Social TV via Second Screening: Exploring Non-Verbal Cues for Emotion Detection

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Abstract
Watching TV with second screens is a newly developed social phenomenon among people. People are active for seeking other viewers and tweeting about their subjective experiences. Emotions in tweets are not only expressed in words, but also through some conventions, such as lengthening words to indicate the strength of emotions. When the users are emotionally aroused, they will change their Interactional typing behavior on the phone. In this paper, we explored non-verbal cues of the behavior for emotion detection. Pilot study presents a positive relation between user emotions and typing behaviors. This method can provide language independent emotion detection of social TV viewers.

Author Keywords
Mobile affective computing, affective typing, Social TV viewing with second screens

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI):

General Terms
Human Factors.

Introduction

Watching TV with a second screen is a Social TV viewing model, which gains popularity in recent years[4]. Viewers are physically in different locations, however, having a connection to social media evokes their feeling of social connectedness, and the ready availability, and affordability of second screen devices (i.e. tablets, mobile phones or laptops) facilitates the behavior of connecting with wider viewing audiences either to get feedback from them or share their views with them[5].

TV viewers adopt several usage patterns of social media simultaneously with TV viewing. They selectively seek others who have similar interests to communicate their experiences. The generated contents are mostly created using mobile phones and they include more subjective contents [21]. The type of subjective contents can be either emotional or opinion based on words used in the contents [21]. Today, emotions of the users in social media are mostly investigated via verbal expression analysis based on affective meanings of words in contents[20]. But, this method is challenging for a couple reasons. First, most of current methods rely on manually annotated training data, where the task requires labor-intensive human evaluation of the messages and it is time consuming. Also, human judgments of emotions in text include more subjectivity when compared to other human annotation tasks for texts such as topic detection in the text. Second, emotions are triggered by specific events in contexts and generally are stated implicitly in the contents. Looking some keywords in the content can be, to some extent, misleading as human language usage is so complex that words in the contents may be used to indicate its second or third meaning or even one of its opposite meanings for the indication of sarcasm[9] or else.

The changes of communication medium from face-to-face to written text, and now to typed text cause the lost of most of the prosodic indicators in a speech. Prosodic features of a speech are high pitch, prolonged duration, intensity, vowel quality etc. and simply means that something important is said at a time in the speech. However, new conventions have been developed to substitute some of those prosodic indicators. For instance, Twitter users benefit from word lengthening by repeating letters and punctuation marks to indicate the strength of their emotions such as in the given expression of "Coooooollllll!!!!!!!!!!!!!!!!"[1]. When the users are emotionally aroused, they will change their Interactional typing behavior on the phone besides the changes on the contents. Previous researches supports the idea that device users reflect their personal emotional states to their personal typing behaviors on the device [7,13].

We investigate affective characteristics of typing on the phone for the purpose of the specified type of social interaction and we used mobile phone sensors to explore non-verbal cues of the behavior. We address 7 frequently experienced emotional states in the study: happiness, sadness, disgust, anger, fear, surprise[6] and neutral.

Social TV viewing with Second Screens

Viewers' reactions towards TV contents are investigated to learn about how people experience them. Interviews with 21 Glee viewers, one of popular TV series on TV, demonstrate that live tweeting added a social

Figure 1. Image exemplifies a social media use during broadcasted politician debate [Image source: http://www.second-scream.com/social-tv-advertising-and-monetization-elements/]

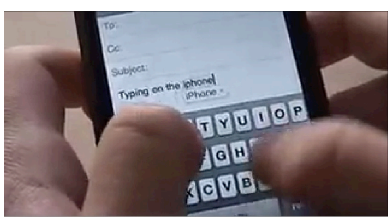

Figure 2. Typing on an iPhone

interactive aspect to watching the show together with thousands of people even they watch it physically alone[15]. Few people actively sought others' posts, writing tweets took precedence reading others comments. Primary tweets related to Glee are about play-by-play of the program and viewers' general comments. Play-by-play tweets are provoked by events within the show and take half of all tweets in quantity. Topics of those tweets are comments about characters in the show, or quotes by characters in the show. General comments addresses Glee or its specific episodes, but not specific scenes of it. Only small amount of tweets includes links such as to blog posts [15].

