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**Studying emotion theories through connectivity analysis: evidence from
generalized psychophysiological interactions and graph theory**

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1 **Abstract**

2 Psychological construction models of emotion state that emotions are variable
3 concepts constructed by fundamental psychological processes, whereas according to
4 basic emotion theory, emotions cannot be divided into more fundamental units and
5 each basic emotion is represented by a unique and innate neural circuitry. In a
6 previous study, we found evidence for the psychological construction account by
7 showing that several brain regions were commonly activated when perceiving
8 different emotions (i.e. a general emotion network). Moreover, this set of brain
9 regions included areas associated with core affect, conceptualization and executive
10 control, as predicted by psychological construction models. Here we investigate
11 directed functional brain connectivity in the same dataset to address two questions:
12 1) is there a common pathway within the general emotion network for the
13 perception of different emotions and 2) if so, does this common pathway contain
14 information to distinguish between different emotions? We used generalized
15 psychophysiological interactions and information flow indices to examine the
16 connectivity within the general emotion network. The results revealed a general
17 emotion pathway that connects neural nodes involved in core
18 affect, conceptualization, language and executive control. Perception of different
19 emotions could not be accurately classified based on the connectivity patterns from

1 the nodes of the general emotion pathway. Successful classification was achieved
2 when connections outside the general emotion pathway were included. We propose
3 that the general emotion pathway functions as a common pathway within the
4 general emotion network and is involved in shared basic psychological processes
5 across emotions. However, additional connections within the general emotion
6 network are required to classify different emotions, consistent with a constructionist
7 account.

8

9

10 Keywords: Emotion, Basic Emotion Theory, Psychological Construction Model,
11 Generalized Psychophysiological Interaction, Graph Theory.

1 Introduction

2 Basic emotion theory (Darwin, 1873; Ekman, 1992; Tracy & Randles, 2011) has
3 long dominated the field of emotion research but is currently being challenged by
4 psychological construction models (Barrett, 2006; Lindquist, Wager, Kober,
5 Bliss-Moreau, & Barrett, 2012). According to basic emotion theory, there is a limited
6 set of universal emotions, typically including anger, disgust, fear, happiness and
7 sadness. These emotions cannot be deconstructed into more fundamental units and
8 are associated with an innate distinct physiology and neural circuitry. Although
9 under-acknowledged, basic emotion theory thus implies that each instance of a
10 particular (basic) emotion is associated with a dedicated and emotion-specific neural
11 circuit and physiological response. Accurate classification of basic emotions based on
12 neural patterns has been interpreted as evidence supporting basic emotion theory,
13 as these patterns would reflect so called “fingerprints” (Saarimäki et al., 2016). These
14 “fingerprints” are the biologically primitive causes of emotion specific instances at
15 the psychological level, i.e. they define all instances of e.g. anger, and differentiate
16 them from all other basic emotions such as fear or disgust. Interestingly, accurate
17 classification of emotions based on neural patterns has also been interpreted as
18 support for an alternative and incompatible view: construction models (Clark-Polner,
19 Johnson, & Barrett, 2017). According to construction models, emotions arise from a

constructive process that involves components that are not specific to particular emotions (Gross & Barrett, 2011). Instead of distinct circuitries per emotion, construction models propose that large scale brain circuits (associated with core affect, conceptualization, executive control, etc.) are engaged for a variety of emotions (Barrett, 2006; L.F. Barrett, 2017; Lindquist et al., 2012; Oosterwijk et al., 2012). Constructionists have argued that accurate emotion classification from neural patterns does not reflect a “fingerprint” or “essence”, as this would imply that the pattern is not subject to significant change and should occur for any instance of the associated emotion, while it has been shown that this is not what pattern classification entails. Instead, a diagnostic neural pattern represents a statistical summary of a categorical abstraction and in principle, a single instance of that category could occur without adhering to any of the features of the pattern, as proposed by constructionist accounts (Clark-Polner et al., 2017).

So far, neuroimaging studies mainly focused on absolute differences between different emotions. Two meta-analyses provide support for distinct arrays of cortical and subcortical structures per emotion (Fusar-Poli et al., 2009; Vytal & Hamann, 2010). Others yield mixed results regarding specificity (Murphy, Nimmo-Smith, & Lawrence, 2003; Phan, Wager, Taylor, & Liberzon, 2002), whereas a more recent one

1 concluded that the same brain regions show consistent activation for a variety of
2 emotional states (Lindquist et al., 2012).

3 Studies looking at differences in functional connectivity between emotions are
4 sparse. Two studies focused on intrinsically connected brain networks defined by
5 resting state fMRI to investigate their involvement in different emotions. These
6 studies mainly show that multiple networks are involved in individual emotions and
7 that the same networks are involved in different emotions (Raz et al., 2016;
8 Touroutoglou, Lindquist, Dickerson, & Barrett, 2015). These observations support
9 the idea that emotions are constructed from domain-general brain systems that
10 perform more basic psychological functions, such as salience detection, core affect,
11 memory, conceptualization, etc. On the other hand, an effective connectivity study
12 using Dynamic Causal Modeling revealed emotion-specific interactions between
13 regions that were commonly activated by different emotions and regions that
14 showed selective responses to individual emotions, arguing for distinct pathways of
15 different emotions (Tettamanti et al., 2012).

16 In a recent event-related fMRI study, we used human-like avatars with
17 emotionally expressive gaits to investigate whether perception of distinct emotions
18 (angry, happy, fearful, and sad) is processed by distinct neural regions or by a
19 common array of brain regions with patterns that allow to discriminate between

1 perception of different emotions (Jastorff, Huang, Giese, & Vandenbulcke, 2015). We
2 used morphed stimuli (between neutral and emotional) to investigate the activations
3 that are related to emotion detection sensitivity at subject level. Therefore, we
4 studied brain-behavior correlations to investigate the brain regions associated with
5 sensitivity for detecting emotions, rather than the brain activation differences of
6 emotional and neutral stimuli (Jastorff et al., 2015). In agreement with psychological
7 construction models, the results showed largely overlapping brain-behavior
8 correlations for the different emotions. The regional distribution was in line with the
9 networks proposed to contribute to the 'construction' of emotions, i.e. core affect,
10 conceptualization, executive control, etc. (Barrett & Satpute, 2013; Kober et al., 2008;
11 Lindquist & Barrett, 2012; Lindquist et al., 2012; Touroutoglou et al., 2015). We
12 termed this the general emotion network (GEN). None of the emotion-sensitive
13 nodes in GEN seemed exclusively involved in the perception of only one particular
14 emotion (Jastorff et al., 2015). Multi-voxel pattern analysis of brain activity revealed
15 that the nodes of the general emotion network contained information to reliably
16 classify perception of different emotions (Jastorff et al., 2015). This raises questions
17 about how nodes interact with each other e.g. how does GEN process perception of
18 different emotions? Are there non-overlapping emotion-specific subnetworks or

1 connections within GEN? Or, are there flexible interactions between regions within
2 GEN, such that emotions share common networks or other specific connections?

