Predicting Emotional Granularity with EEG Coherence

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Understanding the system operator's resilience to stressful situations is very important in designing adaptive systems. In this study we suggest a method to predict emotional granularity, a crucial personality trait that influences one's ability to cope with highly demanding situations. To predict emotional granularity, we measured the coherence of brain activities with EEG, while participants were viewing affective images, and used random forest learning method for classification of participants. The results showed that EEG coherence could predict the individual's emotional granularity with up to 88% accuracy.

INTRODUCTION

In order to design more effective human-machine systems that produce minimal demands on the operator, there have been many efforts to assess the system operator's status in real time and adjust the system's function accordingly. Measuring neurophysiological signals can help develop an operator model and aid regulation of automation (Byrne & Parasuraman, 1996). Thus far, real-time analysis of an operator's mental workload state using EEG achieved 70%-86% accuracy (Parasuraman, 2013). For example, there is a visual monitoring task and classification with artificial neural networks by Wilson and Russell (2007), a reading span task, visuospatial n-back task, and sternberg task and classification with artificial neural networks by Baldwin and Penaranda (2012), or the Multi-Attribute Task Battery (MATB) and classification with Bayesian networks by Wang, Hope, Wang, Ji, and Gray (2013).

Measuring the emotional state of the user and reflecting it on adaptive systems has been studied in many areas, as emotional states can influence perceived workload, attention, risk perception, decision-making, and subsequent coping behaviors (Jeon & Zhang, 2013; McKeown, 2014). In the current study, we focus on the granularity of with which individuals experience their emotional state. Psychological research demonstrates that individuals differ in the ability to experience emotions in a precise manner (*emotional granularity*; Barrett, Gross, Christensen, & Benvenuto, 2001). If someone reports multiple emotions (e.g., angry, sad, anxious) to the same degree across instances, s/he would be low in granularity. By contrast, if someone is being specific about his/her emotions by indicating a different emotional feeling on each occasion, s/he would be high in granularity.

Emotional granularity is associated with emotional and social wellness. For example, high granularity individuals possess greater emotion-regulation skills (Barrett et al., 2001), greater resilience in the face of stress (Tugade, Fredrickson, & Barrett, 2004), and show less aggressive behavior in anger-inducing situations (Pond et al., 2012). Low granularity individuals who experience emotions as more general states of negativity, on the other hand, are more likely to have major depression (Demiralp et al., 2012). Hence, assessing emotional granularity can help infer how system operators cope with difficult situations and what feedback the system should provide to mitigate successful human-computer interaction.

METHODS

In this study, we used *coherence,* as the strength of synaptic connections between two distant brain regions, which is a measure of synchrony between two distant brain areas. High coherence is interpreted as functional cortical integration (Maurits, Scheeringa, van der Hoeven, & de Jong, 2006), whereas low coherence is taken as functional isolation of brain regions associated with a cognitive task (Weiss & Mueller, 2003) and with more focal activity (Reiterer, Pereda, & Bhattacharya, 2011). With the observed change in coherence value, we predicted the emotional granularity of the system operator using the random forests method.

Participants

A total of 38 participants were recruited from a local university. Two of them were excluded from the data analysis due to recording error and excessive signal noise. As a result, brain signals from 36 participants were analyzed (male = 25, female = 11). Average age was 21.5 with standard deviation 2.02. There were no participants with previous neurological disease or emotional disorders.

Granularity

The ability to differentiate between emotions, or emotional granularity, was measured based on a survey described below. On the day before the EEG experiment, all participants completed an online questionnaire that measures emotional granularity. The questionnaire asked participants to recall fifteen episodes from the day before the questionnaire and to report to what extent (from 0 to 6) he/she experienced each of 20 emotional states (ten positive words: amusement, awe, contentment, excitement, gratitude, happiness, love, pleased, pride, serenity; ten negative words: anger, boredom, disgust, dissatisfied, downhearted, embarrassment, fear, gratitude, sadness, tired). This questionnaire was created based on the Day Reconstruction Method (Kahneman et al., 2004) modified by Rice and Lindquist (in prep).

