Characterizing Emotion Entrainment in Social Media

Saike He[1], Xiaolong Zheng[1], Xiuguo Bao[2*], Hongyuan Ma[2], Daniel Zeng[1,3],
Bo Xu[4], Changliang Li [4], Hongwei Hao[4]
[1]State Key Laboratory of Management and Control for Complex Systems, Institute of Automation,
Chinese Academy of Sciences, Beijing 100190, China
[2] CNCERT/CC, Beijing, China
[3]Department of Management Information Systems, University of Arizona, Tucson, AZ 85721, USA
[4] Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China
{saike.he, xiaolong.zheng, dajun.zeng, boxu, changliang.li, hongwei.hao}@ia.ac.cn, bxg@isc.org.cn, mahongyuan@foxmail.com
* The corresponding author

***Abstract*—The sociological theory of entrainment accounts for the synchronization of human rhythmic modalities through social interactions: they coordinate in a variety of dimensions including linguistic styles, facial expressions, music pace, applause, and so on. Though highly relevant, emotion entrainment has received little attention to date. In addition, most previous studies on entrainment are done through small scale or controlled laboratory studies. In this paper, we investigate emotion entrainment in the context of online social media. To the best of our knowledge, this is the first time that emotion entrainment has been examined on a large scale, real world setting. For this purpose, we propose a framework that can model entrainment phenomenon and measure its effect. Our framework differentiates from previous research by its model-free essential and discerning in entrainment directions. These traits enable us to model entrainment dynamics under few assumptions, and distinguish emotion flow of entrainment. In our studies, we investigate entrainment patterns under different emotion states, i.e. positive, neutral and negative. We discover that entrainments under different emotions all follow a power law distribution. Besides, people are willing to entrain to others under positive emotion, and users with positive emotion are more likely to be entrained. By inspecting the interactions between entrainment and emotion, we reveal that entrainment has an effect of negotiating different emotion types toward an even distribution.**

Keywords—emotion entrainment; transfer entropy; social media

I. INTRODUCTION

In sociology, the principle of entrainment refers to the ubiquitous phenomenon that people unconsciously converge to another's modalities, i.e. they coordinate in a variety of ways including: psycholinguistics [1-5], facial expression [6, 7], music pace [8-10], applause [11, 12], and so on. Among these, emotion is essential to the quality and scale of routine experience for human, sine it provides the prime currency in social relationships. There are also evidences of emotion entrainment in everyday life. For instance, sharing good news between intimate friends will make them all happy; argument between conversation partners will make them assume bad tempers. Though highly relevant, studies on entrainment at emotion level, is highly scarce. Existing work just focuses on emotion related behaviors, such as linguistic styles [2], acoustic patterns in conversation [13, 14], facial feedbacks [6, 7], and more. In addition, most of these studies are conducted with small scale laboratory studies. It is still unclear a) what patterns entrainment will present in a large scale real word setting, and b) how entrainment differs under different emotion states.

In this paper, we investigate human entrainment under different emotions in the context of online social media. To the best of our knowledge, this is the first time that emotion entrainment has been examined in a large scale, real world setting. To investigate this, we propose a framework that can model entrainment phenomenon and measure its effect. Our framework differentiates from previous studies by its model-free essential and differentiation in entrainment directions. Under this framework, we can depict complex emotion interactions without making explicit assumptions for social dynamics. Measuring entrainment asymmetrically allows us to distinguish entrainment directions across different emotion states. In our study, we explore entrainment patterns under different emotion states, i.e. positive, neutral and negative. Empirical studies indicates that entrainment under different emotions all follow a power law distribution, like other online user behaviors [15-17]. Besides, people are willing to entrain to others under positive emotion, and positive users are more likely to be entrained. We also reveal that entrainment has an effect of negotiating different emotion types toward an even distribution. This process is Markovian to some extent. Findings uncovered in this paper may provide both industrial and academic implications in emotion related analysis for sociologists and psychologists, such as empathy, persuasion, and market campaign.