Another study was about human reactions toward political and entertainment programs on TV through Twitter [21]. Figure 1 exemplifies the Social TV viewing experience of a political program. The types of shared messages are grouped into four including attention, information, emotion, and opinion. People share subjective messages (emotion or opinion) on social media more than objective messages[21]. The percentage of message types varies by the programs, which shows that TV viewers have different interests [21]. The frequencies of messages drop in commercial breaks[21] and high percentage of tweets are generated using mobile devices[21]. This is reasonable that mobile phones are easy to afford, and mostly carried wherever people go, even at home.

Twitter Usage in Everyday Experience Sharing

Twitter connects people to each other and facilitates instant sharing of everyday life experiences in short messages. This form of communication is called "microblogging" and that causes more emotional content generation that might normally occur. Mobile devices affect microblogging behavior of the users. Mobile users are active to create contents, and the contents are more contextual and conversational. They contain relatively few links and are more personal such as status updates (activity, or feeling) or opinions[17].

A person may generate content (Figure 2) consisting of 2-3 sentences and 11 words on average using the 140 characters. The strict design of Twitter for content generation encourages people to create more direct contents related to contextual events. On the other hand, it may cause the expression of only certain emotions, as the content length is not enough for rich set of emotional expressions[11]. Besides that, sharing personal experiences using short sentences can cause the elimination most expressions and those will be expressed in the form of nonverbal behaviors. It is reasonable if we think that a cognitively well-thought sentence requires relatively much time and long or connected sentences, but it contradicts with the instant sharing of everyday life on Twitter. So, the social media will not be able to transfer them to other social connections using current methods. Considering these effects, we address 7 frequently experienced emotional states in this study: happiness, sadness, disgust, anger, fear, surprise[6] and neutral. Also, we investigate affective meaning of typing behavior on the phone for the purpose of the addressed social interaction.

Expressive Typing Behavior on the Phone

If an individual uses the mobile phone on 3d free space, emotions can affect human attention and control of the device. Affective bodily expression analysis

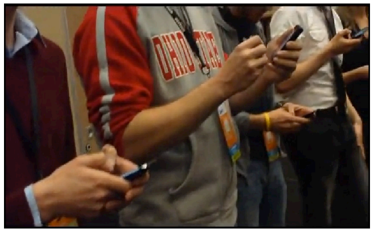

Figure 3. Different typing behaviors with different mobile phones

Arousal	
Calm	Sadness, Disgust, Neutral
Medium	Happiness
Activated	Anger, Fear, Surprise
Valence	
Pleasant	Happiness
Neutral	Surprise, Neutral
Unpleasant	Sadness, Disgust, Anger, Fear
Dominance	
Low	Sadness, Fear, Surprise
Normal	Neutral
High	Disgust, Anger, Happiness

Table 1. Mapping between emotion labels and its dimensional Features [8].

studies provide supportive results regarding the difference in body-based response to emotional change. First, when compared to face actions, people are applying fewer censors to their body movements[10]. Second, Body based expressions have correlation with dimensional features of emotions (arousal, valence, dominance). Affective body expressions are investigated through motion and form of the body and The information about motion of the body is efficient for identifying basic emotions[12]. When people are angry, the characteristic movement of the body is like "large, fairly fast and jerky movements"[12]. On the other hand, when people are sad, movements of the body has been changed to "fluid slow movements"[12]. Table 1 shows basic emotions and their dimensional relationships. For instance, happy state is given with dimensional features of medium arousal, positive valence (pleasure) and medium/high dominance.