Granularity is a behavioral measure in the sense that participants are not necessarily aware that they are reporting on their emotions in a more or less granular manner. Intraclass correlations (ICCs) for both positive and negative valence emotions were calculated and averaged to quantify individuals' level of granularity (Kimhy et al., 2014; Tugade et al., 2004). A low ICC value implied that the participant could differentiate discrete emotional categories and express his or her experience with different emotional terms. Thus, average ICC value was subtracted from 1 to make higher value correspond to higher emotional granularity. The average granularity of all participants was 0.765 with standard deviation 0.168. Participants were grouped into three: High, Med, and Low. The high granularity participants' value was higher than average plus one standard deviation (0.933; 5 participants), while Low granularity group participants' granularity value was lower than average minus one standard deviation (0.597; 6 participants). The rest of the participants who had a granularity value between 0.597 and 0.933 were categorized as the Mid-granularity group (25 participants).

Stimuli

Images from the International Affective Picture System (Lang, Bradley, & Cuthbert, 1999) were used. We selected 40 emotional images that have been normed to induce awe, excitement, fear, and disgust, according to Mikels et al. (2005), in addition to 10 neutral images. Each image was presented for 3 seconds with 10 seconds of rest. A black cross in the grey background was presented for 2 seconds every time before the stimulus presentation. The whole set was repeated after 3 minutes of rest. Participants passively viewed these stimuli.

Collecting EEG signal

The participants were seated in front of a 40" TV monitor and 50" away from the TV. On the EEG cap they wore, 16 electrodes (i.e., channels) were embedded covering Fp1/Fp2, F7/F8, FC3/FC4, T7/T8, P7/P8, FT7/FT8, P3/P4, C3/C4 areas, based on the modified 10-20 systems of the International Federation. Fpz was used as a ground, and left ear lobe was used as a reference. Signal was sampled 256 Hz, notch filtered at 60Hz using g.USPamp and g.tec LabVIEW modules from g.tec Medical Engineering.

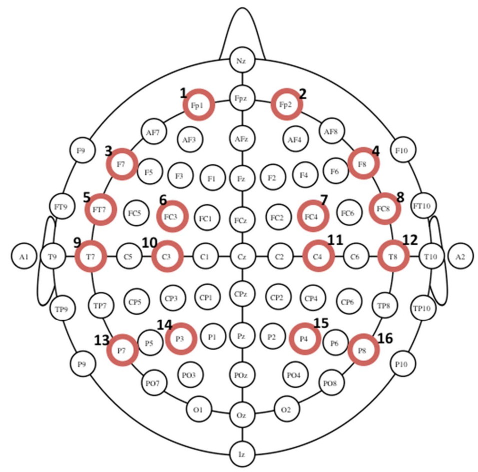

Figure 1 Montage of 16 EEG electrodes (marked with thick red circles) based on International 10-20 system

The placement of electrodes was derived from meta-analyses of the neuroimaging literature on emotion from "psychological constructionist" perspective (e.g., Kober et al., 2008; Lindquist et al., 2012). Table 1 summarizes the location of 16 electrodes and related emotional processes.

Table 1 Electrode locations and related emotional processes

10-20 Location	Related emotional processes
Fp1/Fp2	Affect generation and representation
F7/F8	Integration of contextual information and previous knowledge of affect
FT7/FT8	Categorize and apply a label to the current feeling
FC3/FC4	Motor preparation
T7/T8	Categorize and apply a label to the current feeling
C3/C4	Representation of previous knowledge of affect
P7/P8	Visual perception; attention to affectively salient stimuli
P3/P4	Categorize and apply a label to the current feeling

Calculating change of coherence

The EEG signal was band-pass filtered to get signal from the following four frequency bands: theta (4-7Hz), alpha (8-12Hz), beta (13-30Hz), and gamma (30-50Hz). We paired 2 channels and made 120 combinations of channel pairs (${}_{16}C_2$), and for each pair (channel *x* and *y*) calculated the coherence value using power spectrum functions and the formula below.

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f) * P_{yy}(f)}$$

Three coherence values were calculated for two epochs: from 1s before the stimulus onset to the stimulus onset (-1 ~ 0s; baseline) and from the stimulus onset to 1s after the stimulus onset (0 ~ 1s). The first value was subtracted from the latter value to obtain 'change of coherence' values. The values indicate how the coherence between two distinct brain areas has been changed while viewing emotional images.