The rest of the paper is structured as follows. Section 2 reviews work most relevant to our task. Section 3 describes the experimental setup. Section 4 reports the results of evaluation studies. Section 5 concludes this paper with a summary and areas for future investigation.

II. Related Work

Since acoustic, linguistic and facial expressions are three main communicative channels to signal emotions of people [18, 19], thus, in what follows, we present a brief survey for emotion entrainment from these three aspects.

A. Acoustic Entrainment

Considering the mutual influence effect existing in dyadic human interactions, Lee et al. [13] utilize a Dynamic Bayesian Network (DBN) framework to model conditional dependency between interlocutors' emotion states. Though resting on a dynamic network structure, their approach only models dependency rather than causality in emotion interactions, whereas the latter is more essential in characterizing emotional behaviors. Afterwards, to quantify entrainment in prosodic entrainment, Lee et al. [20] propose to use three measure, i.e. Pearson's correlation, mutual information, and coherence. Yet, such measures are totally correlation based, thus are incapable to distinguish entrainment directions. Motivated by the benefits of estimated emotions in emotion recognition, Metallinou et al. [14] propose a hierarchical framework to model emotional evolution in the context of emotional dialog. However, their framework requires facial cues, which is highly scarce in most scenarios. Unlike all these work, the framework proposed in this paper is asymmetric and does not need additional information except for user emotions.

B. Linguistic Entrainment

Nenkova et al. [1] examine entrainment in use of high-frequency words between conversation partners. Their entrainment measure is symmetric and distance based, which makes it incapable to differentiate entrainment directions. Besides, their research is conducted with small datasets, which may weaken the soundness of their conclusions thus derived. Cristian et al. [2] investigate linguistic style entrainment occurs in Twitter conversation. Accordingly, they define stylistic cohesion to detect whether entrainment phenomenon occurs in each conversational turn. Their entrainment measure also fails to distinguish entrainment directions, which may inform more detailed implications for entrainment process. Levitan et al. [3] search for evidence of entrainment on backchannel-preceding cues (BPC)s, i.e. various conversational cues to signal one's interlocutor. Specifically, they use Common cues, BPC realization and Local BPC entrainment to quantify entrainment. Metrics they used are totally heuristic and similarity based, thus could not provide an in-depth characterization for the underlying dynamics during entrainment process. Unlike these work, our framework can model emotion dynamics and characterize nonlinear relationships.

C. Facial Expression Entrainment

Andréasson [6] explores emotional empathy by examine the empathy degree in a) mimicking facial expression and b) sensitiveness in facial response. Their research approaches are heuristic, which require much manual manipulation. This drawback may severely limit the volume of data samples used in experiments. Li and Hashimoto [7] develop a communication system between robot and human based on entrainment among human emotional states. They synchronize robotic emotion to human emotion via a vector field. However, the emotion expression space used in constructing vector filed is the limited. This may severely bound its application scale in synchronizing exuberant feeling expression of human. Hess and Fischer [21] propose a model to depict emotion mimicry based on emotional intention in specific circumstances. Their model requires knowledge about the relationship of observer and expresser. Maybe a relationship independent model would be more useful in practical applications.

III. Experimental Setup

In this section, we first describe the dataset used for entrainment analysis. Then, we introduce a framework for modeling emotion entrainment phenomenon. Finally, we describe parameter settings used in following studies.

A. Dataset

1) Description

CHI06 [22] is a dataset collected from Livejournal [1], a multi-lingual blogging platform where users share topics, opinion, interest, and so on. Unlike traditional blogging platforms, Livejournal allow its users to label their emotion states when posting blogs. In general, CHI06 dataset contains about 18 million English blog posts generated by approximately 1.6 million bloggers. Besides, it provides a long time observation from 1st May 2001 to 23rd Apr. 2005. This makes it an ideal dataset for emotion based analysis.

2) Preprocessing

For the sake of computation convenience, we select the most commonly used emotion tags (totally 1449) in the dataset, and group them into three categories: positive, neutral, and negative (Table I).

To facilitate mathematical manipulation, we assign tags in positive, neutral, and negative category with valence of [+1, 0, -1] respectively.