The effect of emotion on typing behavior can be observed at least in two ways: First, people type fast when they are in hurry. This indicates the time constraints that they have to send the message. Literally this behavior indicates urgent needs and may point experiencing a problem or a thread in the life in accordance with personal goals, which generally causes the generation of emotional responses to the problem. Second, people benefit from several conventions such as lengthening words[1] to communicate their emotions. In those moments, not only their touch behavior, but also control of the device will be affected and that can give non-verbal cues about the emotions of a person. A non-verbal cue does not represent qualitative aspect or verbal meaning of the contents. It represents quantitative aspects of the behavior based on touch information and movement of the device.

Typing behavior is complex enough that includes several sub forms of the behavior. People may pause writing and perform some extra movements to indicate specific emotion related expressions in the form of gestures. It is estimated that although a remote conversation occurs between partners, if people reach the optimal flow[16][19] in the online social interaction, people will try to use their hands to support their expression behaviors as in a real social interaction and that will be observed from phone usage.

When an individual grasps or holds a device for a usage (see Figure 3 for different usage), s/he is able to develop some of the following behavioral patterns to indicate different emotions.

- Pressing hard on the screen
- Typing fast
- Generating contents at different length
- Moving the device on 3d space
- Rotating the device on 3d space
- Grasping strongly the device

If we build a complex model enough for addressing the needs of those touch and control based behaviors, we will identify emotions of mobile users. Sensors on mobile phones can help learn about non-verbal Interactional behavior on the phone. We used three sensors (accelerometer, gyroscope, touch) on an iPhone to model the behavior and uses the relationships given at Table 1. We sampled the typing behavior at 100 MHz and processed the raw data to create feature vectors. List of features are given at Table 3.

Figure 5. Interfaces of Data Collection Software

Previous field tests for measuring Interactional-typing dynamics on keyboards demonstrate that people have different typing behaviors depending on their emotional states. A study based on typing on standard PC keyboards results in identification of 6 different emotional states of 12 PC users with accuracies ranging from 77.4% to 87.8[7]. The emotional labels in the study generally address the long-term subjective states such as confidence and nervousness, and the term of mood might be better to call them. A pilot field study with touch based software keyboard on Android phones demonstrate that when an individual was sharing everyday experiences on social media, the Interactional typing behavior on the phone varies depending on emotional states and it helps identify 7 basic emotions with 67.52% accuracy using accelerometer, touch sensors and contextual factors such as weather, location, and time[13]. This method was tested with only 1 user. On the other hand, both methods are based on self-reporting of emotional states; however, they do not apply a control mechanism for evoking the certain emotions of people and that challenges the replication of those studies. Besides those methods, Interactional applications usage dynamics on mobile phones (call, SMS, specific applications such as e-mail, web browser), and hybrid methods that integrates several contextual information to them, such as activity of users, show that mobile users reflect their emotional expressions on their phone usage behaviors [3,14]. In other words, people's Interactional behavior on the phone differs with the change of their emotional states.

Research Design

The overall research question is: While users tweet in reaction to emotionally engaging moments in TV contents, do they also express their emotions on the

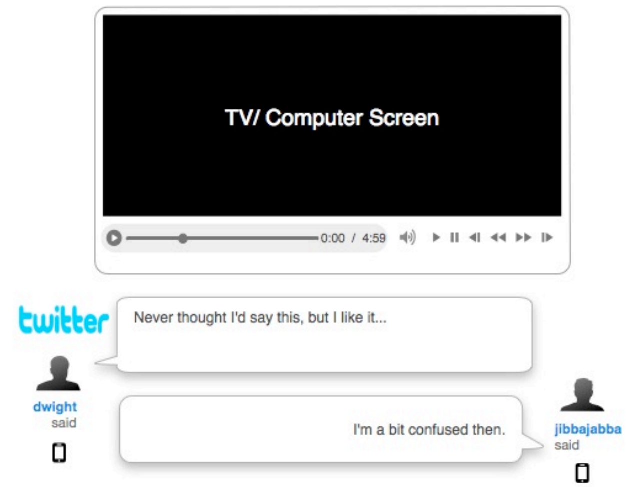

Figure 4. Design of the research

phone? If so, do those non-verbal expressions are enough to identify the emotions of the users? There are several factors affecting the design of the TV viewing experience: individuals' interests and finding appropriate TV contents, design of rich contextual emotional experience and social media app design. Considering high human factors role exemplified with studies the literature, we developed a method with two steps given below.

