Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X

IJCSMC, Vol. 3, Issue. 3, March 2014, pg.1 – 6

RESEARCH ARTICLE

IDENTIFICATION OF THE DEGREE OF PARTICIPATION BASED ON HMM

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Abstract—

Meetings or conferences play a crucial role in workplace dynamics. Active human participation is the vital component of a group social dynamics in meetings or conferences. Smart meeting has got three phases. They are capturing phase, processing phase and information exchanging phase. This work aims at identifying the degree of participation, which makes sense that the involvement and the movement of every participant are tracked. This can be used for future decision making. Also, the gestures, eye gaze frequencies are also taken into account, while identifying the degree of participation of the participant.

Key Terms- Smart meeting

I INTRODUCTION

Meetings or conferences play a crucial role in workplace dynamics. Active human participation is the vital component of a group social dynamics in meetings or conferences.

In order to save the time of transportation, most of the companies prefer smart meetings. In this concept, no conveyance is needed and the person can attend meeting from anywhere.

Smart meeting has got three phases. They are capturing phase, processing phase and information exchanging phase. The capturing phase is concerned with capturing the audio and video.

This phase aims at recognizing the person and the activity. The video is captured by an effective camera and the audio is captured by a number of microphones placed on the table, ceiling and the collar of the person. This is to enhance the quality of the audio.

All the captured audio and video are needed to be processed to get the expected outcome. The next phase is the processing phase in which each participant is uniquely identified by the ID and the gestures and movements of every participant are detected.

The speech is recognized by combining the voice and the face recognition, so as to detect the speaker accurately. We also employ writing recognition algorithm to identify the written information on the board.

The degree of participation of the participant is found out and this is achieved by Hidden Markov Models. The degree of participation makes sense that the how well the participant is involving in the meeting.

The processing phase initially does the following. It determines the action of each person in the meeting by clubbing person identification, degree of participation identification and the gesture identification.

Using the above information, all the participant's activity and gesture are grabbed at a single point of time, in order to obtain the silent feedback that is through facial expression or gesture.

At last, all the above gathered information is taken into account and the system is learnt with the meeting followed by the creation of useful models.

Finally, all the meeting segments are labelled and indexed semi-automatically. Every segment of the meeting is indexed so that the specific point of the meeting can easily be obtained.

This work aims at extracting frequent patterns of human interaction. These patterns are found to be useful for the interpretation of the person's participation in the meeting. Patterns make sense that the nonverbal behaviour of the participant of the meeting. In this work, we consider the eye gaze movement, facial expression, movement of the head, and posture of the body. All the above mentioned points are taken into account and the action-reaction combinational pairs are traced out.

This information is quite useful to track the involvement and active participation
of the participant and also the true opinion or the remark of the participant can be figured out by the gesture of the participant. SVM is employed as the discriminator to classify between the patterns.

This work distinguishes between the participants by means of a unique ID and this is achieved by RFID cards. Each participant of the meeting has to swipe the card before entering into meeting, such that the ID gets added to the participant's list.

To be specific, the proposed work can be summarized as below.

1. Capturing Phase

This phase aims at recognizing the person and the activity. The video is captured by an effective camera and the audio is captured by a number of microphones placed on the table, ceiling and the collar of the person.

2. Processing Phase

This phase exploits the above gathered information to track the involvement and active participation of the participant and also the true opinion or the remark of the participant can be figured out by the gesture of the participant. SVM is employed as the discriminator to classify between the patterns.

3. Information Exchange Phase

In this phase, all the meeting segments are labelled and indexed semi-automatically. Every segment of the meeting is indexed so that the specific point of the meeting can easily be obtained.

The remainder of the paper is organized as follows. Section II deals with the review of literature, section III is presented with the proposed work and the conclusion is presented in Section IV.

II REVIEW OF LITERATURE

Human interaction in meetings has attracted much research in the fields of image/speech processing, computer vision, and human computer interaction (see [9] for a full review).

Stiefelhagen et al. [10] used microphones to detect the current speaker and combined acoustic cues with visual information for tracking the focus of attention in meeting situations.

McCowan et al. [11] recognized group actions in meetings by modelling the joint behaviour of participants based on a two-layer Hidden Markov Model (HMM) framework.

The AMI project [12] was proposed for studying human interaction issues in meetings, such as turn-taking, gaze behavior, influence, and talkativeness.

Otsuka et al. [13] used gaze, head gestures, and utterances in determining interactions regarding who responds to whom in multiparty face-to face conversations. DiMicco et al. [14] presented visualization systems for reviewing a group's interaction dynamics, e.g., speaking time, gaze behaviour, turn-taking patterns, and overlapping speech in meetings.