3 To discriminate between distinct emotion-specific subnetworks versus different
4 interaction patterns within common networks, we now studied connectivity within
5 the set of emotion-sensitive regions (GEN) by means of general psychophysiological
6 interaction (gPPI) and information flow analysis from graph theory. While previous
7 meta-analyses have focused on univariate absolute differences, the present study
8 makes use of a multivariate approach to investigate connectivity patterns. gPPI
9 provides information of how one brain region influences other brain regions under a
10 certain task (Friston et al., 1997; McLaren, Ries, Xu, & Johnson, 2012) and
11 information flow indexes help to identify how information is relayed within the
12 network (Seth, 2005). We anticipated to find a common emotion pathway within the
13 general emotion network compatible with basic psychological functions that interact
14 while perceiving different emotions, as predicted by the constructionist accounts
15 (Barrett, 2006; Lindquist & Barrett, 2012) and in line with our previous findings
16 (Jastorff et al, 2015). We further hypothesized that this common emotion pathway
17 would be supported by more distributed connections within GEN to classify
18 individual emotions. Alternatively, no significant coupling between nodes of the GEN

would argue against psychological construction models since they predict that areas of the GEN are working together, and hence connect, to construct emotions.

Methods

Participants

Sixteen healthy volunteers (8 females, mean age 25 years, range 23-32 years) participated in the experiment. All participants were right-handed without neurological or psychiatric history and without any medication at the time of the experiment. This study was approved by the Ethical Committee of the University Hospitals Leuven and all participants gave written informed consent in accordance to the Declaration of Helsinki.

Stimuli and experiment paradigm

A detailed description of stimulus generation and design of the experimental paradigm can be found in Jastorff et al. (2015). In brief, the whole stimulus set contained 30 stimuli displaying a walking avatar with four types of expressive emotion (angry, happy, fearful and sad) and one emotionally neutral type. During the task, participants were asked to press a button to judge whether the stimulus was emotional or not. Of note, participants were not requested to categorize the emotion. The experiment consisted of 8 runs and each run contained 60 trials in

1 which a stimulus was shown (12 trials per condition: angry, fearful, happy, sad,
2 neutral) and 12 baseline fixation trials. All of the trials were arranged in a
3 pseudo-randomized order to eliminate ordering and learning effects. In each trial,
4 the stimulus was shown for two gait cycles. A trial lasted between 2 and 4 seconds,
5 due to the different movement speeds of each motion clip. A fixation trial with a
6 fixation dot displayed on a black screen lasted 3 seconds. The inter-stimulus interval
7 varied between 2300ms and 5000ms determined by an exponential random variable
8 (Burock, Buckner, Woldorff, Rosen, & Dale, 1998).

9

10 *Experimental setup and data acquisition*

11 All the stimuli were projected via a liquid crystal display projector (Barco Reality
12 6400i; 1024x768, 60Hz refresh frequency; Barco) on to a screen placed in the bore.
13 The participants could observe the screen via a tilted mirror placed on the head coil.
14 During the experiment, eye movements of the participants were monitored with an
15 eye tracking system (60Hz; ASL 5000, Applied Science Laboratories).

16 All brain images were acquired using a 3T MR scanner (Intera; Philips Medical
17 Systems) with a 32 channel receive-only head coil at the University Hospitals Leuven,
18 Belgium. Functional images were acquired using gradient-echo planar imaging with
19 the following parameters: 37 slices; sequential slice acquisition order; 0.3mm

interslice gap; voxel size: $2.75 \times 2.75 \times 3 \text{ mm}^3$; repetition time: 2 s; echo time: 30ms; flip angle: 90 degrees; SENSE accelerate factor 2. A structural whole brain three dimensional high resolution T1-weighted image was acquired using an MPRAGE sequence with parameters: matrix size: 256×256 ; 182 coronal slices with 1.2 mm thickness; repetition time: 9.7ms; echo time: 4.6 ms; inversion time: 900ms; SENSE acceleration factor: 2.5.

Data analysis

Regions of interest

The general emotion network (GEN) was reported in our previous study (Jastorff et al., 2015), and comprises regions involved in core affect, conceptualization, language and executive control. We obtained the peak coordinates of those regions in GEN that were at least 12mm apart. The ROIs were defined as spheres positioned in each peak coordinate with a 6mm radius. Consequently, we obtained 61 ROIs which are listed in Table 1 and shown in Figure 1. For visualization purposes, these 61 ROIs were manually divided into 8 clusters based on the spatial location. The clusters are: anterior, middle and posterior midline regions, lateral frontal regions, limbic regions, anterior and posterior

1 temporal regions and cerebellum. Notably, the manual clustering does not change
2 the results in any way and is merely performed for visualization purposes.

3

4 Functional imaging analysis

5 All functional data were analyzed with SPM12 (Wellcome Department of
6 Cognitive Neurology, London, UK), and in-house developed scripts for computing
7 information flow indices and classification of the four emotions. The functional
8 connectivity results were mapped on the brain using the BrainNet Viewer toolbox
9 (Version 1.53, Beijing Normal University, Beijing, China) (Xia, Wang, & He, 2013). All
10 software was running on Matlab (version 2013b, The Mathworks, Inc. Natick, MA).

11 1. Preprocessing

12 All functional images were processed using the following five steps: (1) Slice timing
13 correction; (2) Realignment to correct for small head movements (Kayl, Moore,
14 Slopis, Jackson, & Leeds); (3) Coregistration between the mean functional image and
15 the structural image; (4) Warping the structural image to MNI-space and applying
16 this transformation to the individual functional images with a voxel size of 2 x 2 x 2
17 mm³ in MNI space; (5) Spatial smoothing using a 3D isotropic Gaussian kernel with
18 FWHM = 8 mm.

19 2. gPPI analysis

1 Friston et al. (1997) introduced the psychophysiological interaction analysis
 2 (Philippi, Motzkin, Pujara, & Koenigs) to examine the influence from one area
 3 (source) to another area (receiver) under a certain psychological task. In other words,
 4 it represents the condition-specific functional connection between two brain regions.
 5 McLaren et al. (2012) extended PPI to a general form, called general PPI (gPPI),
 6 which appeared to have more flexibility and sensitivity than standard PPI. In order to
 7 examine the interaction between psychological parameters and a neural basis signal,
 8 gPPI excludes both of the main effects of the neural basis from the source and the
 9 psychological parameters. The formula of gPPI is

$$Y_r = \beta_{int}Hrf(X_sP) + \beta_{psy}Hrf(P) + \beta_{phy}Hrf(X_s) + E$$

10 Where Y_r denotes the observed time course in the receiver, X_s denotes the estimated
 11 neural basis of the source, P denotes the psychological parameters, Hrf denotes the
 12 hemodynamic response function, E is the residual term and β_{int} , β_{psy} and β_{phy} are the
 13 estimated parameters. $Hrf(X_sP)$ represents the interaction between neural basis and
 14 psychological parameters. $Hrf(X_s)$ and $Hrf(P)$ represent the main effect of neural
 15 basis from the source and psychological parameters, respectively. A gPPI test would
 16 examine β_{int} , which is the influence of the interaction of source (X_s) and the
 17 experimental parameters (P). This kind of influence is known as directed functional
 18 connectivity.

1 According to the formula above, a gPPI test in this study was formulated as a
 2 general linear model (GLM) with 23 regressors: a neural basis regressor of the source
 3 (X_s), 8 experimental parameter regressors (P), 8 PPI regressors (X_sP) of the
 4 interaction between neural basis and experimental parameters, and 6 motion
 5 regressors of head movement. The 8 experimental parameters were formed by the
 6 onset times of angry, happy, fearful, sad, neutral, baseline, left and right button
 7 pressing, respectively. We used the SPM built-in PPI functions to calculate the
 8 interaction term X_sP .