TABLE I. Categories of Mood Tags

Category	Examples of Mood Tags	Sample Number
Positive	great, elated, cheerful, ecstatic, jovial, fantastic, whee, triumphant, perky	285
Neutral	calm, so so, at peace, normal, ready for bed, working, thirsty, busy, blah, snuffly, warm	665
Negative	bored, sore, depressed, homicidal, crappy, yucky, remorseful, bitchy, befuddled, edgy	499
Total		1449

Similarly, to investigate entrainment under different emotion statuses, we also divide users into three groups according to their average emotion valence, as given by an indicator function:

[1] http://www.livejournal.com/

$$
\mathrm{C}(u)=\begin{cases} POS, & if\ 1/|M|\sum_{m\in M} Val(m) > v_0, \\ NEG, & if\ 1/|M|\sum_{m\in M} Val(m) < v_1, \\ NEU, & otherwise. \end{cases} \qquad (1)
$$

where M is a set of $|M|$ = N blog messages m written by user u; $Val(m)$ represents the emotion valence of message m; v_0 and v_1 are respectively the upper and lower valence boundary that separates the three user groups. In general, we consider users within each group possess a certain kind of emotion 'tone', i.e. users within POS group possess an overall positive mood in the whole observation period, though with fluctuations in their emotion dynamics.

To avoid data sparsity problem, users with less than 5 emotion tags are pruned out. Considering the confounding factors existing in user heterogeneity, we randomly select 20K users from the three user groups.

B. *Computational Framework*

In designing the computational framework, we keep two aspects in mind. First, to make framework rational and feasible for large scale data settings, we should assume as few hypotheses as possible in modeling. Second, the framework should be capable to distinguish entrainment directions, as revealed by Will and Berg [23]. As a result, we employ transfer entropy [24, 25] to quantify the entrainment strength of an individual based on his peer's capacity to predict his emotions. Transfer entropy is a causality detection technique grounded in information theory, and has been widely used in computational neuroscience [26, 27]. It allows differentiation in the direction of information flow, and excels in capturing complex nonlinear relationships in a model-free manner. Suppose we can represent the emotion time series of two users x and y with two Markov processes $X = x_t$ and $Y = y_t$, then the entrainment strength from x to y *Entrain* $(X\rightarrow Y)$ can be formulated as the transfer entropy from y to x, as shown in (2).

$$
TE(\mathrm{Y}\rightarrow\mathrm{X}) = H\left(x_{t+1}\middle|\mathbf{x}_t^m\right) - H\left(x_{t+1}\middle|\mathbf{x}_t^m,\mathbf{y}_t^n\right) \qquad (2)
$$

where $\mathbf{x}_t^m = \left(x_t,\ldots,x_{t-m+1}\right)$, $\mathbf{y}_t^n = \left(y_t,\ldots,y_{t-n+1}\right)$, while m and n are the orders of each of the Markov processes; $H(*)$ calculates the entropy of the probability distribution enclosed. (2) measures the amount of information manifested in user y, which reflects the emotion dynamics of x. We consider this amount of information as a proxy that suggests the potential of user x entraining toward y.

Estimation for (2) based on limited data samples will lead to biases [28]. To alleviate this problem, previous studies mainly focus on two strands of solutions: ex-ante limitation (e.g. Simpson's rule [29]) and ex-post elimination (e.g. Panzeri-Treves bias estimate [30]). We choose the Simpson's rule as the estimator for approximating (2), since it does not require a priori knowledge and can give accurate approximation for the objective function via "piecewise" quadratic. In addition, the computational complexity of Simpson's rule is $O(N \log(N))$. This is really acceptable in our studies. $\alpha + \beta = \chi$. (1) (1)

C. *Parameter Settings*

In following studies, we assign v_0=0 and v_1= -0.334[2] in (2). This setting will guarantee each user group contains enough user samples. Consequently, there are 4261, 10625 and 5114 users in POS, NEU and NEG user group respectively. Besides, we set the Markov orders m=n=3 in (2). According to our empirical analysis, this order is high enough, for higher order merely increases computational cost without present much quantitative differences.

