neural networks (NN) are used to compute head pose of each person concurrently from the panoramic image. Then use a Bayesian approach to estimate a person's focus of attention from the computed head pose. Because Hand-recorded notes have many drawbacks. Taking notes is time consuming; it requires additional focus and thus reduces one's attention .For this reason and remarks tend to be incomplete and moderately summarized.

In our framework, the layer models [7] typical actions of individuals in meetings using supervised HMM learning and low-level audio-visual features. Numerals of options that explicitly model certain aspects of the data. In this HMM model second layer the group actions using unsupervised learning. These two layers are linked by a set of probability-based features produced by the individual action. The methodology was assessed on a set of multimodal turn-taking group actions, using a public -hour meeting corpus. From the results says that layered framework are compared to various baseline methods.

The head gestures [8] including shaking and tilt, nodding are recognized with a Wavelet-based technique from magnetic sensor signals. The simple utterance of a few platitudes is detected using data captured by lapel microphones. Experiments were conducted on four-person conversations, it validates the effectiveness of the framework in discovering interactions such as question-and-answer and addressing behavior followed by back-channel responses. Face-to-face conversation is one of the most basic forms of communication in our life and is used for conveying/sharing information, understanding others' intention/emotion, and making decisions. To enhance our communication capability beyond conversations on the spot, the automatic analysis of discussion scenes is a basic technical to realize communication via social agents and robots. The discussion scene analysis targets various aspects of conversation, from individuals.

A pattern mining method [9] to extract important patterns of interaction from a data set that contains primitive information of interaction like gazing or utterance. The method extracts coincidental patterns of interaction formed by a set of primitive events when such a pattern occurs more than randomly an interaction corpus is used for several purposes. With machine-readable indices, we can summarize a set of events and search for particular events because they contain various kinds of context information. Such a corpus is also a useful tool for cognitive science researchers in analyzing human interactions. Data mining is a powerful method that discovers new knowledge from a large set of data. It is used in many domains, e.g., medical, genetic research, and marketing, and has produced many good results. The patterns of interaction fall into two categories. One is a simultaneously occurring pattern. This pattern can be represented by a combination of events. The types of patterns can exist, for instance, the sequential happening of simultaneously happening patterns. Even in such a complicated case, however, the structure of the pattern falls into one of the two category types. The Research [10] and rigorous structure of spoken language, some of which is now articulated in grammars, remained largely unnoticed through thousands and thousands of years. It seems therefore quite possible that much structure in human interactions remains undiscovered, but it also appears result becomes misleading oversimplification. Because understanding will have to deal with complex real-time streams of behavior concurrently produced by two or more individuals. It is assumed that interaction implies more than one party where, minimally, one is influencing one another, while social imply some kind of system within, which each interaction takes place, involving different types of entities or individuals. The function and place of an individual within the interaction system is affected by its interactions

V. HUMAN INTERACTION AND PROPOSED SYSTEM

A. Human Interaction

The definition of human interaction types naturally varies according to the usage of the meetings or the types of the meetings. In this research, I mainly focus on the task-oriented interactions.

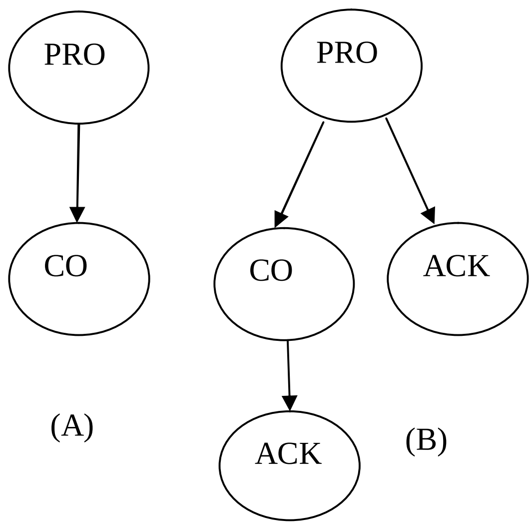

Fig. 2. Examples of tree representation human interaction flow

The other communicative actions that concern the meeting and the group itself (e.g., when someone invited another participant to take the floor) are not included. For a statistical framework for conceptualizing, investigating, and designing interaction flow , create a set of interaction types based on a standard utterance-unit tagging scheme: propose, comment, acknowledgement, requestInfo, askOpinion, posOpinion, and negOpinion.

