Role of Facial Emotion in Social Correlation

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Abstract. Diffusion of information can be found in any social networks, either it be a small network of co-workers or large network in social networking applications like Facebook, Twitter, LinkedIn, etc. In this work, we propose a methodology to analyse the correlation amongst the group of people by analysing the emotion diffusion among them. Moreover, we adopted a multi-agent paradigm to maintain the robustness and scalability of the algorithm. Finally, the work is validated by comparing the results with ground truth of a scripted discussion. Such knowledge of the influences among the participants of the network, could be used to find the influential individual; further can find many applications such in consensus, negotiation, viral marketing, etc.

Keywords: Multi-agent System, Facial Feature Extraction, Social Correlation, Social Influence.

1 Introduction

A social influence can be seen as the behavioural change of a person because of perceived relationship with other person, or influence of the person. In the recent years, many works were proposed to analyse the social correlation in the social network comprising of small group of people or large social networking applications like Twitter, Facebook, etc. In any social network, correlation is observed between any two nodes, mainly because of three ties [1]; namely, homophile [7]: when the two nodes have some social relationship, co-founding [7]: when the two nodes share similar belief or habits and lastly the induction ties: when one node is capable of imposing its belief on the other. In any given network tracking the homophile and co-founding is tracked by analysing the basic profile of all the nodes; profile may include information such as, age, profession, social ties, etc. And, the social influence in the network is analysed by tracking the action, location or pose of the nodes.

The work discussed in [2], tracks the location and head pose of the colleagues in the office environment, to build the correlation among them. Similar work was proposed in [13], to analyse the behaviour of the participants in the meeting, by tracking the actions (speaking and writing) of the participants. Whereas, social correlation in larger

[1] Node, people and participants are used interchangeably

networks like Facebook, Twitter, etc., were analysed by tracking the online activity as discussed in [11, 1].

Briefly, all the existing works to analyse the social correlation focuses on the pose detection, namely, head pose, shoulder pose, hand pose or their online interaction, etc. And not considering the facial emotions for the same. In this paper, we shall discuss a facial emotion based social correlation analysis among small group of people, comprising of co-workers in discussion, members in the business meeting, etc. Because, in any such groups, people have the tendency to come together and form virtual groups and the actions of the influential person is propagated to others. Also, facial emotions are important aspect for human communication and can be used to understand the social relationship between them closely.

Further, considering the fact that size of such social network may vary; so we adopt multi-agent paradigm for implementation of the proposed methodology and avoid the problem of robustness and scalability. In this multi-agent paradigm, each participant in the network is considered as a homogenous and autonomous agent. This system could be discover the hidden correlation among the small group of people and later be used to build the consensus among them.

1.1 Contribution

We have made two main contributions: (i) We introduced two social correlation parameters, which describes the correlation between all pairs of nodes in the network. (ii) The influence of one node on the other node is represented by weights, in addition to that our algorithm reflects the positive and negative orientation of the induced influence; a $+$ or $-$ sign is associated with the influence denoting positive and negative orientation respectively. Apart from this, the testing video dataset, which was a scripted discussion, could be used to build the similar emotion based systems.

1.2 Proposed Architecture

The proposed architecture consists of two main modules, facial emotion analysis and social correlation analysis. After pre-processing the video data of the discussion, each participant is represented by autonomous and homogenous agent. Then these agents interact with the two modules: facial emotion analysis module and social correlation analysis module independently. And finally, the acquired information by the agents are used to build the influential correlation among them; represented in the form of directed weighed graph.

The rest of the paper is organised as following. Section 2 explains the details about facial emotion analysis, which is divided into two main steps; feature extraction and emotion recognition. Section 3 explains the social correlation analysis algorithm. Section 4 presents the experimental results that validate our proposed algorithm. Finally, we conclude and provide the future work.