IV. Entrainment Under Different Emotions

We now proceed to investigate entrainment patterns under different emotion states. Specifically, we attempt to examine three issues:

(1) How does user entrainment distribute under different emotion states?

(2) Does entrainment strength differ significantly between users under distinct emotions?

(3) How does entrainment process drive emotion evolution?

In the following we attempt to answer these issues in turn, and present according experimental results.

A. *Entrainment Distribution under Different Emotion*

We first check whether entrainment differs significantly between users with distinct emotions. As such, we draw the distributions of entrainment strength (γ) for the three user groups, as shown in Fig. 1.

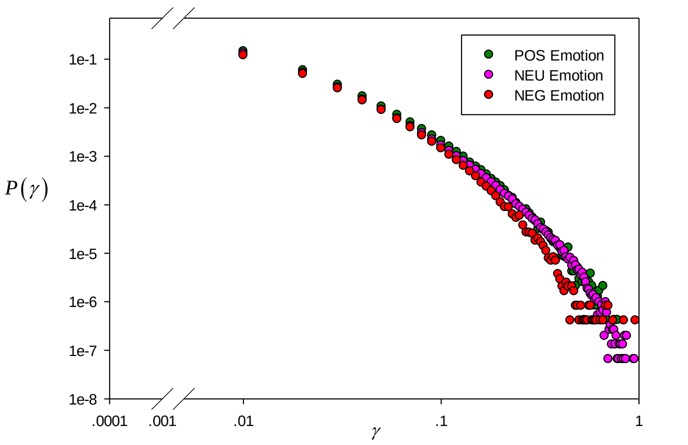

Fig. 1. Distribution of entrainment strength in three user groups.

Fig. 1 suggests that emotion entrainment in three user groups are all power-law distributed $P(\gamma) = \gamma^{-\alpha}$ with some cut-off. The exponent α equals to 1.330 ± 0.165, 1.390 ± 0.154

[2] This equals to two times of the average emotion valence among all users selected, i.e. -0.167.

and 1.332 ± 0.176 respectively in POS, NEU, and NEG group. These fits are based on the maximum likelihood estimation proposed by Clauset et al. [31], and they could not be rejected with p=0.681, p=0.685 and p=0.823 for each. Thus, we consider entrainment distributes consistently without apparent difference under distinct emotions.

Besides, the power-law nature of emotion entrainment implies that emotion dynamics is inline other user activities uncovered in online social media. They are no different in providing currency in social interactions.

B. *Entrainment across Different Emotions*

In the literature of emotion analysis, it has been long postulated that emotion states exert dramatic influence on user's decision making [32], reasoning [33], and reaction to circumstances [34]. Thus, we attempt to exploit how user entrains to another under different emotion states. Specifically, we compare the entrainment strength between users in different groups, and wonder if there are apparent differences. Average entrainment strengths in three user groups are shown in Table II.

TABLE II. ENTRAINMENT STRENGTH IN EACH USER GROUP

User Groups	**Average Entrainment Strength**
POS	10.316 (±20.181)
NEU	9.759 (±19.432)
NEG	9.484 (±18.588)

Magnitude of entrainment strength is a 10^{-3};

The number enclosed in the parenthesis is the standard deviation.

Table II suggests that people with positive emotion have stronger entrainment strength than people with neutral or negative emotion ($p < 0.0001$ based on a two-tailed t-test), indicating that people are willing to entrain to others with good mood. At the same time, people are reluctant to entrain to others with negative emotion ($p < 0.0001$ based on a two-tailed t-test). If entrainment can be generally considered as a kind of social interaction, our findings are identical with previous research findings [35, 36], which suggest that in social interactions, people are more active in a good mood, while they tend to be 'quiet' in bad mood.

Further, we delve deeper into how users entrain to others with alternate emotions. For this purpose, we calculate the average entrainment strength between user groups, as shown in Table III.