B. Human Interaction Flow

Human interaction flow is designed as the tree .An interaction flow is a list of all interactions in a discussion with the relationship between them. An interaction flow is a list of all interactions in a discussion session with triggering relationship between them. L = {PRO; COM; ACK; REQ; ASK; POS; NEG} Labels are abbreviated names of interactions, i.e., PRO—Propose, COM—comment, ACK—acknowledgement, REQ— request Info, ASK—askOpinion, POS—posOpinion, and NEG-negOpinion .Three examples of interaction trees shown in the figure 2

C. Tree Baesd Pattern Mining Algorithm

Designed a tree based pattern mining algorithm for interaction flow mining. It formulates the frequent tree pattern mining algorithm for each node in the tree .For each tree in TD the algorithm first exchanges the places of siblings (i.e., performs commutation processing) to generate the full set of isomorphic trees (ITD). The purpose of generating isomorphic trees is to ease string matching. After generating the isomorphic trees then calculates support values of each tree at Steps 2-3. In Step 4, it selects the trees whose supports are larger than σ and detects isomorphic trees within them. If m trees are isomorphic, it selects one of them and discards the others. It finally outputs all frequent tree patterns with respect to σ .

Where,

TD –A dataset of interaction trees.

ITD-The full set of isomorphic trees to TD

t–ATree

t^k –A subtree with k nodes, i.e K-subtree ,

C^k –A set of candidates with k-nodes.

F^k–A set of frequent k-subtrees

σ–A support threshold minsup

Algorithm 1. FITM (TD,) (Frequent interaction tree pattern mining)

Input: Tree database (TD) and a support threshold σ

Output: Frequent tree patterns with respect to σ

Procedure:

(1) Scan database TD, generate its full set of isomorphic trees, ITD

(2) Scan database ITD, count the number of occurrences for each tree t

(3) Calculate the support of each tree

(4) Select the trees whose supports are larger than σ and detect isomorphic trees; if m trees are isomorphic, select one of them and discard the others

(5) Output the frequent trees

D. Frequent Interaction Subtree Pattern Mining

It first calculates the support of each node and selects the nodes whose supports are larger than σ to form the set of frequent nodes, F^1 (Steps 2-3). It then adds a frequent node to existing frequent i-subtrees to generate the set of candidates with i + 1 node (Steps 4-8).

Algorithm 2. FISTM (TD;) (Frequent interaction subtree pattern mining)

Input: Tree database (TD) and a support threshold σ

Output: Frequent subtree patterns with respect to σ

Procedure:

(1) i ← 0

(2) Scan database TD, calculate the support of each node

(3) Select the nodes whose supports are larger than σ to form F^1

(4) I ← i +1

(5) For each tree t^i in F^i, do

(6) For each node t^1 in F^1, do

(7) Join t^i and t^1 to generate C

(8) Subtree Support Calculating (TD; t^{i+1})

//calculate the support of each tree in C^{i+1}

(9) if there are any trees whose supports are larger than ,then select them to form F^{i+1} and return to Step (4)

(10) Else output the frequent subtrees whose supports are larger than σ

If there are any trees whose supports are larger than , it selects them to form F^{i+1} and repeats the procedure from Step 4; otherwise, it stops to output of frequent subtrees. In Step 7, it is joined t^i and t^1 to generate the candidate subtree set of size.

Sub procedure: Subtree_Support_Calculating (TD,st)

Count ← 0

Supp(st) ← 0

(1) for each tree t ϵTD do

(2) create subtree S of t with any item s ϵ S,|s| = |st|

(3) flag ← false

(4) for each item s ϵ S do

(5) generate isomorphic trees IS of s

(6) For each item is ϵ IS do

(7) if tsc(st) = tsc(is) then

(8) count ← count + 1

(9) flag ← true

(10) break

(11) if flag = true then

(12) break

(13) supp(st) ← count/|TD|

(14) return supp(st)

E. Various Categories of Datasets

In proposed system the tree mining algorithm is applied for extracting interaction pattern from debates . The common pattern from all types meetings and unique patterns of different types of meetings are analyzed.They are, panel, debate and general meetings ect., I investigate data mining techniques to detect and analyze frequent interaction patterns .It also develops several applications based on the discovered patterns from data. In this step develops various categories of the datasets in frequent common interaction mining.