9 The gPPI analysis consisted of two levels, an individual and a group level analysis.
 10 At the first level, we applied a gPPI test on each of 61 ROIs from each subject. We
 11 extracted 61 time courses from 61 ROIs as the sources X_s and generated the
 12 interaction term X_sP where the parameters P were obtained from the experimental
 13 paradigm. Thereafter, we estimated the GLM model for each of the 61 sources. As a
 14 result, we obtained functional connectivity maps of the whole brain, which reflect
 15 the influence of the source X_s on the brain voxels taking into account the interaction
 16 with the experimental parameters P. We then defined 5 main contrasts: “general
 17 emotion > neutral”, “angry > neutral”, “happy > neutral”, “fearful > neutral” and
 18 “sad > neutral”. The contrast “general emotion > neutral” compared the average

1 beta value for the 4 emotions (angry, happy, fearful and sad) against the one
2 obtained in the neutral condition.

3 At the second level, we first conducted a random effect analysis by performing
4 one-sample t-tests on each of the con-images corresponding to the 5 main contrasts
5 that were conducted at the first level to obtain a group level based functional
6 connectivity map for the following contrasts: “general emotion > neutral”, “angry >
7 neutral”, “happy > neutral”, “fearful > neutral” and “sad > neutral”. Second, we
8 performed a one-way ANOVA between the con-images from the 4 contrasts from
9 the individual analysis: “angry > neutral”, “happy > neutral”, “fearful > neutral” and
10 “sad > neutral”. The following contrasts were analyzed: “angry > other 3 emotions”,
11 “happy > other 3 emotions”, “fearful > other 3 emotions” and “sad > other 3
12 emotions”. Notably, the group level analysis was done 61 times (i.e. once per ROI).

13 In order to obtain a global view of the connectivity from the 61 ROIs, we
14 converted 61 group level connectivity maps into a gPPI matrix under the same
15 contrast. Each entry of this gPPI matrix $gPPI(m,n)$ is the positive peak value of T maps
16 within the m^{th} ROI (source) which contributes to the n^{th} ROI (receiver). That is, the
17 rows of the gPPI matrix represent the sources and the columns of the gPPI matrix
18 denote the receivers. By using a gPPI matrix, we studied the mutual connectivity
19 within all of the 61 ROIs in a single graph. Figure 2 illustrates the work flow to

1 generate the gPPI matrix. Noteworthy, $gPPI(m,m)$ is the self-connection, denoting
 2 how the m^{th} ROI would contribute to the m^{th} ROI itself.

3

4 3. Information flow analysis and general emotion pathway (GEP)

5 Graph theory can examine the nodes, edges, topological or geometrical measures
 6 from a network (E. T. Bullmore & Bassett, 2011; van den Heuvel & Sporns, 2013). In
 7 general, a certain threshold is applied to the connectivity matrix to produce an
 8 adjacency matrix from which the network measures are derived. The threshold can
 9 be a statistical value (e.g. a t-value or a correlation coefficient), a density threshold
 10 (i.e. only a certain portion of the connections with the highest strength would
 11 survive), or a range of thresholds (e.g. different density thresholds in a certain range)
 12 (E. Bullmore & Sporns, 2009; E. T. Bullmore & Bassett, 2011). Recently, Wang et al.
 13 reported that the use of a weighted network improves the reproducibility and
 14 robustness of the examined measures in contrast to a binary adjacency matrix which
 15 is less reproducible especially when the density is low and the number of subjects is
 16 limited (Wang et al., 2014). To obtain the weighted gPPI matrix, we first transformed
 17 the t-value of the gPPI matrix to a z-value, and then used the formula below to
 18 transform the z-value to a weight (Wang, Ghumare, Vandenberghe, & Dupont,
 19 2016).

$$\text{Weighted_gPPI_matrix}(m, n) = (2\Phi(|gPPI(m, n)|) - 1)^4$$

1 where Φ denotes the cumulative distribution function of the standard normal
2 distribution.

3 In the information flow analysis, we consider four measures (Seth, 2005): 1)
4 *outdegree(m)* denotes the total strength of connectivity from the m^{th} source to the
5 receivers and is defined as:

$$6 \quad \text{outdegree}(m) = \sum_{n=1}^{61} \text{Weighted_gPPI_matrix}(m, n);$$

7 2) *indegree(m)* denotes the total strength of the connectivity of sources connected
8 to the m^{th} receiver and is defined as:

$$9 \quad \text{indegree}(m) = \sum_{n=1}^{61} \text{Weighted_gPPI_matrix}(n, m);$$

10 3) *totaldegree(m)* denotes the total strength of connectivity linking outward or
11 inward to the m^{th} ROI and is defined as:

$$12 \quad \text{totaldegree}(m) = \text{outdegree}(m) + \text{indegree}(m);$$

13 4) *directionality(m)* denotes the difference between outdegree and indegree of the
14 m^{th} ROI and is defined as $\text{directionality}(m) = \text{outdegree}(m) - \text{indegree}(m)$. A

15 positive *directionality(m)* indicates that the m^{th} ROI behaves like a “source”, whereas

16 a negative *directionality(m)* indicates that the m^{th} ROI behaves like a “receiver”. To

17 assess the significance of each measure, we used permutation labelling of the ROI's

18 (2000 permutations) in the gPPI matrix.

1 We divided the ROIs into 3 types: “Source ROI”, “Hub ROI” and “Receiver ROI”
 2 using the following criteria. A “Source ROI” should be significant ($p < 0.05$) in
 3 outdegree and positive directionality. A “Receiver ROI” should be significant ($p < 0.05$)
 4 in indegree and negative directionality (Seth, 2005). A “Hub ROI” should be
 5 significant ($p < 0.05$) in totaldegree (Buckner et al., 2009; van den Heuvel & Sporns,
 6 2013). If a ROI shows both high outdegree (or indegree) and totaldegree, the ROI
 7 would be recognized as a “Source ROI” (or “Receiver ROI”). Noteworthy, the degree
 8 we calculated in this study was the weighted degree, sometimes also called the node
 9 strength.

10 To examine the common network within GEN, we first identified a general
 11 emotion pathway and then tested whether this pathway is common for the four
 12 emotion perceptions. We calculated the general emotion pathway from the “Source
 13 ROIs”, “Hub ROIs” and “Receiver ROIs”. First, we reduced the size of the weighted
 14 gPPI matrix so only “Source ROIs”, “Hub ROIs” and “Receiver ROIs” remained.
 15 Secondly, we assigned the threshold at the minimum graph level to the reduced
 16 weighted gPPI matrix, of which the threshold would lead every “Source ROI” to reach
 17 at least one of the “Receiver ROIs” by using the least connections. As such, we
 18 obtained the general emotion pathway which is a set of the most critical and
 19 strongest pathways connected from “Source ROIs” to “Receiver ROIs”.

Next, we verified the concept of a *common* emotion pathway, since the *general* emotion pathway was not the *common* pathway of all 4 emotions. We varied the density threshold from 1% to 50% and examined how many connections from different emotions overlapped with the general emotion pathway. Practically, we calculated the overlapping connections between the general emotion pathway and 4 gPPI matrices from the contrasts “angry > neutral”, “happy > neutral”, “fearful > neutral” and “sad > neutral”. For each connection, we examined the overlap ratio with 4 conditions, including “overlap with 1 emotion”, “overlap with 2 emotions”, “overlap with 3 emotions”, and “overlap with 4 emotions”. For example, the ratio of “overlap with 1 emotion” denotes the portion of connections in the general emotion pathway that overlap with at least one emotion. Similarly, “overlapped with 4 emotions” denoted the percentage of connections in the general emotion pathway that overlap with 4 emotions. Finally, we applied a permutation statistical analysis with 2000 permutations to examine the significance level of the overlap. Notably, the varied density threshold would only change the connection pattern of each emotion, without affecting the general emotion pathway.