Classification with random forests

Random forest is one of the ensemble machine learning methods that is easy to train and shows high accuracy and robust performance. In short, it samples attributes, builds multiple decision trees, and classifies observations according to the votes of trees (see Breiman, 2001 for a review). One advantage of random forest is that it can estimate the importance of attributes used to train a model. In this study, we ran the following sequence for each of four frequency bands (alpha, beta, gamma, and theta):

(1) divided the data into 10 samples and used 9 for training and 1 for validating (10-fold cross-validation),
(2) used MATLAB TreeBagger class to create bagged decision trees for each training set,
(3) calculated the average accuracy of 10 runs by comparing classification results with the actual data (see Figure 3),
(4) picked top 10 important channel pairs (with all data as a training set), and
(5) ran 10-fold cross-validation random forests again with 1, 2, 3, …, and 10 top pairs (see Figure 4)

RESULTS

Overall coherence change

In all frequency bands, most of the channel pairs showed a decrement in coherence after the stimulus onset. Table 2 shows how many channel pairs had decreased coherence value on average in each frequency band and granularity group. It shows that at least 101 out of 120 (84.2%) channel pairs showed coherence reduction in all cases. In high frequency bands (i.e., beta and gamma), the reduction was greater when granularity was higher. For example, in the gamma band a large number of channel pairs (34 pairs) showed significantly greater reduction in coherence. Figure 2 visualizes some of the channel pairs that revealed significantly greater coherence reduction in high granular group. Those channel pairs were broadly distributed over brain areas.

Table 2 The number of channel pairs that showed decreased coherence (out of 120 channel pairs) for each frequency band and granularity group

Granularity Group	Theta (4-7Hz)	Alpha (8-12Hz)	Beta (13-30Hz)	Gamma (30-50Hz)
Low	120	107	114	101
Mid	119	112	116	108
High	118	108	117	115

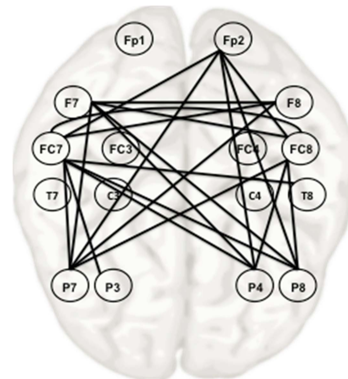

Figure 2 Channel pairs in gamma band that showed significantly more coherence reduction in high than low granularity group (only those with *p-value* less than α=0.005 was used here to avoid cluttered graph)

Overall accuracy

The accuracy of predicting granularity group (i.e., Low, Mid, and High group) with coherence change ranged from 82% to 89%. Figure 3 shows the average accuracy in each frequency band, when the random forest was created 10 times with 90% of data and tested with the rest of the data. The 10% of test data was different for all 10 runs (i.e., 10-fold cross-validation).

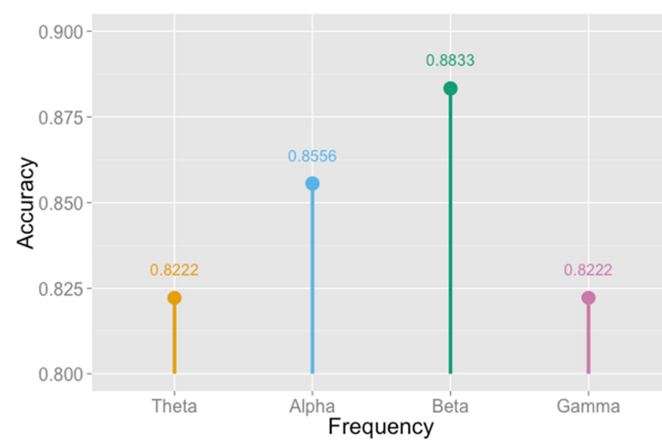

Figure 3. Accuracy of classification for each frequency band, obtained from 10-fold cross-validation (note that y-axis starts at 0.800)

For an overview, here we report the result of all data as a training set (i.e., step (4) in the 'Classification with random forests' section). Table 3 shows the error rates. "Inaccurate by one level" shows the proportion of instances that the actual group was adjacent to the predicted group (e.g., predicted to be Low when actual group is Mid, and vice versa). "Inaccurate by two levels" indicates the proportion of instances that Low was predicted to be High, or vice versa. These values can change as random forest method resample attributes to make decision trees every time the model runs.