F. Modified Embedded Sub-Tree Mining

In this modified embedded subtree mining is also plan to explore embedded tree mining for hidden interaction pattern discovery. Modified Embedded subtrees(MEST) are a generalization of induced subtrees, which allow not only straight parent and child branches, also considering the ancestor-descendant branches. For example, when there is an interaction of propose, there always follows a comment, directly or indirectly. It focuses on mining frequent embedded subtrees from databases of rooted labeled ordered sub trees.

Algorithm 3. MESTM (TD;) (Modified Embedded subtree pattern mining)

Input: Tree database TD and a support threshold σ

Output: Embedded subtree patterns with respect to σ

Procedure:

(1) i $\leftarrow$ 0

(2) Scan database TD, calculate the support of each node

(3) Select the nodes whose supports are larger than σ to form F^1

(4) I $\leftarrow$ i +1

(5) For each tree t^i in F^i, do

(6) For each parent node P in the tree t^1 in F^1, and each child node C, ancestor (their child) -descendant branches in the tree tree t^1 in F^1 do

(7) Join t^i and t^1 to generate C

(8) Subtree Support Calculating (TD; t^i +1)

//calculate the support of each tree in C^i+1

(9) if there are any trees whose supports are larger than , then select them to form F^i+1 and return to Step (4)

(10) Else output the embedded subtrees whose supports are larger than σ

G. Association Rule

The association rule learning is a popular and well researched method for discovering interesting relations between variables in large databases. It describes analyzing and presenting strong rules discovered in databases using different measures of interestingness. In our approach the association rules mining are used to discovering the confidence and support value.

H. Confidence and Support Value

Confidence value is calculated to find or how much time the event occurs at the during the frequent pattern mining .Support value is calculated between the number of occurrences of tree or sub-tree and the total number of the trees in the dataset of interaction trees. The support value is calculated using the following formula;

Support =number of occurrences of T/ total number of trees in TD

Finally it discovers the maximum support value is displayed after the embedded sub tree mining is performed.

VI. RESULTS AND DISCUSSION

In the fig. 3 (graph) result shows that the performance level of the four models: Frequent interaction tree mining (FITM), Frequent interaction subtree mining (FISTM), Modified Embedded subtree mining (MESTM).

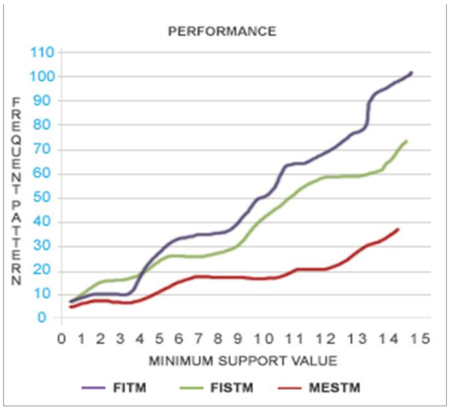

Fig. 3. Performance evaluation with FITM, FISTM, MESTM

I consider the number of frequent patterns and minimum support value is the most considerable parameter to evaluate the performance of the system. So the results show that the X-axis defines the minimum support value and the Y-axis defines the Number of the Frequent Pattern. Finally the performance of the MESTM is high other then two models. Because the human interaction activities varied based on the time to find the frequent patterns.

TABLE I

PERFORMANCE EVALUATION VALUES WITH FITM, FISTM, MESTM

Minimum support value	Frequent patterns		
	FITM	FISTM	MESTM
0	2	3	5
1	3	5	8
2	10	17	8
3	12	20	8
4	18	25	12
5	25	25	15
6	32	25	18
7	38	29	18
8	50	32	18
9	55	48	18
10	62	53	18
11	69	60	20
12	78	63	25
13	83	63	28
14	96	63	32
15	105	70	35

In this graph the result shows that the performance level of the four models: Frequent interaction tree mining (FITM), Frequent interaction subtree mining (FISTM), Modified Embedded subtree mining (MESTM).