In Table III, we notice that entrainment between user peers with positive emotion are strongest (second row and second column), while weakest under negative emotion (fourth row and fourth column). This finding can only be rejected with p-value smaller than 0.05 in an independent two-tailed t-test. In addition, regardless of their current emotion states, all people are likely to entrain to users with positive emotion, though with different impetus, i.e. users under negative emotion have the weakest entrainment strength toward positive users. This may explain why happy emotion spreads widely among people [37], and why people in bad mood usually take a long time to get out [38].

TABLE III. ENTRAINMENT STRENGTH ACROSS DIFFERENT USER GROUPS

User Groups	POS	NEU	NEG
POS	10.904 (±21.169)	10.347 (±20.696)	9.696 (±18.563)
NEU	10.309 (±20.682)	9.647 (±19.563)	9.321346 (±17.941)
NEG	9.796 (±19.316)	9.440 (±18.586)	9.214 (±1.537)

Magnitude of entrainment strength is a 10^{-3};

The number enclosed in the parenthesis is the standard deviation.

C. *Emotion Evolution under Entrainment*

Last, we investigate how entrainment drives emotion evolution. The average emotion in each day for three user groups is shown in Fig. 2.

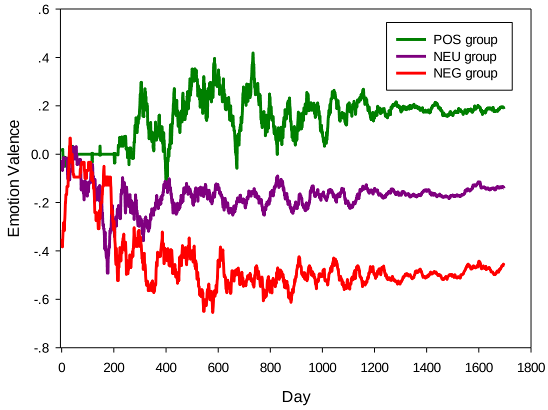

Fig. 2. Daily average emotion in different user groups. Note: this figure is obtained under a short-time moving average (window size=30 days).

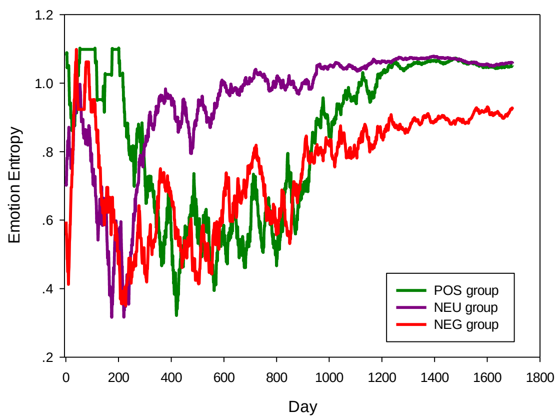

Fig. 3. Emotion entropy in different user groups. Note: this figure is obtained under a short-time moving average (window size=30 days).

From Fig. 2, we find that the emotion strength (absolute value of emotion valence) increases both in POS and NEG user group. While in NEU group, average emotion drifts toward negative direction (after 200 days in Fig. 2). As there are more users in NEU group (approximately the sum of that in POS and NEG), we assume this shifting of emotion valence may drive emotion status toward an even distribution. To examine this hypothesis, we calculate the entropy of emotion distribution in each day for each user group (Fig. 3).

In Fig. 3, we notice that the emotion entropy in each user group dynamically stable at a comparatively high level (after 1400th day), though undergoes vibrant fluctuations initially. This finding is inline with our previous hypothesis that entrainment drives emotion status toward an even distribution, maybe achieving a certain kind of social balance [39].

Besides, we also notice that emotion entropy in POS and NEU group are higher than that in NEG group. This phenomenon may be explained partly by the difference in the process of entrainment evolvement for each user group (as shown in Fig. 4).