Table 3 Inaccuracy of the prediction when all data was used for training set

	Theta (4-7Hz)	Alpha (8-12Hz)	Beta (13-30Hz)	Gamma (30-50Hz)
Overall error rates	15.56%	16.11%	13.85%	12.78%
Inaccurate by one level	15.00%	15.00%	12.74%	12.22%
Inaccurate by two levels	0.56%	1.11%	1.11%	0.56%

Classification with important pairs

By using random forest, we were able to obtain the importance of attributes. We sorted the attributes by the importance, which is obtained from the run with all data as a training set. From the top, we selected n ($1 \leq n \leq 10$) attributes and created random forests. In Figure 4, we report accuracy of 10-fold cross-validation.

The accuracy of classification sharply increased as the number of channel pairs included in the model increases. In all frequency bands, with only 5 pairs of channels the model could predict the granularity group of a participant with 80% accuracy. Note that the accuracy is always 0.6944 with only one pair. It was achieved by classifying all participants as "Mid" granularity group.

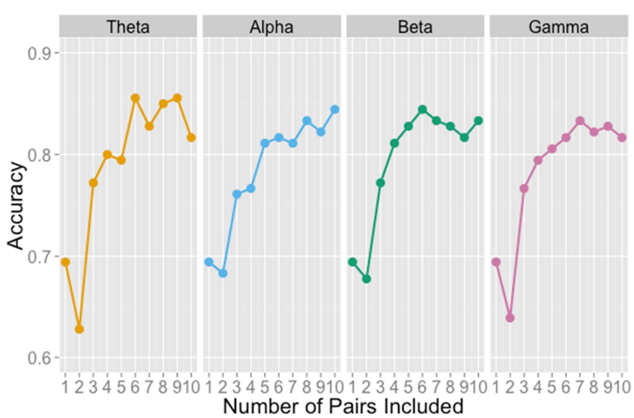

Figure 4. Accuracy of classification when different number of channel pairs was used (1 through 10) for each frequency band and epoch

Table 4 shows which pairs were used to calculate the classification accuracies in Figure 4. For example, accuracy of predicting granularity group was about 80%, with five channel pairs Fp1-Fp2, C3-P3, F7-C3, F7-P4, Fp1-FC8 and their coherence change value.

Table 4 Channel pairs that were important in deciding granularity group

Importance Rank	Theta (4-7Hz)	Alpha (8-12Hz)	Beta (13-30Hz)	Gamma (30-50Hz)
1	Fp1 – Fp2	Fp1 – Fp2	Fp1 – Fp2	Fp1 – Fp2
2	C3 – P3	FC4 – T8	Fp1 – P7	Fp1 – P8
3	F7 – C3	Fp1 – F8	FT7 – P7	P7 – P4
4	F7 – P4	Fp1 – T8	Fp1 – FC8	FC4 – T8
5	Fp1 – FC8	FC4 – C4	FC8 – P7	F7 – P7
6	FC4 – P7	Fp2 – P7	Fp1 – FC4	FC8 – P8
7	F8 – P7	T7 – P4	Fp1 – T7	FT7 – P3
8	T7 – P7	FC5 – P4	Fp2 – P7	FC4 – C3
9	FC5 – C4	Fp1 – P3	FC4 – C3	Fp1 – P7
10	FT7 – P4	Fp1 – C3	Fp1 – T8	FT7 – P7

DISCUSSION

Most channel pairs showed coherence reduction after stimulus onset. This finding implies that brain areas were less synchronized while viewing the emotional images as compared to a rest period. It also indicated that the distant brain areas processed emotional information in more decoupled fashion (Weiss & Muller, 2003).

With these coherence patterns, we were able to predict the granularity level of a participant with adequately high accuracy. It ranged from 82% to 88%, depending on the frequency band. This means that the 2 seconds of EEG data (1 second before viewing an emotional image and 1 second while viewing an emotional image) and random forest method can predict the level of people's granularity. Similar accuracy was achievable, with only about 7 pairs of channel pairs, through the attribute evaluation of the random forest method. It suggests that less than 14 channels can do such an accurate prediction. We expect that the need of channels for prediction will decrease significantly with other EEG measures (e.g., P300). Notably, granularity was assessed the day prior to emotion image viewing. Our findings are thus all the more impressive because they show that brain activity during emotional image viewing can be used to predict emotional granularity, a stable personality trait associated with how individuals experience emotions in daily life.

