Toward EEG-based BCI driven by emotions for addressing BCI-Illiteracy: a meta-analytic review

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Many critical aspects affect the correct operation of a Brain Computer Interface. The term "BCI-illiteracy" describes the impossibility of using a BCI paradigm. At present, a universal solution does not exist and seeking innovative protocols to drive a BCI is mandatory. This work presents a meta-analytic review on recent advances in emotions recognition with the perspective of using emotions as voluntary, stimulus-independent, commands for BCIs. 60 papers, based on electroencephalography measurements, were selected to evaluate what emotions have been most recognized and what brain regions were activated by them. It was found that happiness, sadness, anger and calm were the most recognized emotions. Most discriminant locations for emotions recognition and for the particular case of discrete emotions recognition were identified in the temporal, frontal and parietal areas. The meta-analysis was mainly performed on stimulus-elicited emotions, due to the limited amount of literature about self-induced emotions. The obtained results represent a good starting point for the development of BCI driven by emotions and allow to: 1) ascertain that emotions are measurable and recognizable one from another 2) select a subset of most recognizable emotions and the corresponding active brain regions.

Keywords: Brain-Computer Interface; BCI-Illiteracy; Emotions Recognition; Emotions Brain Mapping

1. Introduction

A Brain Computer Interface (BCI) provides a communication and control tool toward the external environment in alternative to the traditional pathways, such as muscles and nerves, and is based on the direct monitoring of the brain activity (Wolpaw et al. 2002; Kübler and Müller 2007). Since BCI introduction in 1973 (Vidal 1973), the interest has rapidly grown. Main subjects of study are:

- understanding of mental processes and brain activity related to specific mental tasks (del R. Millan et al. 2002);
- creating additional channels to improve the human-computer interaction (HCI) (Mühl et al. 2014);
- finding alternatives for people with reduced or absent communication capabilities (Mak and Wolpaw 2009).

The canonical BCI framework, also known as "BCI cycle" (van Gerven et al. 2009) pointed out in Figure 1, is based on the association between a set of specific brain tasks and a set of commands or actions. The user is asked to focus on univocal tasks associated to commands, while an acquisition system measures the brain activity. During a training phase, the signals corresponding to each task are recorded and analyzed to extract peculiar features. When using the BCI, these features serve to recognize the activated task and to translate it into the corresponding command. The user interface serves to propose different choices to the user (selectable through different tasks), to show the current state of the BCI and to synchronize the acquisition of data with the stimulus presentation (Placidi et al. 2016b).

Some aspects critically affect BCI's correct operation and stimulate the research:

- signal measurement (acquisition hardware);

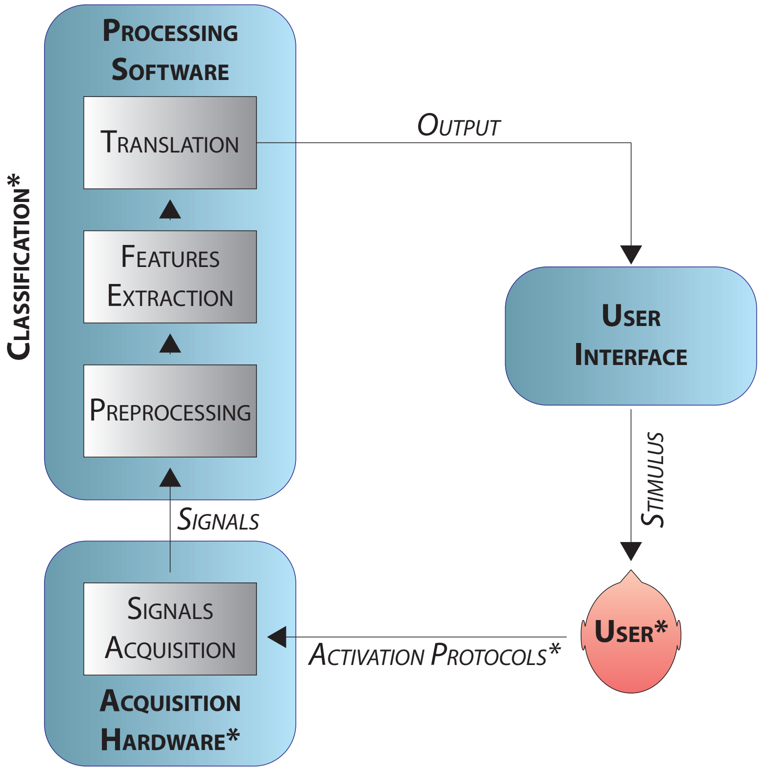

Figure 1. The BCI cycle. The user activates a task; the signal is recorded and processed to be translated into commands. Points indicated by "*" are critical for the BCI. Also user is indicated with "*" because its compatibility with the system is also crucial.

- activation protocols and related brain processes;
- classification and recognition algorithms;
- user-BCI compatibility;

In the following we provide an overview of each of these aspects, by focusing on the user-BCI compatibility issue and on countermeasures for addressing it through the use of emotions.