4. The classification of emotion based on the gPPI connections

The classification was implemented using the LIBSVM toolbox (National Taiwan University, Taipei, Taiwan) (Chang & Lin, 2011). In order to train the classifier, the

individual gPPI matrices of each subject for each emotion were required. We generated 4 gPPI matrices from 4 contrasts (“Angry > neutral”, “Happy > neutral”, “Fearful > neutral”, and “Sad > neutral”) with the procedures described in the gPPI section. We obtained 64 gPPI matrices from 16 subjects labeled with 4 emotions, and each gPPI matrix contained 3721 features (each of the 61x61 connections from the gPPI matrix is considered a feature). Since the number of features was much higher than the number of labeled data (3721 compared to 64), feature selection was essential to avoid overfitting.

We performed two independent classifications, where only one used the features (connections) belonging to the general emotion pathway, and the other one used the features from all the connections in the gPPI matrix.

In the first classification, we used the connections from the general emotion pathway as features. First, we scaled the labeled data of each feature into the range between 0 and 1. The minimum and the maximum of the labeled data were assigned to 0 and 1, and the rest of data were distributed between 0 and 1. The scaling formula is:

$$\text{Scaled Labeled Data}(m) = \frac{\text{Labeled Data}(m) - \text{minimum}}{\text{maximum} - \text{minimum}}$$

The scaling avoids the numerical difficulty for computation and also avoids that greater numeric values dominate (Chih-Wei Hsu, 2010). Second, we optimized the

parameter C and Gamma in the support vector machine (SVM) within the recommended initial range 2^{-10} to 2^{10} and 2^{-16} to 2^5 (Chih-Wei Hsu, 2010) with a leave-four-out cross validation. SVM classifies the data points by finding a hyperplane to separate the data sets in a higher dimension space. Gamma and C are two parameters used by the SVM classifier with RBF kernel (Chih-Wei Hsu, 2010). Gamma is a parameter of the Gaussian kernel. A higher Gamma reflects a smaller FWHM of the Gaussian kernel. C is the penalty of the error term while calculating a hyperplane to separate the data. A lower C denotes a higher tolerance of error. According to the cross validation, the optimal C was 2^0 and the optimal Gamma was $2^{2.5}$. Thirdly, we implemented a feature selection with a leave-one-out external cross validation and a leave-three-out internal cross validation. In each external cross validation, we selected one subject as a testing set, and 15 subjects as the training set. The training set was further used in the internal leave-three-out cross validation. The internal cross validation uses the sequential forward selection method (Guyon & Elisseeff, 2003) to pick up the most useful features and to generate a rank order of each feature. During the external cross validation, we averaged the rank order of features from all the examinations in the internal cross validation. The average rank order helped us to select the features in the external cross validation by monitoring

1 the accuracy rate when sequentially adding the features in the classification
2 according to their average rank.

3 In the second classification, we used all the features of the gPPI matrix to
4 classify perception of 4 emotions. In contrast with the first classification, we need to
5 apply one more feature selection step before optimizing the parameter of SVM,
6 since the number of connections in the gPPI matrix is much higher than the number
7 of connections in the general emotion pathway (3771 versus 115). Four steps were
8 implemented in this part.

9 First, we scaled each of the features similar to the procedure described above.
10 Second, we implemented a preliminary feature selection. In this step, we produced a
11 preliminary rank order by mixing the rank order of the connections from the
12 contrasts of each emotion versus the other 3 emotions. The preliminary rank order
13 helped us to identify the features with the largest difference between one emotion
14 and the others in a low computational loading way. Further, we implemented a
15 leave-four-out cross validated classification with the default parameter of $C = 2^1$ and
16 $\text{Gamma} = 2^{-1}$ (Chih-Wei Hsu, 2010). Therefore, 1820 validations, i.e. $\binom{16}{4}$, were
17 applied where 4 subjects comprised the testing data set and 12 subjects were used
18 as the training data set. In each validation we added the features sequentially by the
19 preliminary rank order and then evaluated the accuracy of the added features to

1 classify 4 emotions. Finally, we selected 63 features out of 3721 features, since with
2 63 features, a balance was reached between the number of features and the
3 accuracy. Note that a higher number of features leads to a decrease in accuracy in
4 the cross validation due to a higher likelihood of overfitting the classifier. In the third
5 step, we optimized the parameter of C and Gamma similar to the procedure
6 described above. The optimal C was 2^3 and the optimal Gamma was $2^{-1.5}$. As a last
7 step, we used the same external and internal cross validation procedure as described
8 in the third step of the first classification. We finally selected the features which
9 could help to classify perception of 4 emotions with the highest accuracy. Using the
10 current classification method, there is the risk of overfitting caused by the
11 cross-validation a large number of features and a small sample size (Cawley & Talbot,
12 2010). To evaluate this classification, we performed a permutation test (100
13 permutations) in which the labels are randomly permuted (Golland & Fischl, 2003).
14 The permutation tests help us to ensure the reliability of the classification (Golland &
15 Fischl, 2003).

16 In order to obtain the sensitivity of the selected features, we further applied a
17 leave-four-out cross validation for each feature to report the mean sensitivity to
18 classify each of the four emotions.

1 Results

2 The general emotion gPPI matrix and the information flow indexes.

3 Each entry of the gPPI matrix (Figure 3A) denotes the weighted directed
4 connectivity between two ROIs. The ROIs of the left side of the matrix denote the
5 sources and the ROIs on top of the matrix denote the receivers. The weights range
6 from 0 (green) to 1 (red). Figure 3A illustrates the gPPI matrix of the main contrast
7 “general emotion vs neutral”. We applied the information flow analysis to the gPPI
8 matrix to obtain information flow indexes (Seth, 2005), namely outdegree, indegree,
9 totaldegree and directionality. The index outdegree, denoting the strength of the
10 source linked to receivers, is presented as the horizontal bar on the left side of the
11 gPPI matrix in Figure 3A. The index indegree, denoting the strength of the receiver
12 linked to sources, is presented as the vertical bar above the gPPI matrix in Figure 3A.
13 Figure 3B shows the index totaldegree which denotes the strength of total
14 throughput. Figure 3C demonstrates the index directionality, which is the difference
15 of outdegree and indegree. The significant ROIs are represented with filled circles
16 above the bar in Figure 3.

17 The information flow indices show different trends in sending and receiving
18 information across different brain regions. Posterior midline regions (yellow),
19 anterior temporal regions (blue) and posterior temporal regions (purple) show a high

1 proportion of ROIs with a high outdegree (Figure 3A), which are 3 out of 7 ROIs, 3/6
 2 ROIs and 5/8 ROIs, respectively. Anterior midline regions (red) and middle midline
 3 regions (orange) show a high proportion of high indegree ROIs (Figure 3A), i.e. 6/ 10
 4 ROIs and 4/5 ROIs, respectively. Middle midline regions (orange), lateral frontal
 5 regions (green) and posterior temporal regions (purple) show a high proportion of
 6 high totaldegree ROIs (Figure 3B), i.e. 4/5 ROIs, 5/10 ROIs and 4/8 ROIs, respectively.
 7 Furthermore, anterior midline regions (red) show a high proportion (5/10) of ROIs
 8 with negative directionality, and posterior midline regions (yellow) show a high
 9 proportion (4/6) of ROIs with positive directionality (Figure 3C). Lateral frontal
 10 regions (green) show diverse directionality, i.e. 4/10 are positive and 4/10 are
 11 negative (Figure 3C).

