Supplementary Material

Methods

Clustering analysis

We applied *k*-means clustering to the electrodes in the 2D space of MNI ycoordinate and peak classification time for facial expressions, with different values of k, and evaluated the model performance by computing the Bayes information criterion (BIC) and the mean Silhouette coefficient (SC) across all points.

Following (Kass RE and L Wasserman 1995; Pelleg D and AW Moore 2000), the BIC was estimated using Schwartz criterion. Specifically, $BIC = l(D|\hat{\theta}) - \frac{p}{2}logN$, where $l(D|\hat{\theta})$ is the log-likelihood of the data under the assumption of *k*-means (spherical Gaussian) taken at the maximum likelihood estimation of parameters $\hat{\theta}$, *p* is the total number of parameters in the model, and *N* is the total number of data points.

Following (Kaufman L and PJ Rousseeuw 2009), the Silhouette value for the *i*-th point was computed as $S_i = (b_i - a_i)/\max(a_i, b_i)$, where a_i is the average within cluster distance for the *i*-th point, and b_i is the minimum average between cluster distance for the *i*-th point (minimized over all other clusters). The mean SC was then estimated by averaging the Silhouette value over all data points.

Meta-analysis

Activation likelihood estimation (ALE, (Laird AR et al. 2005; Eickhoff SB et al. 2012)) was used for the meta-analysis of the neuroimaging literature. We first searched the online database of neuroimaging studies on Neurosynth.org and found around 300 imaging studies with the keyword "facial expressions". We then further narrowed the list

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down to 64 fMRI by only including the studies that had a direct full brain mapping by contrasting between emotional facial expressions, e.g. fear vs neutral, happy vs sad, etc. We only took into account the reported activation foci for the contrast between facial expressions. Then all of the activation foci in those relevant full brain map results were collected and extracted as 3D coordinates in MNI space. In the ALE, each of the extracted foci was assigned as the center of a Gaussian distribution, whose variance was scaled by the number of subjects in the corresponding experiment. These Gaussian distributions were then combined to build a full brain map of ALE. The ALE map was corrected for multiple comparison using cluster-based permutation test. Then we performed a spatial permutation test with 1000 permutations to construct a null distribution of the full brain activation. The ALE and the corresponding statistical analysis were performed based on GingerALE 2.3.6 (Eickhoff SB et al. 2009; Turkeltaub PE et al. 2012).

Results

Comparison of the contributions from ERP and ERBB features to the classification Here we compared the classification results using both ERP and ERBB vs using ERP or ERBB alone. As shown in Figure S1, both ERP and ERBB contributed to the expression decoding (left panel has higher *d'* than the other two panels). The posterior d' peak improves from 0.19 with only ERP features to .23 combining both ERP and ERBB features. The mid-fusiform d' peak improves from 0.19 with only ERP features to .21 combining both ERP and ERBB features. ERP features made greater contribution to the expression discrimination than ERBB (the middle panel has larger *d'* than the right panel,

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and the results in the middle panel are very close to results in the left panel). Due to the 1/f decay in the power spectrum, the ERP signal is dominated by low frequency components (mainly alpha and beta bands). This suggests that it is the low frequency components in ERP that mainly contributes to the facial expressions representation in the fusiform (Furl N et al. 2017).

Selection of models for k-means clustering

We applied *k*-means clustering to the electrodes in the 2D space of MNI ycoordinate and peak classification time for facial expressions, with different values of k, and evaluate the model performance by computing the Bayes information criterion (BIC) and the mean Silhouette coefficient (SC) across all points.

As shown in Figure S4, for k = 1, BIC = -61.28; for k = 2, BIC = -54.63. Therefore, Bayes factor between the hypothesis (H1) that there is a cluster structure (k = 2) and the null hypothesis (H0) that there is no cluster structure (k = 1) can be approximated as $BF \approx \exp(\frac{BIC_1 - BIC_0}{2})$. This approximation yields a BF > 20, which suggests a strong evidence of H1 over H0. In other words, there is a strong clustering structure in the data.

Moreover, for k = 2, BIC = -54.63, the mean SC = 0.601; for k = 3, BIC = -56.29, the mean SC = 0.490; for k = 4, BIC = -58.54, mean SC = 0.428. Both BIC and mean SC suggest that k = 2 is the optimal number of clusters. Therefore, k = 2 was used in the study.