In general, the above-mentioned systems aim at detecting and visualizing human interactions in meetings, while our work focuses on discovering higher level knowledge about human interaction.

There have been several works done in discovering human behaviour patterns by using stochastic techniques. Bakeman and Gottman [15] applied sequential analysis to observe and analyze human interactions.

Magnusson [16] proposed a pattern detection method, called T-pattern to discover hidden time patterns in human behaviour. T-pattern has been adopted in several applications such as interaction analysis [17] and sports research [18].

A number of studies have been conducted on discovering knowledge about human actions by applying the concept of data mining. Casas-Garriga [19] proposed algorithms to mine unbounded episodes (those with unfixed window width or interval) from a sequence of events on a time line.

The work is generally used to extract frequent episodes, i.e., collections of events occurring frequently together. Morita et al. [20] proposed a pattern mining method for the interpretation of human interactions in a poster exhibition.

It extracts simultaneously occurring patterns of primitive actions such as gaze and speech. Sawamoto et al. [21] presented a method for extracting important interaction patterns in medical interviews (i.e., doctor-patient communication) using nonverbal information.

The patterns are defined as a set of concurrently occurring primitives, e.g., utterance, gazing, and gesture. Liu et al. [22] applied data mining techniques to detect and analyze frequent trajectory patterns for activity monitoring from Radio frequency Identification (RFID) tag data.

Cao et al. [23] proposed models and algorithms for mining frequent periodic human trajectories from historical spatio-temporal data, such as mobile phone tracing.

In [24], the authors presented approaches to discover impact targeted activity patterns, i.e., identifying those activities that are likely to lead to the targeted impact. Perera et al. [25] conducted sequential pattern mining in collaborative learning data to characterize the behaviour of strong groups and group interaction.

The Discussion Ontology [26], which forms the basis of discussion methodology, was proposed for discovering semantic information such as a statement's intention and the discussion flow in meetings.

Unlike mining patterns of actions occurring together [19], [20], [21], patterns of trajectories [22], [23], and patterns of activities [24], [25], our study aims at discovering interaction flow patterns in meeting discussions, such as relationships between different types of interactions.

Although the Discussion Ontology also extracts discussion flow [26], it merely considers two intention tags co-occurring frequently.

III PROPOSED WORK

This system comprises of three phases namely the capturing phase, processing and information exchanging phase. The capturing phase deals with capturing both audio and video and this is accomplished by several microphones placed on the table, ceiling and the collar of every participant, in order to capture the audio clearly.

The video is captured by an equipped camera that has various built-in functionalities.

The processing phase deals with the recognition, in which the participant is uniquely identified by the ID which arrived by simply swiping the RFID card, and then the ID of the participant is added to the list of participants.

The gestures and movements of every participant are detected. The speaker is accurately identified by combining the voice and the face recognition. The degree of participation is identified by the hidden markov model and also a writing recognition algorithm is included to recognize the written information on board.

The information exchanging phase labels and indexes all the meeting segments semi-automatically. Every segment of the meeting is indexed so that the specific point of the meeting can easily be obtained.

3.1 RFID Card

RFID card is employed to distinguish between the participants of the meeting and the reasons for why RFID card is employed are given below.

1. RFID cards are embedded with anti-cloning technology, and thus they are safer than the traditional cards with magnetic strips.
2. RFID tags ensure an advanced security rather than a traditional bar code and electromagnetic strips.
3. The anti-theft detection of Radio Frequency is found to be safer.
4. RFID cards are less prominent to damages.
5. RFID is advisable in terms of wireless data collection and faster registration.

3.2 Hidden Markov Model

The observation is turned to be a probabilistic function (discrete or continuous) of a state instead of an one-to-one correspondence of a state Each state randomly generates one of M observations (or visible states) $\{v_1, v_2, \dots v_M\}$.

To define hidden Markov model, the following probabilities have to be specified: matrix of transition probabilities $A=(a_{ij})$, $a_{ij}= P(s_i \mid s_j)$, matrix of observation probabilities $B=(b_i(v_m))$, $b_i(v_m) = P(v_m \mid s_i)$ and a vector of initial probabilities $\pi=(\pi_i)$, $\pi_i = P(s_i)$. Model is represented by $M=(A, B, \pi)$.