12

13 The general emotion pathway (GEP)

14 Table 2 lists all the Source ROIs, Hub ROIs and Receiver ROIs. Based on these ROIs,
 15 we determined GEP. As displaying the pathways from 10 Source ROIs, 11 Hub ROIs,
 16 and 11 Receiver ROIs within a single figure is challenging, we selected the most
 17 significant ROIs which satisfied $p < .0005$ in the permutation test (Table 2) to build a
 18 compact general emotion network. The compact general emotion network includes
 19 the “Source ROIs”: PCC-L-2, dlPFC-L-1, Amygdala-R, Ant-Mid-Temp-L and

1 Occi-Temp-L; the “Hub ROIs”: vmPFC-R, adACC-L, PCC-R-1, dIPFC-L-2 and TPJ-R-1,
2 Mid-Temp-L; and the “Receiver ROIs” vmPFC-L-2, adACC-R-3, Hippocampus-R-2 and
3 Parahippocampus-L.

4 Figure 4A and 4C demonstrate the compact GEP with a gPPI matrix and brain
5 map respectively. The Source ROIs (red) could connect to Receiver ROIs (blue)
6 through the Hub ROIs (green). Note that a pathway between two ROIs does not
7 represent the only pathway but the most significant one. At lower thresholds,
8 alternative pathways are detectable. Figure 4B shows how the 4 emotions overlap
9 within GEP by calculating the proportion of overlap with 1, 2, 3, or 4 emotions. We
10 varied the density threshold to comprehensively examine the proportion of overlap,
11 with higher density thresholds reflecting more included connections. At 10% density
12 threshold, the GEP overlaps 97% with at least one emotion (black line), 84% with 2
13 emotions (blue line), 37% with 3 emotions (green line) and 11% with 4 emotions (red
14 line). Moreover, 80% overlap between GEP and at least 3 or 4 emotions was found
15 around the density threshold 20% and 40%, respectively. The reported results
16 satisfied the criteria significant with $p < .05$ in a permutation examination. The dot
17 line presents the average overlapped portion of permutation test across each
18 density threshold.

19

The classification of perception of 4 emotions with GEP

We classified perception of 4 emotions by using the features (connections) of GEP.

Figure 5A demonstrates all 115 connections (features) of GEP that we used in the classification. Table 2 lists all of the 10 Source ROIs, 11 Hub ROIs and 11 Receiver ROIs in GEP. Figure 5B demonstrates the accuracy matrix to discriminate perception of 4 different emotions. In this case we used 25 features from the 115 features, but performance did not improve when we used more features, as shown in Figure 5C.

The sensitivity of detecting the correct emotion anger, happiness, fear and sadness is 20%, 24%, 33% and 77%, respectively. The high sensitivity for detecting sadness results from the over misrecognizing rate for recognizing other emotions as sad. The misrecognizing rate for anger was 60%, for happiness 42% and for fear 36%. The mean accuracy to classify 4 emotions by using GEP as features was around 35% as shown in Figure 4C.

The classification of 4 emotions with all possible connections within gPPI matrix

Next, we studied classification of the 4 emotions using all possible connections within gPPI matrix. The average accuracy of classification linearly increases and saturates at 67.5 % when 28 features are added as shown in Figure 6C. Therefore,

we selected 28 features (listed in Figure 6B) to classify the 4 emotions to obtain the accuracy matrix as shown in Figure 6A. The sensitivity for detecting angry, happy, fearful and sad was 70%, 70%, 66% and 64%, respectively. The false alarm rate was 14%, 13%, 7% and 10% and the false negative rate was 30%, 30%, 34% and 36% for angry, happy, fearful and sad, respectively. The misjudgments mainly resulted from misclassifying fearful and sad (22% and 11% error), and angry and happy (21% and 22% error). Figure 6B demonstrates the 28 features used in the classifier and its sensitivity for classifying perception of 4 emotions. Most of the features were sensitive to one emotion, but some of them were sensitive to 2 emotions. Figure 6D maps the 28 features on the brain surface. Most of the connections were linked from posterior regions to anterior regions, and some of them were cross-hemisphere.

Discussion

The study objective was to test predictions of theoretical emotion models at the level of the interaction between nodes in the brain that are sensitive to emotion perception. Therefore, we used gPPI and information flow indexes from graph theory to study connectivity within a previously described emotion perception sensitive network (Jastorff et al., 2015). Specifically, we addressed three questions: Is there a common pathway for perception of different emotions? If so, does the

1 common pathway discriminate between different emotions? Or, do other pathways
2 than the common pathway discriminate between different emotions?

3

4 Is there a common pathway for perception of different emotions?

5 First we looked at connectivity for the contrast emotion versus neutral stimuli. We
6 observed abundant interactions between the nodes of the GEN shown in Figure 5A
7 and visualized the compact GEP in Figure 4A and 4C. Second, we investigated
8 whether GEP denotes a common pathway of 4 different emotions. An overlap of
9 80% was observed at 40% density threshold for the 4 emotions and at 20% density
10 threshold for at least 3 emotions (Figure 4B). These results strongly suggest common
11 connectivity patterns within the general emotion network for the 4 different
12 emotions.

13

14 Does the GEP discriminate between different emotions?

15 Does perception of different emotions rely on the same brain network but is it
16 triggered by different connectivity patterns? To examine this assumption, we used a
17 classifier within GEP (as shown in Figure 5A) to discriminate perception of 4
18 emotions. Figure 5B shows that the general emotional pathway is unable to
19 accurately classify 4 emotions. It failed in recognizing anger, happiness and fear

1 perception. The high sensitivity (77%) of perceiving sadness does not correspond to
2 successful classification of sadness perception, since the specificity of sadness
3 perception is only 46%. Figure 5C demonstrates that if we add increasingly more
4 features in GEP, discrimination of 4 emotions does not exceed 40% accuracy. This
5 suggests that the connections of GEP do not discriminate between the 4 emotions.

6

7 Do other connections discriminate between different emotions?

8 Next, we applied the classification to all possible connections in the gPPI matrix
9 in order to examine whether information to discriminate between emotions is
10 included in GEN or not.

11 Figure 6A displays that the average sensitivity of classifying 4 emotions is 67.5%
12 which exceeds chance level (25%). It shows a high sensitivity (70%, 70%, 66%, 64%
13 for perception of angry, happiness, fear and sadness respectively), but also low false
14 alarm rate and false negative rate. The accuracy linearly increases by adding more
15 features and saturates when 28 features are included as shown in Figure 6C. The 28
16 connections are listed in figure 6B, most of them are sensitive to one emotion, and
17 some of them are sensitive to two emotions. Importantly, those 28 connections did
18 not overlap with the general emotional pathway. In general, the classification using

1 all possible connections performed much better than using GEP only. The
2 distribution of these 28 connections is shown in Figure 6D.