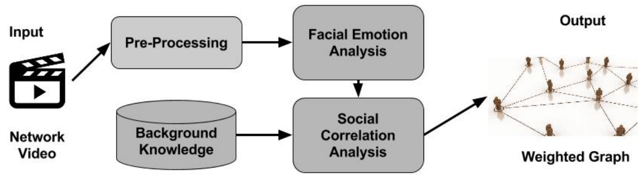

Fig. 1: System Architecture

2 Facial Emotion Recognition

Our proposed system expects a frontal video data [2] of a group of participants in discussion or in a business meeting. Wherein, change in one's emotion being induced on the other's emotions can be observed. Then, this video is pre-processed, wherein it undergoes framing of the video and later locating and cropping the frontal image in all the frames; locating and cropping of frontal image is done using Voila Jones algorithm [6]. After pre-processing, the facial features are extracted using the Active Appearance Model (AAM) [3].

Later, these extracted feature vectors are classified using the trained binary Scalar Vector Machine [10]; which is trained to classify the vector set in to one or more Facial Action Coding System (FACS) [4] present. Further, the combination of FACS present denotes one of the seven emotion listed in the table 1.

Label	Emotion	FACS
1	Neutral	null
2	Happy	6+12
3	Surprise	1+2+4+25
4	Sad	1+4+15
5	Angry	4+7+23+25
6	Fear	1+2+4+5+7+20+26
7	Disgust	9+15+16
8	Contempt	R12A+R14A

Table 1: FACS and Emotions

3 Social Correlation Analysis

From the previous section, we get stream of emotions of all participant for every second; this stream of emotion data (E) and background knowledge database (K_{db}) are used to build the social correlation amongst them. Where, K_{db} is the information database of

[2] Cameras focused on the faces

participants, which may consist of information about the participant; such as, age, gender, profession, seniority, etc. Based on this background knowledge(K_{db}), we label all the individuals on the basis of their importance and affinity among them, a.k.a nodal affinity (γ). Nodal affinity can be calculated using the algorithm used in customer profiling problem.

As, in any given social graph, emotion propagates among the nodes of the graph. So this knowledge of emotion propagation helps to find the influential correlation amongst all the nodes. This is done by analysing the change in one's emotion or action causing change in the emotions of others. In order to track and analyse such emotional change or diffusion, we propose a mathematical model to represent this diffusion of emotion, termed as emotion diffusion parameter (ΔE_{ab}), influence of node *a* on node *b*, is calculated using the equation 1.

$$\Delta E_{ab} = \frac{\tau^e_{ab} \times \omega^e_b}{T_a} \tag{1}$$

In the equation 1, τ^e_b is the time interval of a particular emotion *e* when node *a* and *b* had same emotion *e* , and ω^e_b is a participant's emotion coefficient for a particular emotion *e* of node *b*. The T_a is the total time instance. Whereas, ω_e is calculated using the equation 2, where t^e_b is the total time instance, for which participant *b* has an emotion *e* and N_e is the total number of time instance, when all the participants has emotion *e*.

$$\omega^e_b = \frac{\gamma_b \times t^e_b}{N^e} \tag{2}$$

We also assign, orientation (δ) to each emotion which is later used to define the orientation of emotion diffusion; δ can be *1 or -1* as discussed in [5]. The emotion diffusion is calculated using the algorithm 1; $e \rightarrow e'$ denotes emotion e inducing emotion e'. In algorithm 1, emotion diffusion ΔE and δ are calculated for all the pairs of nodes. Based on the obtained values, we build the correlation graph, where weights denoted the influence.