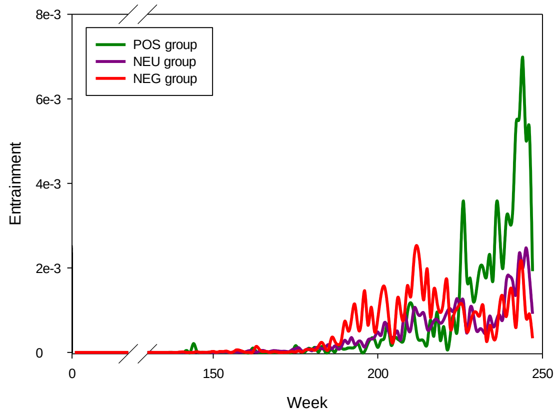

Fig. 4. Evolvement of entrainment strength. Note: this figure is obtained under a short-time moving average (window size=7 days).

Fig. 4 suggests that entrainment strength in POS and NEU group enhances with occasional attenuations. However, entrainment strength in NEG group undergoes apparent diminishment at about 220th week (Fig. 4). Such difference leads to higher emotion entropy in POS and NEU group, which undergoes gradually enhanced entrainment.

More concretely, the emotion entropy in the last week for all users is 1.043[3] (Fig. 3). As the evolvement of user emotion is driven by entrainment process, thus, we wonder if we can approximate this value merely through mathematical deduction. For this purpose, we consider that entrainment strength is approximately proportional to the probability for an individual to switch from one emotion state to another. Then, we can convert Table III into a state transition probability matrix (Table IV), and consider emotion dynamics as a Markov process (Fig. 5).

[3] Logarithm is calculated with base 2.

TABLE IV. State Transition Probability Matrix in Emotion Entrainment

Emotion States	POS	NEU	NEG
POS	0.352346823	0.33434842	0.313304757
NEU	0.352116401	0.329509871	0.318373728
NEG	0.3443351	0.331807164	0.323857736

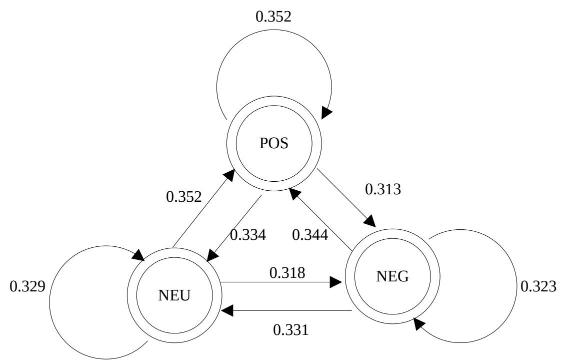

Fig. 5. Markov process for emotion entrainment.

The stationary distribution calculated from Table IV is π(POS, NEU, NEG) = (0.3497, 0.3319, 0.3183). Emotion entropy calculated based on π is 1.097, which is relatively close to the real value (relative error is 5.17%). This indicates that entrainment dynamics can be seen as a Markov process to some extent.

V. Conclusions and Future Work

In this paper, we have examined entrainment phenomenon under different emotion states on a large scale real world setting. Empirical studies revealed that entrainment strength is power-law distributed under different emotion states. Examination in entrainment between different emotions indicated that people with positive emotion are willing to entrain to others, and users with positive emotion are more likely to be entrained. Finally, we explored the interactions between entrainment and user emotion, and found that entrainment has an effect of driving user emotion toward even distribution, which process is Markovian.

In our future research, we tend to differentiate users according to their time spend in online social media. This may inform how users become accepted through entrainment process. Besides, we are also interested in the interplay between user emotion and behaviors, and hope to discern how emotion will influence people in response and reaction to outside stimulus.

Acknowledgment

We would like to take this opportunity to thank each member of SMILES group in Institute of Automation, Chinese Academy of Sciences. Especially, we would thank Kainan Cui, Zhu Zhang, and Chuan Luo for useful discussions and constructive suggestions. We also thank Guanhua Tian for patience and time in proof checking. This work was supported in part by the following grants: The National Natural Science Foundation of China, Grant No. 71103180, 71472175, 91124001, 71025001, 91024030, 61203281, 61303172, and 91224008, by BJNSF 4132072, by the Early Career Development Award of SKLMCCS and by the Ministry of Health under Grant No. 2012ZX10004801 and 2013ZX10004218, and by the Project, Gran No. 2013A127.