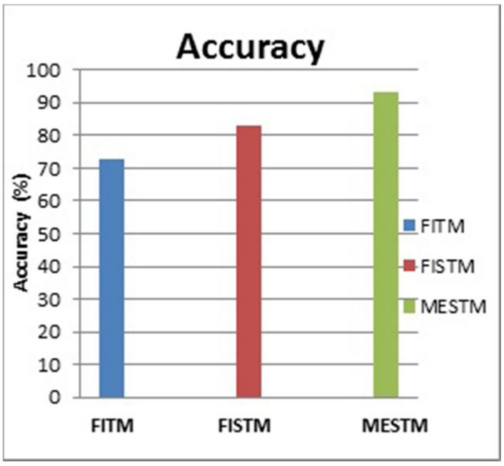

Fig. 4. Accuracy of the system with FITM, FISTM, MESTM

I consider the number of frequent patterns and minimum support value is the most considerable parameter toevaluate the performance of the system. So the results show that the X-axis defines the minimum support value and the Y-axis defines the accuracy percentage of the system. The performance of the MESTM is high because it covers the number of the frequent pattern in the less time of the system. Finally the performance of the MESTM is high other than two models. Because the human interaction activities varied based on the time to find the frequent patterns.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

Discovering frequent patterns for human interaction in meeting Tree-based mining method was proposed. The tree based mining results would be useful for indexing, summarization, and comparison of meeting records. The proposed system is valuable to analysis the various categories of meetings such as panel, debate, and interview. The proposed work is to discover frequent interaction trees and analyzes the behavior of the algorithms with different categories of meetings. The proposed works develop modified embedded subtree mining based on the discovered patterns of human interaction and final plan to incorporate more meeting content in both amount and category. From the results i can say that modified embedded subtree mining is more efficient than frequent interaction mining and frequent interaction subtree mining. Experimental results improve the accuracy by increasing the overall mining results also it is more effective.

B. Future Enhancement

Many data mining problems can be represented by non- linear data structures like trees. In future introduce a new scalable algorithm to mine partially-ordered trees. The algorithm, POTMiner, is able to identify both induced and embedded subtrees; also it can handle both completely ordered and completely unordered trees .I also extend my work to apply T-Map more real datasets and evaluate its performance. Furthermore, the consideration works by constructing of T-Map with temporal interval

REFERENCES

[1] Z.W. Yu, Z.Y. Yu, H. Aoyama, M. Ozeki, and Y. Nakamura, “Capture, Recognition, and Visualization of Human Semantic Interactions in Meetings,” Proc. Eighth IEEE Int’l Conf. Pervasive Computing and Comm. (PerCom ’10), pp. 107-115, Mar.-Apr. 2010.

[2] M.J. Zaki, “Efficiently Mining Frequent Trees in a Forest: Algorithms and Applications,” IEEE Trans. Knowledge and Data Eng., vol. 17, no. 8, pp. 1021-1035, Aug. 2005.

[3] C. Wang, M. Hong, J. Pei, H. Zhou, W. Wang, and B. Shi, “Efficient Pattern-Growth Methods for Frequent Tree Pattern Mining,” Proc. Pacific-

Asia Conf. Knowledge Discovery and Data Mining (PAKDD ’04), pp. 441-451, 2004.

[4] S. Junuzovic, R. Hegde, Z. Zhang, P. Chou, Z. Liu, and C. Zhang, “Requirements and Recommendations for an Enhanced Meeting Viewing Experience,” Proc. ACM Int’l Conf. Multimedia, pp. 539- 548, 2008.

[5] Z. Yu and Y. Nakamura, “Smart Meeting Systems: A Survey of State-of-the-Art and Open Issues,” ACM Computing Surveys, vol. 42, no. 2, article 8, Feb. 2010.

[6] R. Stiefelhagen, J. Yang, and A. Waibel, “Modeling Focus of Attention for Meeting Indexing Based on Multiple Cues,” IEEE Trans. Neural Networks, vol. 13, no. 4, pp. 928-938, July 2002.

[7] I. Mccowan, D. Gatica-Perez, S. Bengio, G. Lathoud, M. Barnard, and D. Zhang, “Automatic Analysis of Multimodal Group Actions in Meetings,” IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 27, no. 3, pp. 305-317, Mar. 2005.

[8] K. Otsuka, H. Sawada, and J. Yamato, “Automatic Inference of Cross-Modal Nonverbal Interactions in Multiparty Conversations,” Proc. Int’l Conf. Multimodal Interfaces (ICMI ’07), pp. 255- 262, 2007.

[9] M.S. Magnusson, “Discovering Hidden Time Patterns in Behavior: T-Patterns and Their Detection,” Behavior Research Methods, Instruments and Computers, vol. 32, no. 1, pp. 93-110, 2000.

[10] L. Anolli, S. Duncan Jr, M.S. Magnusson, and G. Riva, “The Hidden Structure of Interaction: From Neurons to Culture Patterns,” Emerging Communication: Studies in New Technologies and Practices in Communication, IOS Press, Apr. 2005.