3

4 Classifying the results according to emotion theories

5 We did not identify a set of separate neural pathways within GEN predictive of
6 individual emotions compatible with basic emotion theory. Rather, we identified a
7 GEP that did not differentiate between perception of different emotions, but
8 required the support of distributed connections between emotion-sensitive nodes
9 outside GEP to classify emotions. This finding is in line with other recent multivariate
10 pattern analyses (MVPA), which reflect probabilistic emotion-specific brain patterns
11 (Kragel & LaBar, 2016; Saarimaki et al., 2016) and supports the constructionist's view
12 of distributed functional assemblies that combine to create emotions (Clark-Polner et
13 al., 2017; Lindquist et al., 2012).

14 Although we focused on the comparison between basic emotion theory and the
15 psychological construction model, there are other emotion theories. Appraisal
16 theories emphasize the appraisal process to generate emotions by linking the
17 stimuli, environmental events or context to a meaning. These theories stand
18 between basic emotion and psychological construction models in the spectrum of
19 emotion theories (Gross & Barrett, 2011; Moors, 2014).

1

2 Anatomy of emotion perception circuits

3 Although we intended to investigate the principles of emotion processing rather
4 than elaborating on individual connections, it is interesting to note that the
5 neuroanatomy of the detected circuits support our claims in two ways.

6 First, several components of our general emotion pathway have been related to
7 fundamental psychological processes associated with construction of emotions such
8 as core affect, conceptualization, language and executive control (Lindquist et al.,
9 2012). For instance, the amygdala, which is believed to play a pivotal role in core
10 affect by integrating sensory, emotional and affective processes and driving
11 autonomic responses across emotions (Barrett & Bliss-Moreau, 2009; Bickart,
12 Hollenbeck, Barrett, & Dickerson, 2012; Cunningham & Brosch, 2012; Kim et al.,
13 2011; Touroutoglou, Bickart, Barrett, & Dickerson, 2014; Whalen, 2007) behaved as a
14 Source ROI (Table 2) and influenced other nodes (Figure 4A). The anterior dorsal part
15 of the anterior cingulate cortex and ventral medial prefrontal cortex have also been
16 proposed as core affect regions (Barrett & Bliss-Moreau, 2009), and behaved as Hub
17 or Receiver ROIs (Table 2). These regions form the frontal portion of the default
18 mode network (Zald et al., 2014) and are involved in evaluating affective value
19 (Duncan & Barrett, 2007) and regulating areas that generate core affect (Etkin,

1 Egner, & Kalisch, 2011). Several regions involved in conceptualization (Buckner,
2 Andrews-Hanna, & Schacter, 2008; Yeo et al., 2011) - such as ventrolateral, dorsal
3 and medial prefrontal cortex, medial temporal regions and posterior cingulate
4 regions (Lindquist et al., 2012) were Receiver ROIs (Table 2). Those ROIs were
5 modulated by dorso-lateral prefrontal or posterior temporal regions, involved in
6 executive control and sensory perception respectively. These connections might help
7 to assign a meaningful context to the sensations. Another essential part of emotion
8 processing is attributing more abstract meaning to feelings (Lindquist et al., 2012).
9 Correspondingly, the anterior inferior temporal region, which behaved as a Hub, is a
10 critical associative structure in the semantics of emotion processing (Hoffman,
11 Binney, & Lambon Ralph, 2015). Our findings also indicate that posterior cingulate
12 cortex, precuneus and anterior temporal lobe have a high outdegree and behaved as
13 Source ROIs, which means that those ROIs are modulating other regions. The high
14 out-degree in posterior midline and anterior temporal regions could suggest that
15 these areas are playing a conceptualization function by contributing to predictions
16 about the meaning of incoming sensory information, in accordance with a recent
17 model of information flow based on cellular structure and animal models (L. F.
18 Barrett, 2017; Chanes & Barrett, 2016). Finally, executive control is essential to
19 integrate and coordinate emotion processes (Lindquist et al., 2012). Dorsal lateral

1 prefrontal cortex plays a major role in executive control and showed a high
2 versatility of connections in our study, supporting its involvement in several aspects
3 of emotion processing (Ochsner, Silvers, & Buhle, 2012).

4 Second, besides the finding that several connections of the general emotion
5 pathway are involved in processes shared by perception of different emotions, we
6 identified nodes that are activated by different emotions but whose interaction
7 patterns were specifically associated with one emotion. For instance, the insula lacks
8 specificity for one emotion (Phan, Wager, Taylor, & Liberzon, 2004) and is involved in
9 the awareness or salience of bodily sensations (Craig, 2009; Gasquoine, 2014; Seeley
10 et al., 2007). However, the connection between insula and subgenual anterior
11 cingulate, known to be involved in the feeling of sadness and in depression (Philippi
12 et al., 2015), was specifically associated with processing of sad expressions in our
13 study. Also, both amygdala and caudate are regarded as regions involved in core
14 affect (Cremers et al., 2010; Lindquist et al., 2012). However, we found that the link
15 between amygdala and posterior part of anterior cingulate cortex, which has been
16 related to emotional conflict (Etkin, Egner, Peraza, Kandel, & Hirsch, 2006; Nomura
17 et al., 2004), decoded anger in our study, whereas connections between caudate
18 nucleus and ventromedial prefrontal cortex were more sensitive to fear (Sehlmeier
19 et al., 2009).

1

2 Limitations and future work

3 From a theoretical point of view, it is important to consider that gPPI yields the
4 directed-functional connectivity but does not examine the effective connectivity.
5 gPPI examines the contribution or influence of one region to another under a certain
6 task, but does not refer to the timing or the causality from one region to another
7 (Friston et al., 1997; Stephan & Roebroeck, 2012). There were several reasons to use
8 gPPI in this study instead of causality tests, such as dynamic causal modeling (DCM)
9 (Friston, Harrison, & Penny, 2003) or granger causality (Seth, Barrett, & Barnett,
10 2015). Combining gPPI with graph theory indices is a straightforward way to study
11 connectivity among a large number of ROI's, whereas DCM with many nodes is less
12 reliable for fMRI. Limitations of Granger causality in fMRI studies are the low
13 sampling rate, the slow hemodynamic response function, increased false positive
14 and false negative rate (Seth et al., 2015), and difficulties associated with
15 event-related fMRI compared to block designs.

16 To limit the number of ROI's, we restricted our analyses to 61 ROIs that were
17 highly correlated with emotion perception in our previous study (Jastorff et al.,
18 2015). However, in doing so, we might have excluded critical emotion pathways. In a
19 next step, the method proposed in this study could be applied to the whole brain

1 level in order to uncover a larger and more comprehensive emotional network. Also
2 it might be used to investigate clinical data to identify dysfunctional, compensatory
3 or alternative pathways for perception of emotions.

4 The small sample size, 16 participants, limited the observed power in this study
5 and in combination with the number of trials might raise the risk of over-fitting in
6 using SVM to classify 4 emotions.

7 Furthermore, we investigated perception of emotions conveyed by whole body
8 movements. Future studies may extend our findings to other modalities of emotion
9 perception (body postures, faces, voices, eyes,...) and on non-perceptual aspects of
10 emotions like generation, regulation, experience or expression. Of note here,
11 according to psychological constructionist approaches, experience and perception of
12 emotions are associated with similar underlying processes (Barrett, 2013, 2014;
13 Lindquist, 2013; Lindquist, MacCormack, & Shablack, 2015; Lindquist et al., 2012).