Meta-analysis of the neuroimaging literature

In the broad neuroimaging literature, we found 64 fMRI studies with full brain contrasts between face expressions (See Table S1). Among the 64 studies, 24 studies report at least one significant focus of fusiform sensitivity to differences in expressions (See Figure S5 for activation map). A total of 999 significant foci were reported in those experiments for contrasts between different facial expressions (Figure S5). A full brain activation likelihood estimation (ALE) was performed and significance was assessed using a cluster-based permutation test. 4 significant clusters were found at the p < 0.01threshold, none of which included the fusiform. The MNI coordinates for the center and the corresponding label names of the 4 clusters are shown in Table S2.



Figure S1. The mean and standard error for pairwise classification between different face expressions in posterior fusiform electrodes and mid- fusiform electrodes, using both ERP and ERBB features (left), using only ERP features (middle), and using only ERBB features (right).



Figure S2. The mean ROC curve and area-under-curve (AUC) for posterior fusiform electrodes and mid-fusiform electrodes at early (150-200 ms after stim onset) and late stage (400-450 ms after stim onset).



Figure S3. The mean and standard error for classification between different face expressions in left and right fusiform electrodes. The timecourse of the left fusiform peaked at 220 ms after stimulus onset with mean d' = 0.19, and the timecourse of the right fusiform peaked at 180 ms after stimulus onset with mean d' = 0.18 (both p < 0.05, binomial test, Bonferroni corrected).



Figure S4. Clustering analysis. A) BIC of *k*-means models with different values of k (k = 1, 2, 3, 4). **B)** Mean SC of *k*-means models with different values of k (k = 2, 3, 4, note that SC is not applicable for k = 1). **C)** The distribution of Silhouette Coefficients (SC) with different values of k in *k*-means clustering. From left to right, k = 2, 3, and 4.



Figure S5. Activation map for facial expressions. (Red) Whole brain activation map from all 64 relevant fMRI studies. (Green square) Voxels in fusiform reported in 24/64 of the fMRI studies that have significant contrast between facial expressions. (Blue dots) iEEG electrodes in fusiform that have significant facial expression decoding. (Blue line) the border between posterior and mid-fusiform clusters based upon clustering analysis in the iEEG electrodes.

Table S1 A summary list for the 64 neuroimaging studies included in the meta-analysis (the 24 studies that report significant emotional sensitivity in fusiform are marked in bold font).

	title	authors	journal	year
1	A common neural code for perceived and inferred emotion.	Skerry AE, Saxe R	Journal of neuroscience	2014
2	A left amygdala mediated network for rapid orienting to masked fearful faces.	Carlson JM, Reinke KS, Habib R	Neuropsychologia	2009
3	A neural network reflecting individual differences in cognitive processing of emotions during perceptual decision making.	Meriau K, Wartenburger I, Kazzer P, Prehn K, Lammers CH, van der Meer E, Villringer A, Heekeren HR	NeuroImage	2006
4	Affect-specific activation of shared networks for perception and execution of facial expressions.	Kircher T, Pohl A, Krach S, Thimm M, Schulte-Ruther M, Anders S, Mathiak K	Social cognitive and affective neuroscience	2013
5	Amygdala activation at 3T in response to human and avatar facial expressions of emotions.	Moser E, Derntl B, Robinson S, Fink B, Gur RC, Grammer K	Journal of neuroscience methods	2007
6	Amygdala integrates emotional expression and gaze direction in response to dynamic facial expressions.	Sato W, Kochiyama T, Uono S, Yoshikawa S	NeuroImage	2010
7	Amygdala reactivity predicts automatic negative evaluations for facial emotions.	Dannlowski U, Ohrmann P, Bauer J, Kugel H, Arolt V, Heindel W, Suslow T	Psychiatry research	2007
8	Amygdala response to facial expressions in children and adults.	Thomas KM, Drevets WC, Whalen PJ, Eccard CH, Dahl RE, Ryan ND, Casey BJ	Biological psychiatry	2001
9	Amygdala response to facial expressions reflects emotional learning.	Hooker CI, Germine LT, Knight RT, D'Esposito M	Journal of neuroscience	2006
10	Anxiety predicts a differential neural response to attended and unattended facial signals of anger and fear.	Ewbank MP, Lawrence AD, Passamonti L, Keane J, Peers PV, Calder AJ	NeuroImage	2009
11	Automatic emotion processing as a function of trait emotional awareness: an fMRI study.	Lichev V, Sacher J, Ihme K, Rosenberg N, Quirin M, Lepsien J, Pampel A, Rufer M, Grabe HJ, Kugel H,	Social cognitive and affective neuroscience	2014