The overall goal of this study is to propose language independent emotion detection for social media users. This study is a first step toward achieving a model to identify the action units of Interactional typing behavior on the phone. Later, those action units will be used to synthesize action behaviors for the demonstration of certain mobile emotional expressions. This study will open up new ways in the exploration of emotions of mobile users from their mobile interaction patterns. It

Emotions	Suggested TV Contents
Happiness	Robin Williams Show
Sadness	Saving Private Ryan
Anger	Zeitgeist documentary
Fear, surprise	Mission Impossible series
Disgust	The same news with image may be used
Neutral	Any Cartoons for created for educational purposes

Table 2. Suggested TV Contents in English

will help developing new methods for affective mobile gestures and help improvement of method for interaction with mobile devices.

Step 1: Investigation of Individual's experience
We mainly focus on the design of a social TV viewing experience with second screens for one person. The design of such an experience is exemplified in Figure 4. An iPhone user views the TV contents on computer screen synchronous with custom developed Twitter based social media app running on iPhone. The main goal of step 1 is to show the applicability of identifying emotions of a mobile user from his/her typing behaviors in response to TV contents. As this is a first step, it is enough for us if we are able to find some non-verbal features describing certain emotional states. In this paper, we share the results of this study.

The contextual design is as follows: An individual sit in a chair where s/he watches TV contents on computer screen in front of her/him. TV contents include event driven stories and are used as stimuli to evoke specific emotions. To enrich the viewing experience and to eliminate contextual distracting factors, individuals wear a headset and use flat, LCD computer screens at possible large sizes. Those contextual factors will increase the engagement with the contents and people have focused attention to the content and have become perceiving it as first person-experience Csikszentmihalyi calls it as optimal flow in the experience [16][19] and that will cause to have better emotional experience. We use self-reporting method to obtain information about the feeling of a certain emotional state, which we believe that when people get optimal flow with the experience, although they may not be meta-aware of their emotions, they have experiential awareness of the emotion[19]. Also, emotion has multi-components including affective, cognitive, physiology and body responses and more, it is not completely known the interrelations of those components, we rely on self-reported emotions, as the person who experiences an emotion only truly describes the felt emotion[19], and it is totally subjective than other human experiences.

The design of experiment provides control over the TV contents used for stimulating a person's emotions and recording on-device sensors' data for verbal and non-verbal expressions in the time of the event through Twitter app running on an iPhone. The advantage of this design is that it is so close to natural interaction and all those steps take place smoothly in its context, without interfering mobile users' social interactions.

Step 2: Investigation of multi-users' experience
After we tested the design of the experience with one user, and saw that it gives proposing results for single user, the study is extended for the identification of multi-users' emotions. We first need to understand the general interests of people on social media and find best TV contents satisfying those interests. We updated the design with new TV contents addressing general interest. Also, rather than providing full TV contents, we study on cutting the content to best emotional scenes that are long enough to evoke same 7 discrete emotional states of multi- users. This will increase the motivation of people to participate in the experiment. This study is in-progress now.

The Design of Mobile Twitter Based Application
This program has 2 basic interfaces for achieving following tasks: writing tweets and reporting emotional

Feature Name	Description
AccX Shake	The Amount of Shake On X Axis
AccY Shake	The Amount of Shake On Y Axis
AccZ Shake	The Amount of Shake On Z Axis
Rot Roll Shake	The Amount of Rotation On X Axis
Rot Yaw Shake	The Amount of Rotation On Y Axis
Rot Pitch Shake	The Amount of Rotation On Z Axis
Typing Speed	Content length divided by time for preparing the content.
Max Text Length	Maximum Text length of the reaction content
Erased TextLength	Erased length of Text in the reaction content
SpecialSymbol Press Frequency	The number of special symbol use in the reaction content
TouchCount	The number of touch to do corrections in the reaction content
TimeOfDay	Morning, afternoon, evening, night

Table 3. Extracted Features from Sensors Data

states (Figure 5). Data collection begins with the tweet writing and ends when finished button is touched. Then users have access to emotion reporting interface. That prevents unwanted sensors' data collection that may influence the results.

