Title	Introducing social networks and brain computer interaction
Authors(s)	Bourke, Steven; Healy, Graham; Smeaton, Alan F.; Smyth, Barry
Publication date	2012-06-21
Publication information	iHCI 2012: Proceedings of the Sixth Anual Irish Human Computer Interaction Conference : Poetics of design, narratives of use
Conference details	iHCI 2012: Irish Human Computer Interaction Conference 2012, Galway, June 20 - 21
Publisher	National University of Ireland, Galway
Link to online version	http://www.nuigalway.ie/edu/downloads/ihci_2012_proceedings_optpdf.pdf
Item record/more information	http://hdl.handle.net/10197/3910

Introducing social networks and brain computer interaction

Steven Bourke
CLARITY: Centre for Sensor Web Technologies
University College Dublin
Belfield, Dublin 4
steven.bourke@ucd.ie

Graham Healy
CLARITY: Centre for Sensor Web Technologies
Dublin City University
Glasnevin, Dublin 9
ghealy@computing.dcu.ie

Alan F. Smeaton
CLARITY: Centre for Sensor Web Technologies
Dublin City University
Glasnevin, Dublin 9
alan.smeaton@dcu.ie

Barry Smyth
CLARITY: Centre for Sensor Web Technologies
University College Dublin
Belfield, Dublin 4
barry.smyth@ucd.ie

ABSTRACT

It is well known that the brain generates electrical patterns of activity in response to visual stimuli such as faces or anything that captures attention in a significant way. Signals of this type can be detected using an EEG (Electroencephalograph) system where we attach electrodes to the scalp and we amplify the detected signals and use a computer to capture them in real time. In this paper we examine the role that automatic sensing of brain activity may have on how users interact with interactive applications like Facebook. This offers a new opportunity for implicit feedback into such systems and in our work we focus on social networking applications. We demonstrate some of these implicit responses with experimental data captured while a user searched Facebook for photos of friends while being connected to an EEG. Finally, we discuss the implications that this kind of automatic implicit feedback may have on future design of such systems.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous; D.2.8 [**Software Engineering**]: Metrics—*complexity measures, performance measures*

General Terms

Human Factors, Experimentation

Keywords

Recommender systems, brain-computer interface, social networking

1. INTRODUCTION

In this paper we examine the role that automatic and passive sensing of brain activity may have on how users interact with online social networks like Facebook. We are particularly interested in online social networks such as Facebook because they have become communication and organisational tools in their own right, whereby users in many cases have hundreds of friends [3] with whom they interact with.

It is well known that the brain generates electrical patterns of activity in response to visual stimuli such as faces or anything that capture attention in a significant way. This response is uncontrollable and automatic, and happens in a fraction of a second, from 200ms upwards. Signals of this type can be automatically detected using an EEG (Electroencephalograph) system whereby we attach electrodes judiciously placed at certain locations on the scalp. If the detected signals are coupled with presentation of visual information as part of a social network application like Facebook then they can detect implicit feedback from the user to that stimulus, which could be, for example, the face of a friend or a recommended connection. Such a scenario would give a fascinating insight into how personalisation algorithms which recommend friends could be improved in online social networks. In addition, because such feedback would be implicit and not explicit, it would reduce the cognitive load a user copes with while they navigate an environment which presents them with an abundance of social information.

We believe that capturing implicit feedback in any kind of interactive system offers huge potential where the response must be fast and the user is under stress. In this paper we use online social network systems as an example of such an interactive system and we discuss the implications this kind of implicit feedback may have on future social networking applications. We also demonstrate some of these responses with experimental data captured while a Facebook user searched for photos of friends though this experiment is just an initial observation regarding the use of brain computer interaction with online social networks.

2. BACKGROUND

In this section we present background information on previous work in electroencephalography and on personalisation. As the fields do not have any kind of combined work, we divide the background into the two primary sections.

2.1 Electroencephalography

It is well known that the brain generates electrical signals as a result of our cognitive reaction to various stimuli, including visual stimuli and that changes in these signals can reflect aspects of our cognitive and sensory processing of these stimuli. Over the past century from the initial discovery of these signals in humans, their detection has provided a mechanism for us to glean insight into on-going processes within the brain.

The human brain generates a constant stream of electrical activity, even when we are sleeping, and these can be sensed and amplified and then captured on a computer. Within the stream of EEG signals are perturbations related to specific cognitive and sensory events. Of particular interest to us are those related to sensory events whose timing and content can be controlled, i.e. we can control an image presented to a user on a computer screen and we can analyse the EEG signal for perturbations at a specific time epoch after the image is presented. Analysis of the EEG signal in the time domain with respect to the time of display of a particular stimulus is more commonly known as an Event Related Potential (ERP) [12]. Several classes of ERPs exist, with some occurring in reaction only to stimuli such as faces. Others are known to be modulated by factors like our attention and arousal levels to outlier stimuli and how these might deviate from a consistent pattern. An example of such a deviation would be a photo stream of photos with a photo of a friend suddenly appearing in the stream when not expected.