14 Finally, the methodological limitations that are inherent to fMRI influence on
15 the scope of the interpretation. Due to the hemodynamic response and the limited
16 spatial resolution, it cannot be excluded that neurons with different functions could
17 be located within one voxel. This might lead to a misinterpretation of the BOLD
18 results at the disadvantage of basic emotion theory.

19

1 Conclusion

2 In this study, we aimed to investigate the connectivity within the general
3 emotion network, consisting of 61 brain regions associated with perception of
4 emotions conveyed by whole body movements. We used general PPI and
5 information flow indexes to investigate the general emotion pathway. It connected
6 core affect, conceptualization, language, and executive control networks. However,
7 the general emotion pathway could not discriminate anger, happiness, fear and
8 sadness. Twenty-eight additional connections outside the general emotion pathway
9 successfully classified the 4 emotions. Our findings support a psychological
10 construction account. The general emotion pathway can be regarded as the most
11 important pathway to process emotion, however, additional connections within the
12 general emotion network are required to discriminate emotions. The method
13 proposed in this study could be further used to study larger and more
14 comprehensive emotional networks, and identify compensatory or alternative
15 pathways from clinical data.

16

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ACCEPTED MANUSCRIPT

1 References

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Table 1.

Table 1 lists the 61 ROIs of GEN. Those ROIs were manually divided into 8 clusters according to the anatomical position, including: Anterior Midline Structure (10 ROIs), Middle Midline Structure (5 ROIs), Posterior Midline Structure (7 ROIs), Lateral Frontal Structure (9 ROIs), Limbic Structure (9 ROIs), Anterior Temporal Structure (6 ROIs), Posterior Temporal Structure (8 ROIs), and Cerebellum (7 ROIs). All the reported coordinates were in MNI space. Noteworthy, the clusterization does not affect the results and is only used to facilitate interpretation.

Table 2.

Table 2 lists the “Source ROIs”, “Hub ROIs” and “Receiver ROIs” which represent the general emotion pathway. There are 10 “Source ROIs”, 11 “Hub ROIs” and 11 “Receiver ROIs”. A Source ROI should be significant ($p < 0.05$) in outdegree and positive directionality. A “Receiver ROI” should be significant ($p < 0.05$) in indegree and negative directionality. A “Hub ROI” should be significant ($p < 0.05$) in totaldegree. The permutation distribution is measured in the 2000 permutations.

Figure 1.

Table 1 maps the 61 ROIs of GEN on to the brain. Those ROIs were be manually divided into 8 clusters according to the anatomy position, including: Anterior Midline Structure (10 ROIs, red), Middle Midline Structure (5 ROIs, orange), Posterior Midline Structure (7 ROIs, yellow), Lateral Frontal Structure (9 ROIs, green), Limbic Structure (9 ROIs, cyan), Anterior temporal Structure (6 ROIs, blue), Posterior temporal Structure (8 ROIs, purple), and Cerebellum (7 ROIs, pink). Noteworthy, the clusterization would not change the analysis result but only for better presentation.

Figure 2.

Figure 2 depicts the procedure to generate the gPPI matrix. In the individual level analysis, we would applied preprocessing step for each subject. Later on, we extracted the time series of 61 ROIs and examine the individual gPPI test for each of time series. Further, we combined different subjects' data in a group level analysis for each of 61 ROIs. The last step, we combined 61 group level brain maps by generating a gPPI matrix, in which the row denotes a seed connect to 61 ROIs and the column denotes a receiver is connected from 61 ROIs.

Figure 3.

Figure 3 shows the weighted gPPI matrix and the information flow indexes of the contrast “emotion versus neutral”. a) The weighted gPPI matrix. The row of gPPI matrix denotes seeds and the horizontal bar denotes the outdegree of the seed. The column of gPPI matrix denotes receivers and the vertical bar denotes indegree of the receiver. b) The totaldegree of 61 ROIs. c) The directionality of 61 ROIs. The filled circle upon the bar denotes the value satisfied significant level ($p < 0.05$) in the permutation test. The listed order and color coding of the 61 ROIs is equal to Table 1 and Figure 1.

Figure 4.

Figure 4 demonstrate the general emotion pathway. Since it is difficult to display whole view of general emotion pathway, we generated a compact general emotion pathway for display purpose. a) The gPPI matrix of compact general emotion pathway which is a subnetwork of general emotion pathway. The first 5 ROIs are the "Source ROIs", the middle 6 ROIs are the "Hub ROIs", and the 4 ROIs in the end are the "Receiver ROIs". b) The overlapping rate between each emotion and general emotion pathway. c) The compact emotion pathway map on brain. Red nodes denote "Source ROIs", green nodes denote "Hub ROIs", and blue nodes denote "Receiver ROIs".

Figure 5.

The classification of 4 emotions by using the information in general emotion pathway. a) The gPPI matrix of general emotion pathway. The first 10 ROIs are the “Source ROIs”, the middle 11 ROIs are the “Hub ROIs”, and the 11 ROIs in the end are the “Receiver ROIs”. b) The accuracy matrix of classify 4 emotions by 25 features (connections) selected from general emotion pathway. The row denotes the test data set of 4 emotions and the column denotes the data set that was classified to 4 emotions. The diagonal is the successful classification rate of 4 emotions. c) The accuracy of classifying 4 emotions by increasing features number in the classifier. Yellow denotes angry, green denotes happy, blue denotes fear, pink denotes sad, and black denotes average of 4 emotions.

Figure 6.

The classification of 4 emotions by using the information in the whole GEN. a) The accuracy matrix of classify 4 emotions by 28 features (connections) selected from the whole GEN. The 28 features are not overlapped to general emotion pathway. The row denotes the test data set of 4 emotions and the column denotes the data set that was classified to 4 emotions. The diagonal is the successful classification rate of 4 emotions. b) The sensitivity of the selected 28 features (connections). Most of features are sensitive to one emotion, but some of them are sensitive to two emotions. c) The accuracy of classifying 4 emotions by increasing features number in the classifier. The accuracy saturated while 28 features were included. Yellow denotes angry, green denotes happy, blue denotes fear, pink denotes sad, and black denotes average of 4 emotions. The gray line denotes mean accuracy of 100 permutations, whereas the dot line presents the range from one standard deviation below the mean to one standard deviation above the mean. d) The 28 features map on brain. Yellow denotes 8 features with highest sensitivity in angry, green denotes 6 features with highest sensitivity in happy, blue denotes 6 features with highest sensitivity in fear, and pink denotes 8 features with highest sensitivity in sad.