Emotional state questionnaire includes 5 questions. First question asks for selecting emotional states among 7 emotional states: happiness, sadness, disgust, anger, fear, surprise and neutral. Emotions are given with expressive face images. The other four questions help describe the characteristic features of an emotional state: Arousal, valence, dominance and predictability of the event. They are given with 9 scales (1: not exist to 9: exist). We only used discrete emotional labels in this study.

Pilot Field Study

TV Contents

Finding TV contents to evoke certain emotions of people is hard as people have different interests. To simplify the task, we selected the contents according to the participant's interests. Types of TV contents used in the study[1] are comedy show, movie, documentary, educational cartoons and news supported with an image. News content was used for evoking disgust* and it has short text in English with an image. Other contents are video based and each of them is cut into 10 or 15 minutes long parts on average. There are 42 video parts in total. They all include one main topic and non-English contents and equivalent TV contents in English are given at Table 2.

[1] List of TV contents could be shared upon request with the author.

The contents are selected using popularity of the contents on the Internet and conventional wisdom that leads to the decision of films likely to evoke the emotions. A stand-up comedy show is used to evoke happiness state. To evoke sadness, the topic of the selected film is about a team go behind other country to rescue some people. A documentary about a recent controversial issue was one of the suitable content for evoking anger in the study. Fear and surprise were both evoked using a film that is about terror attacks and saving homeland. Lastly, neutral emotional state is evoked using educational cartoons addressing 4-5 aged children, as our participant is young adult.

Participant Information

The user study was conducted on May 2012 with one user participating for two weeks. One graduate student in our university was recruited for the study. Participant was a female in 20s and a new iPhone user with no more than one-year experience at the time of the study. Study materials (TV contents, and mobile application) were given to the participant. This was a field test and there were no restrictions on where, when or in which order participant will watch the TV contents. Participant performed the experiment tasks at her home settings following the instructions given in the sections below.

Data Collection Process

Followings are the steps that a mobile user should follow in the experiment.

1. A user sit in front of a computer screen and wear a headset to increase the engagement with TV content.

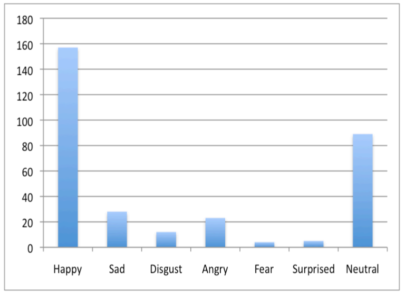

Figure 6. Distribution of responses according to each emotion label (y axis: count of data samples, x axis: discrete emotion labels)

Class	TP	FP
H	0.942	0.18
Sa	0.357	0.031
D	0.167	0.013
A	0.826	0.01
F	0	0.006
Su	0	0
N	0.899	0.053
Weighted Avg.	0.814	0.107

Table 4. Results with 10-fold cross validation method (TP: True Positive, FP: False Positive) (H: Happiness, Sa: Sadness, D: Disgust, A: Anger, F: Fear, Su: Surprise, N: Neutral)

2. The user watches TV contents one by one. One TV content is divided into 10 or 15 minutes parts. Between each video part, user takes breaks. This could be considered as commercial breaks on TV while viewing TV contents. However, as user is viewing TV contents on computer screen, users can even stop it playing, and they may take multiple hours or days as break between two video parts of same TV content or between two different TV contents.
3. When the user would like to react to the events in TV contents, s/he writes tweets and reports the emotional state in the time of writing using provided mobile application. As the experiment design is one-way interaction, tweets are about only sharing views regarding the TV content.
4. These steps will be repeated until all TV contents have been viewed.