		Kersting A, Villringer A,		
12	Beyond threat: amygdala reactivity across multiple expressions of facial affect.	Fitzgerald DA, Angstadt M, Jelsone LM, Nathan PJ, Phan KL	NeuroImage	2006
13	Binding action and emotion in social understanding.	Ferri F, Ebisch SJ, Costantini M, Salone A, Arciero G, Mazzola V, Ferro FM, Romani GL, Gallese V	PloS one	2013
14	Both of us disgusted in My insula: the common neural basis of seeing and feeling disgust.	Wicker B, Keysers C, Plailly J, Royet JP, Gallese V, Rizzolatti G	Neuron	2003
15	Brain networks involved in haptic and visual identification of facial expressions of emotion: an fMRI study.	Kitada R, Johnsrude IS, Kochiyama T, Lederman SJ	NeuroImage	2010
16	Brain responses to dynamic facial expressions of pain.	Simon D, Craig KD, Miltner WH, Rainville P	Pain	2006
17	Brain responses to facial expressions of pain: emotional or motor mirroring?	Budell L, Jackson P, Rainville P	NeuroImage	2010
	motor minoring:			
18	Cerebral integration of verbal and nonverbal emotional cues: impact of individual nonverbal dominance.	Jacob H, Kreifelts B, Bruck C, Erb M, Hosl F, Wildgruber D	NeuroImage	2012
18 19	Cerebral integration of verbal and nonverbal emotional cues: impact of individual nonverbal dominance. Cerebral regulation of facial expressions of pain.	Jacob H, Kreifelts B, Bruck C, Erb M, Hosl F, Wildgruber D Kunz M, Chen JI, Lautenbacher S, Vachon- Presseau E, Rainville P	NeuroImage Journal of neuroscience	2012 2011
18 19 20	Cerebral integration of verbal and nonverbal emotional cues: impact of individual nonverbal dominance. Cerebral regulation of facial expressions of pain. Classification images reveal the information sensitivity of brain voxels in fMRI.	Jacob H, Kreifelts B, Bruck C, Erb M, Hosl F, Wildgruber D Kunz M, Chen JI, Lautenbacher S, Vachon- Presseau E, Rainville P Smith FW, Muckli L, Brennan D, Pernet C, Smith ML, Belin P, Gosselin F, Hadley DM, Cavanagh J, Schyns PG	NeuroImage Journal of neuroscience NeuroImage	2012 2011 2008
18 19 20 21	Cerebral integration of verbal and nonverbal emotional cues: impact of individual nonverbal dominance. Cerebral regulation of facial expressions of pain. Classification images reveal the information sensitivity of brain voxels in fMRI. Converging evidence for the advantage of dynamic facial expressions.	Jacob H, Kreifelts B, Bruck C, Erb M, Hosl F, Wildgruber D Kunz M, Chen JI, Lautenbacher S, Vachon- Presseau E, Rainville P Smith FW, Muckli L, Brennan D, Pernet C, Smith ML, Belin P, Gosselin F, Hadley DM, Cavanagh J, Schyns PG Arsalidou M, Morris D, Taylor MJ	NeuroImage Journal of neuroscience NeuroImage Brain topography	2012 2011 2008 2011
18 19 20 21 22	Cerebral integration of verbal and nonverbal emotional cues: impact of individual nonverbal dominance. Cerebral regulation of facial expressions of pain. Classification images reveal the information sensitivity of brain voxels in fMRI. Converging evidence for the advantage of dynamic facial expressions. Decoding of affective facial expressions in the context of emotional situations.	Jacob H, Kreifelts B, Bruck C, Erb M, Hosl F, Wildgruber D Kunz M, Chen JI, Lautenbacher S, Vachon- Presseau E, Rainville P Smith FW, Muckli L, Brennan D, Pernet C, Smith ML, Belin P, Gosselin F, Hadley DM, Cavanagh J, Schyns PG Arsalidou M, Morris D, Taylor MJ Sommer M, Dohnel K, Meinhardt J, Hajak G	NeuroImage Journal of neuroscience NeuroImage Brain topography Neuropsychologia	2012 2011 2008 2011 2008