However, this coherence difference between granularity groups may be due to other processes that are not immediately related to emotional processes, such as visual search, conscientiousness, attention to detail, and so forth. Further analysis with ERP method will help alleviate these concerns.

Overall, this study confirmed the possibility of EEG coherence metric as a tool to assess the system operator. By understanding the system operators' emotional granularity, we will be able to infer their personalities, such as flexibility in demanding situations (e.g., Tugade, Fredrickson, & Barrett, 2004). This will help identify appropriate adaptive strategies for effective systems that maximize the operator's ability.

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REFERENCES

Baldwin, C. L., & Penaranda, B. N. (2012). Adaptive training using an artificial neural network and EEG metrics for within-and cross-task workload classification. *NeuroImage*, 59(1), 48-56.

Barrett, L. F., Gross, J., Christensen, T. C., & Benvenuto, M. (2001). Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cognition & Emotion*, 15(6), 713-724.

Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32.

Demiralp, E., Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuehl, M., Barrett, L. F., ... & Jonides, J. (2012). Feeling blue or turquoise? Emotional differentiation in major depressive disorder. *Psychological Science*, 23(11), 1410-1416.

Jeon, M., & Zhang, W. (2013, September). Sadder but wiser? Effects of negative emotions on risk perception, driving performance, and perceived workload. *In Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 57, No. 1, pp. 1849-1853). SAGE Publications.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702), 1776-1780.

Kimhy, D., Vakhrusheva, J., Khan, S., Chang, R. W., Hansen, M. C., Ballon, J. S., … Gross, J. J. (2014). Emotional granularity and social functioning in individuals with schizophrenia: an experience sampling study. *Journal of Psychiatric Research*, 53(1), 141–8.

Maurits, N. M., Scheeringa, R., van der Hoeven, J. H., & de Jong, R. (2006). EEG coherence obtained from an auditory oddball task increases with age. *Journal of Clinical Neurophysiology*, 23(5), 395-403.

McKeown, C. (2014). Neuroergonomics: a cognitive neuroscience approach to human factors and ergonomics. *Ergonomics*, 57(1), 137-138.

Mikels, J. A., Fredrickson, B. L., Larkin, G. R., Lindberg, C. M., Maglio, S. J., & Reuter-Lorenz, P. A. (2005). Emotional category data on images from the International Affective Picture System. *Behavior research methods*, 37(4), 626-630.

Parasuraman, R. (2013). Neuroergonomics: brain-inspired cognitive engineering. *The Oxford Handbook of Cognitive Engineering*, 159-177.

Pond Jr, R. S., Kashdan, T. B., DeWall, C. N., Savostyanova, A., Lambert, N. M., & Fincham, F. D. (2012). Emotion differentiation moderates aggressive tendencies in angry people: A daily diary analysis. *Emotion*, 12(2), 326.

Reiterer, S., Pereda, E., & Bhattacharya, J. (2011). On a possible relationship between linguistic expertise and EEG gamma band phase synchrony. *Frontiers in Psychology*, 2.

Tugade, M. M., Fredrickson, B. L., & Barrett, L. F. (2004). Psychological resilience and positive emotional granularity: examining the benefits of positive emotions on coping and health. *Journal of Personality*, 72(6), 1161–1190.

Wang, Z., Hope, R. M., Wang, Z., Ji, Q., & Gray, W. D. (2012). Cross-subject workload classification with a hierarchical Bayes model. *NeuroImage*, 59(1), 64-69.

Weiss, S., & Mueller, H. M. (2003). The contribution of EEG coherence to the investigation of language. *Brain and Language*, 85(2), 325-343.

Wilson, G. F., & Russell, C. A. (2007). Performance enhancement in an uninhabited air vehicle task using psychophysiologically determined adaptive aiding. *Human factors: the journal of the human factors and ergonomics society*, 49(6), 1005-1018.