HMM Assumptions

Markov assumption: the state transition depends only on the origin and destination

Output-independent assumption: all observation frames are dependent on the state that generated them, not on neighbouring observation frames

Issues in HMM

Evaluation problem. Given the HMM $M=(A, B, \pi)$ and the observation sequence $O=o_1 o_2 \dots o_K$, calculate the probability that model M has generated sequence O .

Decoding problem. Given the HMM $M=(A, B, \pi)$ and the observation sequence $O=o_1 o_2 \dots o_K$, calculate the most likely sequence of hidden states s_i that produced this observation sequence O.

Learning problem. Given some training observation sequences $O=o_1 o_2 \dots o_K$ and general structure of HMM (numbers of hidden and visible states), adjust $M=(A, B, \pi)$ to maximize the probability.

$O=o_1 \dots o_K$ denotes a sequence of observations $o_k \in \{v_1, \dots, v_M\}$.

Forward Recursion

Initialization:

$\alpha_1(i)= P(o_1, q_1= s_i) = \pi_i b_i(o_1)$, $1<=i<=N$.

Forward recursion:

$\alpha_{k+1}(j)= P(o_1 o_2 \ldots o_{k+1}, q_{k+1}= s_j)$
$= \Sigma_i P(o_1 o_2 \ldots o_{k+1}, q_k= s_i, q_{k+1}= s_j)$
$=\Sigma_i P(o_1 o_2 \ldots o_k, q_k= s_i) a_{ij} b_j(o_{k+1})$
$=[\Sigma_i \alpha_k(i) a_{ij}] b_j(o_{k+1})$, $1<=j<=N$, $1<=k<=K-1$.

Termination:

$P(o_1 o_2 \ldots o_K) = \Sigma_i P(o_1 o_2 \ldots o_K, q_K= s_i) = \Sigma_i \alpha_K(i)$

Complexity :

N^2K operations.

Backward Recursion

Define the backward variable $\beta_k(i)$ as the joint probability of the partial observation sequence $o_{k+1} o_{k+2} \ldots o_K$ given that the hidden state at time k is s_i : $\beta_k(i)= P(o_{k+1} o_{k+2} \ldots o_K | q_k= s_i)$

Initialization:

$\beta_K(i)= 1$, $1<=i<=N$.

Backward recursion:

$\beta_k(j)= P(o_{k+1} o_{k+2} \ldots o_K | q_k= s_j)$
$= \Sigma_i P(o_{k+1} o_{k+2} \ldots o_K, q_{k+1}= s_i | q_k= s_j)$
$= \Sigma_i P(o_{k+2} o_{k+3} \ldots o_K | q_{k+1}= s_i) a_{ji} b_i (o_{k+1})$
$= \Sigma_i \beta_{k+1}(i) a_{ji} b_i(o_{k+1})$, $1<=j<=N$, $1<=k<=K-1$.

Termination:

$P(o_1 o_2 \ldots o_K) = \Sigma_i P(o_1 o_2 \ldots o_K, q_1= s_i) =$
$\Sigma_i P(o_1 o_2 \ldots o_K | q_1= s_i) P(q_1= s_i) = \Sigma_i \beta_1(i) b_i(o_1) \pi_i$

3.3 Writing Recognition Algorithm

A writing recognition algorithm has two phases namely segmentation and recognition.

Segmentation deals with the line and the word break, thus separating each character. This involves identifying the boundary of the character and separating them for processing. Then the acquired data is pre-processed and enhanced to a good quality. The below given algorithm is an excerpt from [27].

Algorithm

Step1: For every character c in language
Step2: For every input i for the character c in test data
Step3: Generate Graph g_{ci} of i;
Step4: Generate graph t of input image;
Step5: For every character c in language
Step6: Use Genetic Algorithm to generate hybrid graphs;
Step7: Return character corresponding to graph with the minimum most fitness function (out of the graphs generated in any genetic operation).

IV CONCLUSION

This system aims at identifying the degree of participation of every participant in a meeting and this is accomplished by hidden markov model. A writing recognition algorithm which proves 98% accuracy in detection that was excerpted from [27] is employed to find the written information on board. This system works well in identifying the degree of participation.

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. YU ET AL.: TREE-BASED MINING FOR DISCOVERING PATTERNS OF HUMAN INTERACTION IN MEETINGS 765 TABLE 2 Association Rules (Refer to Fig. 8 About Subtree Patterns)

[2] Q. Yang and X. Wu, "10 Challenging Problems in Data Mining Research," Int'l J. Information Technology and Decision Making, vol. 5, no. 4, pp. 597-604, 2006.

[3] 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.