EEG signals have been typically used in a diagnostic application to detect epilepsy or brain death, or in the study of the various processes in brain, and with modern advances in computational power they are now capable of being studied and classified in real-time, allowing them to drive brain computer interface (BCI) systems. EEG signals have even been shown to be modulated by affective picture processing, indicating their suitability for use in applications that involve sensing aspects of sentiment and emotion [13]. Blankertz *et al.* [2] highlights a number of application area where BCI technology and particularly EEG could prove beneficial in.

With the recent availably of consumer EEG hardware making EEGs with small numbers of nodes (8 or 16) cost-effective as opposed to EEGs with up to 256 nodes, research efforts are now endeavouring to find applications almost at the consumer level. Indeed Wikipedia lists 9 consumer-level EEG systems, all but one costing less than US$300 [1]. One example of this is the Emotiv EPOC EEG system being used for control of a cellular telephone [4]. Other applications include image-search applications [10].

In a modern social networking system, a user selecting an option indicating that they like some multimedia content such as a video on a friend's page can be telling of both their opinion of that content and their relationship to the person who shared it. Conversely, a user might browse the content made available by a friend in a way that would typically be expected to result in explicit feedback, but without this the user may be implicitly informing us of a fundamentally different type of relationship with the person who posted the content at that time. An example of this might be the Facebook stalker phenomena [15]. In effect the degree of understanding we can have about each user in an online social networking system like Facebook is limited by the sum of their explicit and implicit feedback.

Modern algorithmic techniques used to understand the relationships between users like this to find significant relationships remain fundamentally limited by the degree to which such systems can sense the user. For this reason we envision the use of sensing devices like EEG responses to begin playing a more integral role in the future of social-networking applications.

2.2 Personalisation

The use of personalisation techniques which leverage social networks has become increasingly prominent due to the availability of social data. There has already been significant exploration into what is known as social ties [8]. A social tie is the online world is simply some form of interaction with a friend in an online environment. In the work carried out by Gilbert *et al.* [8] a large scale qualitative survey was carried out to try and understand which online interactions were more meaningful or representative of friendship in online environments. Similar work has also been performed that looked beyond social ties into what is known as trust [9]. Here, the authors look to identify traits that make a user more truth-worthy as opposed to measuring social interactions as seen in [8]. Other work which explicitly looked into the likelihood of social influence correlating with similarity was carried out in [5] where the authors performed an analysis of two large-scale online communities where individuals interacted with each other, namely `wikipedia.org` and `blogger.com`. They found that over time users with social ties do become more similar. Finally in the case of social ties directly infused into personalisation, work was carried out to measure the effectiveness of social ties compared to similarity at predicting relevant items [3], where the authors found in most cases no significant increase could be determined computationally. Other relevant works which measure social tie exposures was carried out to determine if personality traits impact someone's popularity amongst their social network [14].

In the subsequent sections we discuss this further demonstrating one potential application using through experimental means.

3. EXPERIMENTAL SETUP

To combine implicit feedback from EEG readings with recommendations of friends from one's social network and using face recognition as the visual stimulus, our implementation consisted of two elements. The first was the social network application, a tool used to collect relevant information from our subjects' social networks for our experiment. The second component was the EEG configuration which involved the physical configuration of the hardware as well as the machine learning techniques to identify event-related potentials.

3.1 Social Network

For the purpose of our study we used the widely-known social networking website `Facebook.com`. Each test subject in our experiment used a custom Facebook application we created specifically for this work. This application gathered the profile pictures of the test subjects' friends so that these could later be used in the experiment. During the experiment, each subject would be shown 1440 images of people in total, with 120 of these being friends and the other 1,320 being people the subject had no known familiarity with. Following the experiment the subject was asked to filter through the 120 friend images to label those whom they recognised as friends. The sample of friends were prescreened to ensure that their profile pictures actually contained that particular users profile picture as well as meeting size constraints. We assigned a very simple social tie score to each friend (Equation 1). Where a is our experiment user and we want to generate a social tie score for their friend i, we take the total number of public interactions between both users and divide that over the total number of public interactions user a has.

$$SocialTie(a,i) = \frac{InteractionBetween_{(a,i)}}{TotalInteraction_{(a)}} \qquad (1)$$

3.2 EEG Configuration

We used a KT88-1016 EEG system to record EEG signals from the subjects. Electrodes were placed at sites Fz, Cz, Pz, Oz, P3 and P4 as per the international 10-20 system placement map [11]. The left earlobe was used as a reference and the chin was used as ground. Signals were digitised at 100Hz and subsequently band-passed from 0.1Hz to 20Hz.