REFERENCES

[1] A. Nenkova, A. Gravano, and J. Hirschberg, “High frequency word entrainment in spoken dialogue,” in Proceedings of the 46th Annual Meeting of the Association for Computational Linguistics on Human Language Technologies: Short Papers, 2008, pp. 169-172.

[2] C. Danescu-Niculescu-Mizil, M. Gamon, and S. Dumais, “Mark my words!: linguistic style accommodation in social media,” in Proceedings of the 20th international conference on World wide web, 2011, pp. 745-754.

[3] R. Levitan, A. Gravano, and J. Hirschberg, “Entrainment in speech preceding backchannels,” in Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers-Volume 2, 2011, pp. 113-117.

[4] C. Danescu-Niculescu-Mizil, L. Lee, B. Pang, and J. Kleinberg, “Echoes of power: Language effects and power differences in social interaction,” in Proceedings of the 21st international conference on World Wide Web, 2012, pp. 699-708.

[5] R. Levitan, and J. B. Hirschberg, “Measuring acoustic-prosodic entrainment with respect to multiple levels and dimensions,” 2011.

[6] P. Andréasson, “Emotional Empathy, Facial Reactions, and Facial Feedback,” 2010.

[7] Y. Li, and M. Hashimoto, “Effect of emotional synchronization using facial expression recognition in human-robot communication,” in Robotics and Biomimetics (ROBIO), 2011 IEEE International Conference on, 2011, pp. 2872-2877.

[8] M. Clayton, R. Sager, and U. Will, “In time with the music: The concept of entrainment and its significance for ethnomusicology,” in European meetings in ethnomusicology, 2005, pp. 3-142.

[9] G. Lucas, M. Clayton, and L. Leante, “Inter-group entrainment in Afro-Brazilian Congado ritual,” *Empirical Musicology Review,* vol. 6, no. 2, 2011.

[10] W. Trost, C. Labbé, and P. Vuilleumier, “The physiological signature of musical emotions,” in The Annual Research Forum of the Interdisciplinary Centre of Affective Sciences, Geneva, Switzerland, 2010.

[11] Z. Néda, E. Ravasz, Y. Brechet, T. Vicsek, and A.-L. Barabási, “Self-organizing processes: The sound of many hands clapping,” *Nature,* vol. 403, no. 6772, pp. 849-850, 2000.

[12] Z. Néda, E. Ravasz, T. Vicsek, Y. Brechet, and A.-L. Barabási, “Physics of the rhythmic applause,” *Physical Review E,* vol. 61, no. 6, pp. 6987, 2000.

[13] C.-C. Lee, C. Busso, S. Lee, and S. S. Narayanan, “Modeling mutual influence of interlocutor emotion states in dyadic spoken interactions,” in INTERSPEECH, 2009, pp. 1983-1986.

[14] A. Metallinou, A. Katsamanis, and S. Narayanan, “A hierarchical framework for modeling multimodality and emotional evolution in affective dialogs,” in Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on, 2012, pp. 2401-2404.

[15] D. Rybski, S. V. Buldyrev, S. Havlin, F. Liljeros, and H. A. Makse, “Scaling laws of human interaction activity,” *Proceedings of the National Academy of Sciences,* vol. 106, no. 31, pp. 12640-12645, 2009.

[16] G. Grinstein, and R. Linsker, “Power-law and exponential tails in a stochastic priority-based model queue,” *Physical Review E,* vol. 77, no. 1, pp. 012101, 2008.

[17] R. Crane, F. Schweitzer, and D. Sornette, “Power law signature of media exposure in human response waiting time distributions,” *Physical Review E,* vol. 81, no. 5, pp. 056101, 2010.

[18] S. Yildirim, M. Bulut, C. M. Lee, A. Kazemzadeh, Z. Deng, S. Lee, S. Narayanan, and C. Busso, “An acoustic study of emotions expressed in speech,” in INTERSPEECH, 2004.