Data Analysis Process

This step includes extracting features for modeling the typing behavior and proposing a machine-learning algorithm for performing classification task. 321 data instances were collected in field test study, technical problems cause to lose some data instances and 317 valid data instances were used in the study. Figure 6 shows the distribution of the emotion responses collected in the study. The exploration of relations between users' emotional state and typing behavior is complex and this is the first step toward achieving that goal, we chose neural network implementation in Weka machine learning tool to build user-specific emotion model and model is tested with 10 fold cross validation method. Table 3 gives the definition of the extracted features. Best informative features selection method has been performed to see whether small set of features could work for the same task. The correlation-based feature subset selection (CfsSubsetEval) method in Weka was used to select best-first features in features list. Selected features are TypingSpeed, MaxTextLength, AccXShake, AccZShake, RotRollShake, RotPitchShake, and TimeofDay.

	H	Sa	D	A	F	Su	N
H	147	1	3	3	0	0	2
Sa	10	10	0	0	1	0	7
D	8	0	2	0	1	0	1
A	2	1	1	19	0	0	0
F	2	2	0	0	0	0	0
Su	1	2	0	0	0	0	2
N	6	3	0	0	0	0	80

Table 5. Confusion Matrix (H: Happiness, Sa: Sadness, D: Disgust, A: Anger, F: Fear, Su: Surprise, N: Neutral).

Results

Neural network performance was tested with 10 fold-cross validation method. Table 4 presents the individual recognition rate for each emotional state and overall recognition rates as well. Column representing true positive values gives correct recognition rate of the addressed emotional state and false positive gives the rate of false recognition rate. For instance, happiness is correctly identified with 94%accuracy; on the other hand it is confused with other emotional state and miss-identified as happiness with 18% rate. Besides that, Table 5 gives the confusion matrix representing the performance of the algorithm for the given data set. Each row and column on the table represents an emotional state; the numbers gives how many of data samples are recognized or confused with other emotional state. For instance, 147 of 156 happiness-data sample in the set are correctly identified as happiness. The rest is identified as different emotions. Top three features that have high correlation with emotions are typing speed, maximum text length, and amount of acceleration on X axes.

Discussion

This field test is designed as a first step towards detection of mobile emotions from the interaction behavior on the mobile devices. We used 7 main features describing different typing behaviors on the phone. Those features are not based on the behaviors of experienced mobile users. It seems like mobile users' experience plays a role on typing behavior development. We believe that this method has potential to improve not only for social media and social TV experience but also recognition of mobile emotions.

Improved Social Media Experience

The information of emotional state of mobile users can be used to improve the social media experiences such as developing methods for embedding emotional gestures to the text message.

Improved Social TV Experience

Consumers' purchase behaviors of any media content are affected by subjective evaluation of TV contents. As this study adopt social viewing experience of social media users, this technique can be used to get information about subjective ratings of broadcasted TV contents.

Affective Mobile Input Technique Development

Emotion data can be used to develop affective gestures and personalization of input technologies for mobile and wearable devices.

Related Work

Affective Computing

Affective computing includes the description of emotions and the methods to identify emotions of people and affective Interactional method development[18]. Current emotion identification methods are mostly based on changes on emotional expression channels such as face, body, and voice. The study in [2] can provide a comprehensive overview about the techniques based on audio and visual and spontaneous affective expression. Those methods require special instruments that makes it difficult to implement them in real life settings. This study uses on-device sensors to develop an unobtrusive method for the detection of emotions of mobile second screen owners.

Conclusion

We presented the results of a pilot field study to explore non-verbal cues for emotion detection of mobile second screen owners in response to TV contents. This is the first trial based on proposed experimental design; we run an on-going multi-user study.

Acknowledgements

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References

[1] Brody, S. and Diakopoulos, N. Cooooooooooooooollllllllllllll!!!!!!!!!!!!!!: using word

lengthening to detect sentiment in microblogs. In proc of *EMNLP '11:*, 562–570.