[4] 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.
[5] W. Geyer, H. Richter, and G.D. Abowd, "Towards a Smarter Meeting Record—Capture and Access of Meetings Revisited," Multimedia Tools and Applications, vol. 27, no. 3, pp. 393-410, 2005.
[6] P. Chiu, A. Kapuskar, S. Reitmeier, and L. Wilcox, "Room with a Rear View: Meeting Capture in a Multimedia Conference Room,"
IEEE Multimedia, vol. 7, no. 4, pp. 48-54, Oct.-Dec. 2000.
[7] Z. Yu, M. Ozeki, Y. Fujii, and Y. Nakamura, "Towards Smart Meeting: Enabling Technologies and a Real-World Application,"
Proc. Int'l Conf. Multimodal Interfaces (ICMI '07), pp. 86-93, 2007.
[8] 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.
[9] 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.
[10] 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.
[11] 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.
[12] A. Nijholt, R.J. Rienks, J. Zwiers, and D. Reidsma, "Online and Off-Line Visualization of Meeting Information and Meeting Support," The Visual Computer: Int'l J. Computer Graphics, vol. 22, no. 12, pp. 965-976, 2006.
[13] 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.
[14] J.M. DiMicco, K.J. Hollenbach, A. Pandolfo, and W. Bender, "The Impact of Increased Awareness while Face-to-Face," Human-
Computer Interaction, vol. 22, no. 1, pp. 47-96, 2007.
[15] R. Bakeman and J.M. Gottman, Observing Interaction: An Introduction to Sequential Analysis. Cambridge Univ. Press, 1997.
[16] 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.
[17] 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.
[18] K. Gudberg, M. Jonsson, T. Anguera, P. Sa´nchez-Algarra, C. Olivera, J. Ssantos, J. Campanico, M. Castaner, C. Torrents, M. Dinusova , J. Chaverri, O. Camerino, and M.S. Magnusson, "Application of T-Pattern Detection and Analysis in Sport Research," Open Sports Sciences J., vol. 3, pp. 95-104, 2009.
[19] G. Casas-Garriga, "Discovering Unbounded Episodes in Sequential Data," Proc. European Conf. Principles and Practice of Knowledge Discovery in Databases (PKDD '03), pp. 83-94, 2003.
[20] T. Morita, Y. Hirano, Y. Sumi, S. Kajita, and K. Mase, "A Pattern Mining Method for Interpretation of Interaction," Proc. Int'l Conf.
Multimodal Interfaces (ICMI '05), pp. 267-273, 2005.
[21] Y. Sawamoto, Y. Koyama, Y. Hirano, S. Kajita, K. Mase, K. Katsuyama, K. Yamauchi, "Extraction of Important Interactions in
Medical Interviews Using Nonverbal Information," Proc. Int'l Conf. Multimodal Interfaces (ICMI '07), pp. 82-85, 2007.
[22] Y. Liu, L. Chen, J. Pei, Q. Chen, and Y. Zhao, "Mining Frequent Trajectory Patterns for Activity Monitoring Using Radio Frequency
Tag Arrays," Proc. Fifth IEEE Int'l Conf. Pervasive Computing and Comm. (PerCom '07), pp. 37-46, 2007.
[23] H. Cao, N. Mamoulis, and D.W. Cheung, "Mining Frequent Spatio-Temporal Sequential Patterns," Proc. Fifth IEEE Int'l Conf.
Data Mining (ICDM '05), pp. 82-89, 2005.
[24] L. Cao, Y. Zhao, and C. Zhang, "Mining Impact-Targeted Activity Patterns in Imbalanced Data," IEEE Trans. Knowledge and Data

Eng., vol. 20, no. 8, pp. 1053-1065, Aug. 2008.
[25] D. Perera, J. Kay, I. Koprinska, K. Yacef, and O.R. Zaiane, "Clustering and Sequential Pattern Mining of Online Collaborative
Learning Data," IEEE Trans. Knowledge and Data Eng., vol. 21, no. 6, pp. 759-772, June 2009.
[26] H. Tomobe and K. Nagao, "Discussion Ontology: Knowledge Discovery from Human Activities in Meetings," Proc. 20th Ann.
Conf. New Frontiers in Artificial Intelligence (JSAI '06), pp. 33-41, 2006.
[27] Rahul KALA, Harsh VAZIRANI, Anupam SHUKLA and Ritu TIWARI, "Offline Handwriting Recognition using Genetic Algorithm", IJCSI International Journal of Computer Science Issues, Vol. 7, Issue 2, No 1, March 2010.

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