Each image of a face, which was our visual stimulus, was shown centrally on a screen for 750 milliseconds. Both target (friend) and non-target (unknown person) images were preprocessed prior to the experiment to adjust them so there was a consistent profile and aspect ratio. The experiment was broken into two blocks with each lasting approximately 9 minutes, in order to avoid subject fatigue.

To determine whether patterns of differentiating EEG activity exist following the presentation of an image of a recognised friend vs. a non-friend profile picture, we used a machine learning analysis on the subject's EEG signals. Epochs of 1s following the presentation of each image were extracted for the 6 channels or in other words we captured the EEG signal from the 6 channels for 1000ms after initial presentation, sampling every 10ms. These values were amalgamated to form a labelled feature vector corresponding to pictures of recognised friends vs. unrecognised people.

We used a repeated random sub-sampling cross validation with a linear SVM kernel approach. Testing sets were comprised of 5 randomly-sampled examples from each of the cases to be compared, with the remaining examples used for training by the SVM training algorithm.

The validation procedure was repeated 100 times with randomly sampled training and testing sets. On each iteration of the validation procedure we used the trained model to generate predictions for the examples in the testing set. By demonstrating that the trained model is capable of doing this above the likelihood of chance we can assert the presence of discriminative information present in the signals that allows them to be differentiated. We use ROC-AUC [7] as a measure of accuracy. Accuracies across all iterations were then averaged to give an overall score.

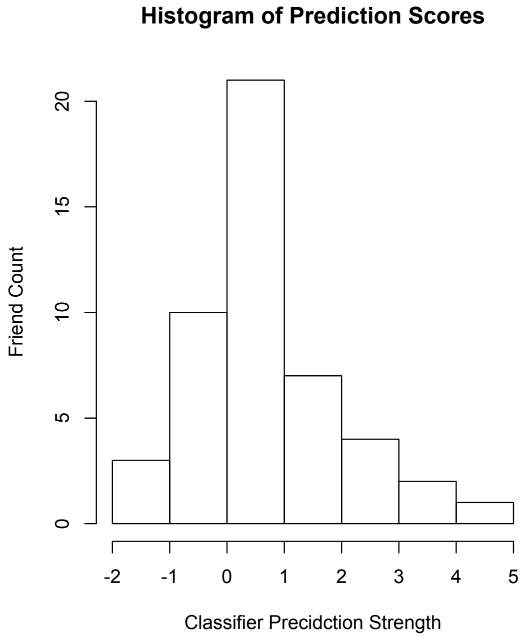

Figure 1: Predicted value if friend or not.

4. EXPERIMENTAL RESULTS

To date we have tested our experimental configuration on one test subject, a male in the age range 28 to 32. As previously mentioned our experiment is an initial observation regarding the use of brain computer interaction with online social networks. Our test subject who completed the experiment had in total 753 Facebook friends, and we took a sample of 120 of these friends. Out of these 120 friends, the subject recognised 48 in total (a recognition rate of only 40%). This is interesting because the widely known Dunbar number [6] suggests that a cognitive load of 100 to 230 friends is possible. In the case of Dunbar's number this relates to how many friends a person can actually remember with ease. In the case of our experiment the EEG measurements are actually measuring how likely a user is to recognise a friend the instant that they see their face on-screen. In Figure 1 we can see the prediction scores for how accurately we could classify each of the 48 friends. The AUC for our classifier was 0.757. Our results only include the 48 friends our test subject labelled as recognised. What we can see from these results is that 13 of the 48 friends had a negative prediction score, meaning that the classifier was unable to correctly relate the brain activity of our test subject with the ground truth. We can see that the positively predicted users are in the majority with 35 users being correctly classified. Importantly, the correctly classified users have a stronger prediction score in general. Figure 2 gives us the social tie scores associated with the correctly identified users from our experiment. The first observation is that only 23 of the recognised friends had some form of public interaction with our test subject on the Facebook. The second observation that can be made is that the accuracy of our predictor does not appear to have any resemblance to how often the friend would interact with our experiment user.

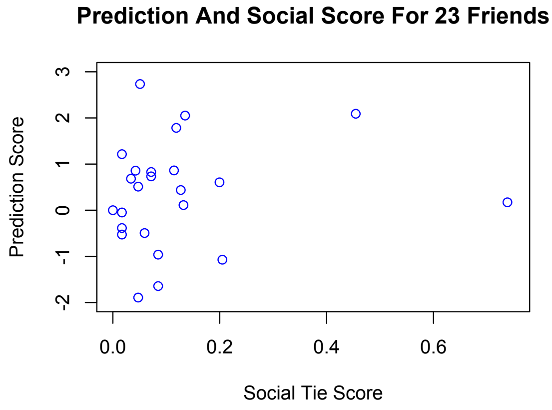

Figure 2: Prediction and Social Tie results.