Algorithm 1 Emotion Propagation $(e \rightarrow e')$

procedure EMOTION DIFFUSION
  Input: A List of all agent
  B List of all agent
  Output: ΔE^2 and δ^2 for all pair of nodes
  // where δ is -1 or 1
  for all a enumerate(A) **do**
    for all b enumerate(B) **do**
      for all e Emotion E **do**
        $\{\Delta E^e{}_{ab}\} \leftarrow \frac{\tau^e{}_{ab} \times \omega^e{}_b}{T_a}$
    // Maximum of ΔE^e is final ΔE
    // δ^e is emotion having maximum for ΔE^e
    $\Delta E_{ab} \leftarrow max(\{\Delta E^e{}_{ab}\})$
    $\delta_{ab} \leftarrow \delta_a \times \delta^e{}_b$
  End

4 Experimental Results and Discussion

In he facial emotion analysis module; feature is extractor AAM is implemented using AAM [8] python libraries to extract different feature vectors similar to discussed in [3]. Whereas, we used Support Vector Machine (SVM) classifier for classification of these feature vectors. The AAM and SVM are trained using the two publicly available databases: FERA database [12] and LFPW database [9].

In order to validate the proposed system; we carried out a 360 seconds long scripted video conferencing discussion among 3 persons; for simplicity lets call them as A, B, and C. The evaluation and validation of the results are done on the basis of the ground truth of this input data, which is interpreted using the script and change in emotion in the curve 2. The table 2 represents the emotions detected per second for all the agents at the end of classification of all the 360 frames. Whereas, table 3 enlist the obtained ΔE_{ab} for all the pairs of nodes, this value is used to calculate the influence between each pair in both the direction, in terms of weights of weighted graph in figure 3. Further, If curves on the figure 2 is tracked for all the pairs, then the correlation among the agents is fairly reflected in the graph 3, thus validating our methodology.

Person	Neutral	Happy	Surprise	Angry	Sad
A	100	20	100	45	95
B	22	190	75	33	40
C	27	140	80	53	60

Table 2: Detected Emotion per seconds

Agent	A	B	C
A	0	1.8	0.9
B	2.5	0	2.2
C	0.8	1.5	0

Table 3: Emotion Diffusion ΔE

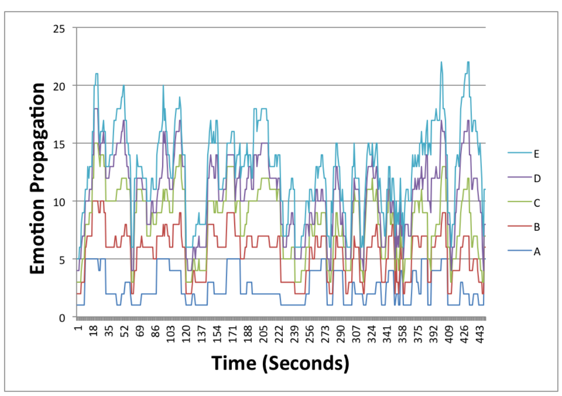

Fig. 2: Emotion Propagation

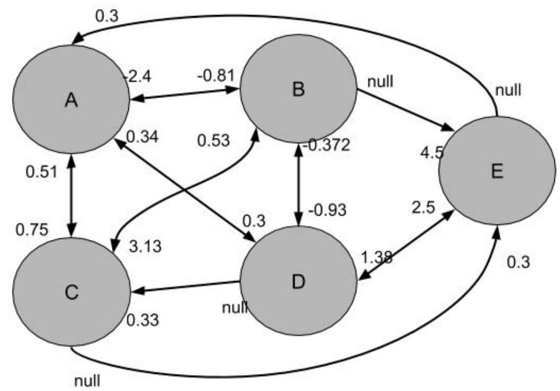

Fig. 3: Influence Graph

5 Conclusion

We proposed a multi-agent system to analyse the influential correlation in the small social networks formed by group of people in discussion or business meetings. Intuitively, the measure of social correlation gives an idea of how the change of emotions of one person affects the emotions of another person. The correlation was built using the nodal affinity and emotion diffusion parameters and finally we correlation is obtained in terms of a directed weighted graph. The proposed methodology was evaluated using the scripted discussion carried in our laboratory. As our next step is considered, it would be interesting to extend our method on larger real life networks. Moreover, we are thinking of incorporating the other influence causing aspects; such as, body actions, dialogues, etc., along with facial emotion. We are also investigating on how social association can be build on any anonymous network, irrespective of the network information.

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