[19] P. Ekman, and E. L. Rosenberg, *What the face reveals: Basic and applied studies of spontaneous expression using the Facial Action Coding System (FACS)*: Oxford University Press, 1997.

[20] C.-C. Lee, M. Black, A. Katsamanis, A. C. Lammert, B. R. Baucom, A. Christensen, P. G. Georgiou, and S. S. Narayanan, “Quantification of prosodic entrainment in affective spontaneous spoken interactions of married couples,” in INTERSPEECH, 2010, pp. 793-796.

[21] U. Hess, and A. Fischer, “Emotional mimicry as social regulation,” *Personality and Social Psychology Review,* vol. 17, no. 2, pp. 142-157, 2013.

[22] G. Leshed, and J. J. Kaye, “Understanding how bloggers feel: recognizing affect in blog posts,” in CHI'06 extended abstracts on Human factors in computing systems, 2006, pp. 1019-1024.

[23] U. Will, and E. Berg, “Brain wave synchronization and entrainment to periodic acoustic stimuli,” *Neuroscience Letters,* vol. 424, no. 1, pp. 55-60, 2007.

[24] R. Vicente, M. Wibral, M. Lindner, and G. Pipa, “Transfer entropy—a model-free measure of effective connectivity for the neurosciences,” *Journal of computational neuroscience,* vol. 30, no. 1, pp. 45-67, 2011.

[25] S. He, X. Zheng, D. Zeng, K. Cui, Z. Zhang, and C. Luo, "Identifying peer influence in online social networks using transfer entropy," *Intelligence and Security Informatics*, pp. 47-61: Springer, 2013.

[26] E. N. Brown, R. E. Kass, and P. P. Mitra, “Multiple neural spike train data analysis: state-of-the-art and future challenges,” *Nature neuroscience,* vol. 7, no. 5, pp. 456-461, 2004.

[27] B. Gourévitch, and J. J. Eggermont, “Evaluating information transfer between auditory cortical neurons,” *Journal of Neurophysiology,* vol. 97, no. 3, pp. 2533-2543, 2007.

[28] G. Ver Steeg, and A. Galstyan, "Information transfer in social media." pp. 509-518.

[29] F. B. Hildebrand, *Introduction to numerical analysis*: Dover Publications, 1987.

[30] J. D. Victor, “Approaches to information-theoretic analysis of neural activity,” *Biological theory,* vol. 1, no. 3, pp. 302, 2006.

[31] A. Clauset, C. R. Shalizi, and M. E. Newman, “Power-law distributions in empirical data,” *SIAM review,* vol. 51, no. 4, pp. 661-703, 2009.

[32] A. Damasio, "The feeling of what happens," Harcourt Brace & Company. Copyright 1999, 1999.

[33] R. J. Dolan, “Emotion, cognition, and behavior,” *Science,* vol. 298, no. 5596, pp. 1191-1194, 2002.

[34] J. P. Forgas, “Mood and judgment: the affect infusion model (AIM),” *Psychological bulletin,* vol. 117, no. 1, pp. 39, 1995.

[35] J. P. Robinson, and S. Martin, “What do happy people do?,” *Social Indicators Research,* vol. 89, no. 3, pp. 565-571, 2008.

[36] M. R. Cunningham, “What do you do when you're happy or blue? Mood, expectancies, and behavioral interest,” *Motivation and emotion,* vol. 12, no. 4, pp. 309-331, 1988.

[37] E. Diener, and C. Diener, “Most people are happy,” *Psychological science,* vol. 7, no. 3, pp. 181-185, 1996.

[38] J. P. Forgas, G. H. Bower, and S. E. Krantz, “The influence of mood on perceptions of social interactions,” *Journal of Experimental Social Psychology,* vol. 20, no. 6, pp. 497-513, 1984.

[39] X. Zheng, D. Zeng, and F.-Y. Wang, “Social balance in signed networks,” *Information Systems Frontiers*, pp. 1-19, 2014.