[2] Calvo, R.A., Member, S., Mello, S.D., and Society, I.C. Affect Detection : An Interdisciplinary Review of Models , Methods , and Their Applications. *1*, 1 (2010), 18–37.

[3] Chittaranjan, G., Blom, J., and Gatica-Perez, D. Who's Who with Big-Five: Analyzing and Classifying Personality Traits with Smartphones. In Proc ISWC *2011*, 29–36.

[4] Clark, D. Why TV Is Going Social. 2012. http://www.forbes.com/sites/dorieclark/2012/09/06/why-tv-is-going-social/.

[5] Doughty, M., Rowland, D., and Lawson, S.C.-2325635. Who is on your sofa?: TV audience communities and second screening social networks. *Proceedings of the 10th European conference on Interactive tv and video*, 2012, 79–86.

[6] Ekman, P. *Universals and Cultural Differences in Facial Expressions of Emotion*. 1972.

[7] Epp, C., Lippold, M., and Mandryk, R.L. Identifying emotional states using keystroke dynamics. In Proc CHI 2011, (2011), 715.

[8] Fontaine, J.R.J., Scherer, K.R., Roesch, E.B., and Ellsworth, P.C. The World of Emotions Is Not Two Dimensional. *Pyschological Science 18*, 12 (2007), 1050–1057.

[9] González-Ibáñez, R., Muresan, S., and Wacholder, N. Identifying sarcasm in Twitter: a closer look. In Proc of Assoc. Comp. Linguistics, Association for Computational Linguistics (2011), 581–586.

[10] Gunes, H. and Pantic, M. Automatic, Dimensional and Continuous Emotion Recognition. *International Journal of Synthetic Emotions 1*, 1 (2010), 68–99.

[11] Kim, H.J., Park, S.B., and Jo, G.S. Affective social network—happiness inducing social media platform. *Multimedia Tools and Applications*, (2012), 1–20.

[12] Kleinsmith, A. and Bianchi-Berthouze, N. Affective Body Expression Perception and Recognition: A Survey. *IEEE Transactions on Affective Computing*, (2012), 1–1.

[13] Lee, H., Choi, Y.S., Lee, S., and Park, I.P. Towards Unobtrusive Emotion Recognition for Affective Social Communication. In Proc IEEE CCNC 2012, 276–280.

[14] Ma, Y., Xu, B., Bai, Y., Sun, G., and Zhu, R. Daily Mood Assessment Based on Mobile Phone Sensing. *2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks*, (2012), 142–147.

[15] McPherson, K., Huotari, K., Cheng, F.Y.-S., Humphrey, D., Cheshire, C., and Brooks, A.L.C.-2141569. Glitter: a mixed-methods study of twitter use during glee broadcasts. In Proc. ACM CSCW 2012, 2012, 167–170.

[16] Norman, D.A. *Things That make us Smart: Defending Human Attributes in the age of Machine*. Addison Wesley, 1993.

[17] Perreault, M. and Ruths, D. The Effect of Mobile Platforms on Twitter Content Generation. (2010), 289–296.

[18] Picard, R.W. Affective Computers. In *Affective Computing*. MIT Press, 1997, 47–84.

[19] Schooler, J.W. and Mauss, I.B. To Be Happy and to Know It: The Experience and Meta-Awareness of Pleasure. In M.L. Kringelbach and K.C. Berridge, eds., *Pleasures of the brain*. Oxford University Press, New York, NY, US:, 2010, 244–254.

[20] Tsytsarau, M. and Palpanas, T. Survey on mining subjective data on the web. *Data Mining and Knowledge Discovery 24*, 3 (2011), 478–514.

[21] Wohn, D.Y. and Na, E.K. Tweeting about TV: Sharing television viewing experiences via social media message streams. *First Monday 16*, (2011), 1–13.

*That image and related news can be found using following search terms on Google: "Japanese artist cut and serve cook his genital".