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Cluster name	ROI name	Brain location	Peak Coordinate (mm)		
			X	Y	Z
Anterior Midline Structure	sgACC-R-1	Right Subgenual Anterior Cingulate Cortex	2	6	-8
	sgACC-R-2	Right Subgenual Anterior Cingulate Cortex	2	18	-6
	vmPFC-R	Right Ventral Medial Prefrontal Cortex	14	46	-4
	pgACC-R-1	Right Pregenual Anterior Cingulate Cortex	6	32	-2
	rmPFC-R-1	Right Rostral Medial Prefrontal cortex	8	62	0
	pgACC-R-2	Right Pregenual Anterior Cingulate Cortex	22	36	2
	rmPFC-R-2	Right Rostral Medial Prefrontal cortex	14	54	14
	vmPFC-L-1	Left Ventral Medial Prefrontal Cortex	-8	60	-8
	vmPFC-L-2	Left Ventral Medial Prefrontal Cortex	-6	44	-6
Middle Midline Structure	rmPFC-L	Left Rostral Medial Prefrontal cortex	-6	54	14
	adACC-R-1	Right Anterior Dorsal Anterior Cingulate Cortex	6	24	18
	adACC-R-2	Right Anterior Dorsal Anterior Cingulate Cortex	22	32	22
	adACC-R-3	Right Anterior Dorsal Anterior Cingulate Cortex	12	12	28
	adACC-L	Left Anterior Dorsal Anterior Cingulate Cortex	-20	30	28
Posterior Midline Structure	pdACC-L	Left Posterior Dorsal Anterior Cingulate Cortex	-14	0	38
	PCC-R-1	Right Posterior Cingulate Cortex	16	-46	26
	PCC-R-2	Right Posterior Cingulate Cortex	22	-12	44
	Precuneus-R-1	Right Precuneus	14	-54	44
	Precuneus-R-2	Right Precuneus	8	-60	58
	PCC-L-1	Left Posterior Cingulate Cortex	-8	-50	12
	PCC-L-2	Left Posterior Cingulate Cortex	-6	-44	42
	PCC-L-3	Left Posterior Cingulate Cortex	-2	-26	44
Lateral Frontal Structure	Insula-R	Right Insula	30	0	22
	Inf-Frontal-R	Right Inferior Frontal	28	20	22
	dIPFC-R-1	Right Dorsal Lateral Prefrontal Cortex	22	44	36
	dIPFC-R-2	Right Dorsal Lateral Prefrontal Cortex	26	32	46
	dIPFC-L-1	Left Dorsal Lateral Prefrontal Cortex	-18	48	32
	dIPFC-L-2	Left Dorsal Lateral Prefrontal Cortex	-18	26	42
	dIPFC-L-3	Left Dorsal Lateral Prefrontal Cortex	-36	20	38
	dIPFC-L-4	Left Dorsal Lateral Prefrontal Cortex	-24	40	44
Limbic Structure	dIPFC-L-5	Left Dorsal Lateral Prefrontal Cortex	-16	28	60
	Amygdala-R	Right Amygdala	22	4	-12
	Hippocampus-R-1	Right Hippocampus	28	-20	-14
	Hippocampus-R-2	Right Hippocampus	36	-32	0
	Caudate-R	Right Caudate	14	12	14
	Parahippocampus-L	Left Parahippocampus	-22	-26	-14
	Putamen-L-1	Left Putamen	-22	6	-8
	Fusiform-L	Left Fusiform	-28	-50	-6
	Putamen-L-2	Left Putamen	-26	-12	4
Anterior Temporal Structure	Caudate-L	Left Caudate	-22	-18	24
	TemporalPole-R	Right Temporal Pole	36	14	-38
	Ant-Inf-Temp-R	Right Anterior Inferior Temporal	54	-6	-30
	Ant-Sup-Temp-R	Right Anterior Superior Temporal	62	6	-4
	Sup-Temp-R	Right Superior Temporal	66	-20	8
	Ant-Inf-Temp-L	Left Anterior Inferior Temporal	-50	-8	-38
Posterior Temporal Structure	Ant-Mid-Temp-L	Left Anterior Middle Temporal	-62	-2	-20
	TPJ-R-1	Right Temporoparietal Junction	60	-54	26
	Sup-Occi-R	Right Superior Occipital	16	-90	26
	Occi-temp-R	Right Occipitotemporal Junction	46	-66	26
	Mid-Temp-L	Left Middle Temporal	-66	-40	2
	TPJ-L-1	Left Temporoparietal Junction	-52	-64	22
	TPJ-L-2	Left Temporoparietal Junction	-40	-72	32
	TPJ-L-3	Left Temporoparietal Junction	-56	-50	36
	Occi-Temp-L	Left Occipitotemporal Junction	-34	-64	18
Cerebellum	Cerebellum-8-R	Right Cerebellum 8	10	-58	-40
	Cerebellum-Crus1-R-1	Right Cerebellum Crus 1	22	-76	-36
	Cerebellum-Crus1-R-2	Right Cerebellum Crus 1	40	-76	-36
	Cerebellum-Crus1-R-3	Right Cerebellum Crus 1	38	-50	-40
	Cerebellum-Vermis6-R	Right Cerebellum Vermis 6	4	-66	-12
	Cerebellum-Crus1-L	Left Cerebellum Crus 1	-24	-78	-32
	Cerebellum-Crus2-L	Left Cerebellum Crus 2	-38	-78	-36

NODE TYPE	ROI NAME	INDEX TYPE	PERMUTATION	INDEX TYPE	INDEX	PERMUTATION
			VALUE		VALUE	DISTRIBUTION
SOURCE	Precuneus-R-2	Outdegree	44.7	0.0105	Directionality	0.0015
	PCC-L-2		50.2	<0.0005		<0.0005
	Insula-R		47.7	<0.0005		0.011
	dIPFC-L-1		55.1	<0.0005		<0.0005
	Amygdala-R		51.4	<0.0005		<0.0005
	Ant-Sup-Temp-R		44.2	0.0115		<0.0005
	Ant-Mid-Temp-L		48.7	<0.0005		<0.0005
	TPJ-L-3		45.2	0.0065		0.001
	Occi-Temp-L		48.3	<0.0005		<0.0005
	Cerebellum-Crus2-L		50.7	<0.0005		0.007
HUB	vmPFC-R	Totaldegree	91.1	<0.0005		
	rmPFC-L		88.2	0.0025		
	adACC-R-1		87.2	0.0035		
	adACC-L		93.5	<0.0005		
	PCC-R-1		90.6	<0.0005		
	dIPFC-L-2		93.6	<0.0005		
	Ant-Inf-Temp-L		84.2	0.028		
	TPJ-R-1		103.1	<0.0005		
	Occi-Temp-R		84.6	0.0275		
	Mid-Temp-L		92.7	<0.0005		
	Cerebellum-Crus1-L		85.7	0.007		

RECEIVER							
	pgACC-R-1	Indegree	46.0	0.002	Directionality	-9.86	0.003
	rmPFC-R-2		49.6	<0.0005		-9.79	0.001
	vmPFC-L-1		47.7	0.0005		-18.09	<0.0005
	vmPFC-L-2		49.4	<0.0005		-19.33	<0.0005
	adACC-R-2		47.9	0.0005		-11.56	0.0005
	adACC-R-3		52.1	<0.0005		-13.03	<0.0005
	Inf-Frontal-R		48.8	<0.0005		-8.43	0.006
	dIPFC-L-4		43.5	0.0235		-10.35	0.0015
	Hippocampus-R-2		52.1	<0.0005		-19.31	<0.0005
	Parahippocampus-L		48.8	<0.0005		-20.66	<0.0005
	Ant-Inf-Temp-R		44.2	0.0175		-8.80	0.007

The 61 ROIs

A. The gPPI matrix with density threshold

B. Totaldegree

C. Directionality

A. The compact general emotion pathway matrix

B. the overlap rate between each emotion perception and general emotion pathway

C. The compact general emotion pathway brainmap

● Source ROIs ● Hub ROIs ● Receiver ROIs

A. gPPI matrix of general emotion pathway

B. The accuracy matrix of 25 features selected from general emotion pathway

C. the accuracy of increasing number of features

(A) The accuracy matrix of 28 selected features

(B) The sensitivity of 28 selected features

(C) The accuracy of increasing number of features

(D) The 28 selected features brainmap