24	Dynamic stimuli demonstrate a categorical representation of facial expression in the amygdala.	Harris RJ, Young AW, Andrews TJ	Neuropsychologia	2014
25	Emotions in motion: dynamic compared to static facial expressions of disgust and happiness reveal more widespread emotion-specific activations.	Trautmann SA, Fehr T, Herrmann M	Brain research	2009
26	Enhanced neural activity in response to dynamic facial expressions of emotion: an fMRI study.	Sato W, Kochiyama T, Yoshikawa S, Naito E, Matsumura M	Cognitive brain research	2004
27	Facial emotion modulates the neural mechanisms responsible for short interval time perception.	Tipples J, Brattan V, Johnston P	Brain topography	2015
28	Facial expression and gaze- direction in human superior temporal sulcus.	Engell AD, Haxby JV	Neuropsychologia	2007
29	Facial expressions and complex IAPS pictures: common and differential networks.	Britton JC, Taylor SF, Sudheimer KD, Liberzon I	NeuroImage	2006
30	Frontal lobe networks for effective processing of ambiguously expressed emotions in humans.	Nomura M, Iidaka T, Kakehi K, Tsukiura T, Hasegawa T, Maeda Y, Matsue Y	Neuroscience letters	2003
31	Functional imaging of face and hand imitation: towards a motor theory of empathy.	Leslie KR, Johnson-Frey SH, Grafton ST	NeuroImage	2004
32	Functional neuroanatomy of perceiving surprised faces.	Schroeder U, Hennenlotter A, Erhard P, Haslinger B, Stahl R, Lange KW, Ceballos-Baumann AO	Human brain mapping	2004
33	Functional responses and structural connections of cortical areas for processing faces and voices in the superior temporal sulcus.	Ethofer T, Bretscher J, Wiethoff S, Bisch J, Schlipf S, Wildgruber D, Kreifelts B	NeuroImage	2013
34	Incongruence effects in crossmodal emotional integration.	Muller VI, Habel U, Derntl B, Schneider F, Zilles K, Turetsky BI, Eickhoff SB	NeuroImage	2011

35	Integration of cross-modal emotional information in the human brain: an fMRI study.	gration of cross-modalPark JY, Gu BM, Kang DH,tional information in the an brain: an fMRI study.Shin YW, Choi CH, Lee JM, Kwon JS		2010
36	Investigating the brain basis of facial expression perception using multi-voxel pattern analysis.	Wegrzyn M, Riehle M, Labudda K, Woermann F, Baumgartner F, Pollmann S, Bien CG, Kissler J	Cortex	2015
37	Is a neutral expression also a neutral stimulus? A study with functional magnetic resonance.	Carvajal F, Rubio S, Serrano JM, Rios-Lago M, Alvarez- Linera J, Pacheco L, Martin P	Experimental brain research	2013
38	Leaving a bad taste in your mouth but not in my insula.	von dem Hagen EA, Beaver JD, Ewbank MP, Keane J, Passamonti L, Lawrence AD, Calder AJ	Social cognitive and affective neuroscience	2009
39	Masked presentations of emotional facial expressions modulate amygdala activity without explicit knowledge.	Whalen PJ, Rauch SL, Etcoff NL, McInerney SC, Lee MB, Jenike MA	Journal of neuroscience	1998
40	Mind your left: spatial bias in subcortical fear processing.	Siman-Tov T, Papo D, Gadoth N, Schonberg T, Mendelsohn A, Perry D, Hendler T	Journal of cognitive neuroscience	2009
41	Multiple mechanisms of consciousness: the neural correlates of emotional awareness.	Amting JM, Greening SG, Mitchell DG	Journal of neuroscience	2010
42	Neural mechanism for judging the appropriateness of facial affect.	Kim JW, Kim JJ, Jeong BS, Ki SW, Im DM, Lee SJ, Lee HS	Cognitive brain research	2005
43	Neural mechanism of unconscious perception of surprised facial expression.	Duan X, Dai Q, Gong Q, Chen H	NeuroImage	2010
44	Neural responses to ambiguity involve domain-general and domain-specific emotion processing systems.	Neta M, Kelley WM, Whalen PJ	Journal of cognitive neuroscience	2013
45	Nonconscious emotional processing involves distinct neural pathways for pictures and videos.	Faivre N, Charron S, Roux P, Lehericy S, Kouider S	Neuropsychologia	2012
46	Orbitofrontal and hippocampal contributions to memory for face-name associations: the rewarding power of a smile.	Tsukiura T, Cabeza R	Neuropsychologia	2008