For instance, 8 of the 14 users who the classifier could not accurately predict are in the set of users who have at least one social interaction.

5. DISCUSSION & CONCLUSION

In this paper we presented preliminary results of a new and innovate area of computing, which is the merging of recommender systems that use social computing with brain computer interfaces. Our preliminary results firstly indicate that it is in fact possible to train classifiers using EEG signals to predict if someone is a friend or not but that the recognition rates are surprisingly low. To the best of our knowledge this has not been done by anyone else and it may be because people do not generally use good profile pictures of themselves because they are meant to reflect their personalities and so not meant to be like passport photos'. We have also found that while users could have hundreds of online friends in these social networks they may struggle to actually associate their profile pictures to known user profiles. Our work presents a number of questions which need to be investigated, such as the exploration between algorithmically generated scores to rank friends and nodes in social networks. There has already been a large body of work completed in that specific area however there is no use of any technology such as EEG signals which sense involuntary responses to classify the underlying results. This could leave an open question as to whether it is even possible to find correlations between EEG signals representing the natural reaction of individuals, and typical trust or social scoring based metrics? If there is no such correlation then which technique would be more beneficial to an end user in a recommender system, a technique derived from EEG activity or one derived from previously standard algorithmic approaches?

6. REFERENCES

[1] Comparison of consumer brain-computer interfaces. `http://en.wikipedia.org/wiki/Comparison_of_consumer_brain_computer_interfaces`, 2008. [Online; accessed 20 April 2012].

[2] B. Blankertz, M. Tangermann, C. Vidaurre, S. Fazli, C. Sannelli, S. Haufe, C. Maeder, L. E. Ramsey, I. Sturm, G. Curio, and K. R. Mueller. The Berlin brain-computer interface: Non-medical uses of BCI technology. *Frontiers in Neuroscience*, 4(0), 2010.

[3] S. Bourke, K. McCarthy, and B. Smyth. Power to the people. In *Proceedings of the fifth ACM conference on Recommender systems - RecSys '11*, page 337, New York, New York, USA, Oct. 2011. ACM Press.

[4] A. Campbell, T. Choudhury, S. Hu, H. Lu, M. K. Mukerjee, M. Rabbi, and R. D. Raizada. Neurophone: brain-mobile phone interface using a wireless eeg headset. In *Proceedings of the second ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds*, MobiHeld '10, pages 3–8, New York, NY, USA, 2010. ACM.

[5] D. Crandall, D. Cosley, D. Huttenlocher, J. Kleinberg, and S. Suri. Feedback effects between similarity and social influence in online communities. In *Proceeding of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '08*, page 160, New York, New York, USA, Aug. 2008. ACM Press.

[6] R. Dunbar. Neocortex size as a constraint on group size in primates. *Journal of Human Evolution*, 22(6):469 – 493, 1992.

[7] T. Fawcett. ROC Graphs: Notes and Practical Considerations for Researchers. Technical report, HP Labs, No. HPL-2003-4, 2004.

[8] E. Gilbert and K. Karahalios. Predicting tie strength with social media. In *Proceedings of the 27th international conference on Human factors in computing systems - CHI '09*, page 211, New York, New York, USA, Apr. 2009. ACM Press.

[9] J. Golbeck. Trust and nuanced profile similarity in online social networks. *ACM Transactions on the Web*, 3(4):1–33, Sept. 2009.

[10] G. Healy and A. F. Smeaton. Optimising the number of channels in EEG-augmented image search. In *The 25th BCS Conference on Human Computer Interaction*, 2011.

[11] R. Homan, J. Herman, and P. Purdy. Cerebral location of international 10-20 system electrode placement. *Electroencephalography and Clinical Neurophysiology*, 66(4):376–382, 1987.

[12] S. J. Luck. *An Introduction to the Event-Related Potential Technique (Cognitive Neuroscience)*. The MIT Press, 1st edition, Aug. 2005.

[13] J. K. Olofsson, S. Nordin, H. Sequeira, and J. Polich. Affective picture processing: an integrative review of ERP findings. *Biological Psychology*, 77(3):247–265, 2008.

[14] D. Quercia, R. Lambiotte, D. Stillwell, M. Kosinski, and J. Crowcroft. The personality of popular Facebook users. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work - CSCW '12*, page 955, New York, New York, USA, Feb. 2012. ACM Press.

[15] E. J. Westlake. Friend Me if You Facebook: Generation Y and Performative Surveillance. *TDR/The Drama Review*, 52(4):21–40, Nov. 2008.