47	Orbitofrontal Cortex Reactivity to Angry Facial Expression in a Social Interaction Correlates with Aggressive Behavior.	Beyer F, Munte TF, Gottlich M, Kramer UM	Cerebral cortex	2014
48	Positive facial affect - an fMRI study on the involvement of insula and amygdala.	Pohl A, Anders S, Schulte- Ruther M, Mathiak K, Kircher T	PloS one	2013
49	Preferential amygdala reactivity to the negative assessment of neutral faces.	Blasi G, Hariri AR, Alce G, Taurisano P, Sambataro F, Das S, Bertolino A, Weinberger DR, Mattay VS	Biological psychiatry	2009
50	Pupillary contagion: central mechanisms engaged in sadness processing.	Harrison NA, Singer T, Rotshtein P, Dolan RJ, Critchley HD	Social cognitive and affective neuroscience	2006
51	Reduced emotion processing efficiency in healthy males relative to females.	Weisenbach SL, Rapport LJ, Briceno EM, Haase BD, Vederman AC, Bieliauskas LA, Welsh RC, Starkman MN, McInnis MG, Zubieta JK, Langenecker SA	Social cognitive and affective neuroscience	2014
52	Segregating intra-amygdalar responses to dynamic facial emotion with cytoarchitectonic maximum probability maps.	Hurlemann R, Rehme AK, Diessel M, Kukolja J, Maier W, Walter H, Cohen MX	Journal of neuroscience methods	2008
53	Similarities and differences in perceiving threat from dynamic faces and bodies. An fMRI study.	Kret ME, Pichon S, Grezes J, de Gelder B	NeuroImage	2011
54	Stop looking angry and smile, please: start and stop of the very same facial expression differentially activate threat- and reward-related brain networks.	Muhlberger A, Wieser MJ, Gerdes AB, Frey MC, Weyers P, Pauli P	Social cognitive and affective neuroscience	2011
55	Temporal pole activity during perception of sad faces, but not happy faces, correlates with neuroticism trait.	Jimura K, Konishi S, Miyashita Y	Neuroscience letters	2009
56	The amygdala and FFA track both social and non-social face dimensions.	Said CP, Dotsch R, Todorov A	Neuropsychologia	2010
57	The amygdala processes the emotional significance of facial expressions: an fMRI	Sato W, Yoshikawa S, Kochiyama T, Matsumura M	NeuroImage	2004

	interaction between expression and face direction.			
58	The behavioral and neural effect of emotional primes on intertemporal decisions.	Luo S, Ainslie G, Monterosso J	Social cognitive and affective neuroscience	2014
59	The changing face of emotion: age-related patterns of amygdala activation to salient faces.	Todd RM, Evans JW, Morris D, Lewis MD, Taylor MJ	Social cognitive and affective neuroscience	2011
60	The functional correlates of face perception and recognition of emotional facial expressions as evidenced by fMRI.	Jehna M, Neuper C, Ischebeck A, Loitfelder M, Ropele S, Langkammer C, Ebner F, Fuchs S, Schmidt R, Fazekas F, Enzinger C	Brain research	2011
61	The highly sensitive brain: an fMRI study of sensory processing sensitivity and response to others' emotions.	Acevedo BP, Aron EN, Aron A, Sangster MD, Collins N, Brown LL	Brain and behavior	2014
62	The Kuleshov Effect: the influence of contextual framing on emotional attributions.	Mobbs D, Weiskopf N, Lau HC, Featherstone E, Dolan RJ, Frith CD	Social cognitive and affective neuroscience	2006
63	The stimuli drive the response: an fMRI study of youth processing adult or child emotional face stimuli.	Marusak HA, Carre JM, Thomason ME	NeuroImage	2013
64	Viewing facial expressions of pain engages cortical areas involved in the direct experience of pain.	Botvinick M, Jha AP, Bylsma LM, Fabian SA, Solomon PE, Prkachin KM	NeuroImage	2005

Table S2 the MNI coordinates for the weighted center, volume, and the corresponding
label name of the significant clusters in the ALE map from meta-analysis

Cluster #	Х	Y	Z	Volume (mm ³)	Lateralization	Label
1	23	-3	-18	6088	right	amygdala
2	-22	-4	-18	4640	left	amygdala
3	56	-42	5	2520	right	middle/superior temporal gyrus
4	3	11	53	1464	right	superior frontal gyrus

Feature #	Feature name
1	eyebrow length
2	inter-eyebrow distance
3	eye width
4	inter-eyes distance
5	vertical distance between eyes and nosetip
6	horizontal length of the nose
7	distance between nose and upper lip
8	face height
9	face width
10	eye height
11	width of the mouth
12	intense of red on cheeks
13	intense of green on cheeks
14	intense of blue on cheeks
15	contrast polarity between eyes and nose
16	eye area
17	eye mouth ratio

 Table S3 17 features used for the facial feature space

Reference:

Eickhoff SB, Bzdok D, Laird AR, Kurth F, Fox PT. 2012. Activation likelihood estimation meta-analysis revisited. Neuroimage 59:2349-2361.

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