1.1. *Acquisition hardware*

Several brain activity measurement systems could be employed for BCI. Invasive equipment like Electrocorticography (ECoG) (Schalk and Leuthardt 2011) have high resolution, but their invasiveness and discomfort limit their effective usefulness. Noninvasive approaches include Magnetoencephalography (MEG) (Mellinger et al. 2007), functional Magnetic Resonance Imaging (fMRI) (Raut and Yadav 2017), functional Near-Infrared Spectroscopy (fNIRS) (Naseer and Hong 2015), Positron Emission Tomography (PET) (Deore, Chaudhari, and Mehrotra 2013), Single-Photon Emission Computed Tomography (SPECT) (Bhattacharyya et al. 2016), and Electroencephalography (EEG) (Moghimi et al. 2013). fMRI and fNIRS based BCIs have limited speed. fMRI, MEG, PET and SPECT need bulky (and expensive) equipment and even fNIRS is far from being re-ally portable. PET and SPECT use ionizing radiations that prevent their frequent and continuous usage for a BCI. On the contrary, EEG is portable, easy to use, cheap and characterized by an high temporal resolution. At present EEG, also thanks to recent advances on amplifiers and elec-trodes (Besio et al. 2006; Liao et al. 2012; Im and Seo 2016), represents the best tradeoff and the most common mean of brain monitoring for BCIs (Vallabhaneni, Wang, and He 2005; Allison and Krusienski 2015) and, for this reason, EEG-based brain activity measurement systems will be treated in this article.

1.2. *Classification techniques*

The process of translating tasks into commands typically includes three steps:

- Preprocessing: the signal-to-noise ratio is improved by suppressing artifacts and noise. The presence of environmental interferences, muscular activity and motion artifacts are filtered off in space, time and frequency (Percival and Walden 1993; Nitschke, Miller, and Cook 1998).
- Features selection and reduction: signal characteristics are extracted both from signal domain and after domain transformations (e.g. Fourier Transform (FT), Wavelet Transform (WT)). These features can be statistical parameters and/or more complex indices, often related to peculiar aspects of the mental protocol (e.g. asymmetry and power indices) (Ehrlichman and Wiener 1980; andR. L. Moses 1997). The simple features computation does not ensure an efficient representation: non-relevant features or groups of highly dependent features could be present and have to be eliminated to avoid computational overhead (Keogh and Mueen 2011). To this aim, features reduction techniques are often employed to maintain only useful features (Jolliffe 2002; Yu and Liu 2003; Peng, Long, and Ding 2005).
- Classification: is the fundamental step to translate brain signals to commands. Initially the machine is trained with a set of signals generated by known mental tasks, in order to define a bijective function from brain signals to the corresponding mental tasks, used to interprete brain signals and translate them into BCI commands. Depending on the characteristics of the tasks, different classification approaches could be chosen. Improved classification methods could be implemented starting from the same dataset and possibly structured in combined classifiers (Iacoviello et al. 2015a). Most commonly used classification approaches have been reviewed in Lotte et al. (2007).

1.3. *Activation protocols*

The aspects that mainly characterize a BCI are the activation protocols used to control it. Particular mental tasks affect the brain activity, by producing signals variations observable in time or frequency domains. In terms of frequency, the brain activities are usually considered separated in bands: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz) and gamma (30-70 Hz), each related with particular brain functions or states (Teplan 2002). Delta waves are the predominant during deep sleep but are also related to the subject attention to internal processing (Harmony et al. 1996); theta band correlates with memory demanding tasks (Klimesch et al. 1996); alpha band is characteristic of relaxed mental states and its changes (in particular its suppression) correlates with increasing arousal, for example during visual processing (Barry et al. 2007); beta waves are related to alertness and focus demanding tasks (Kamiński et al. 2012). Literature mainly reports four categories of BCI paradigms:

I Event-Related Potentials (ERP): are variations in the brain potentials, resulting from sen-sory, motor or cognitive events. ERP waveforms consist of a series of deflections (components), usually signed with a letter indicating the polarity (N or P, negative or positive), and by a number indicating the latency, expressed in milliseconds, from the event. The shapes of components are related to specific events or paradigms. For example, N100-P200 components are elicited by unpredictable stimulus in the absence of task demands (Rao 2013), N200 is often observed during the detection of novelty or mismatch with an attended stimuli (Pa-tel and Azzam 2005), and N400 is related to semantic processing (Kutas and Federmeier 2000). Interesting for BCI applications, during an odd-ball paradigm, is the amplitude of the P300 component which varies with the relevance of the stimulus and with its frequency of presentation (Picton 1992). This allowed the design of speller interfaces based on P300 that employ visual (Farwell, Lawrence, and Donchin 1988), auditory (Furdea et al. 2009) or tactile (Brouwer and Erp 2010) stimuli, and their combination (Barbosa, Pires, and Nunes 2016). Nowadays, P300 spellers have evolved from the original design, and have been refined to enhance signal differences between attended and ignored stimuli and to elicit others component beside P300 (Fazel-Rezai et al. 2012). In visual spellers, this was achieved by using different stimulations instead of flashes, such as moving characters or changing characters in faces (Jin et al. 2012, 2014).

II Motor imagery: the activity of simulating a physical action mentally produces Event-Related Synchronizations (ERS) and Desynchronization (ERD) in beta and mu rhythms over sensorimotor cortex regions (Pfurtscheller and da Silva 1999). A BCI can be trained by analyzing the Sensorimotor Rhythms (SMR) of subjects involved in sequences of motor-imagery tasks, for recognizing the movements and use them as commands (McFarland, Sarnacki, and Wolpaw 2010).

III Steady-State Evoked Potentials (SSEP): are signals variation occurring at a specific frequency when the subject is focusing on a stimulus. They are characterized by the presence of peaks in the power spectra in correspondence of the stimulus frequency and its harmonics. Similarly to ERPs, BCIs can be implemented basing on visual (SSVEP) (Middendorf et al. 2000), auditory (SSAEP) (Hill and Schölkopf 2012) or tactile (Somatosensory, SSSEP) (Severens et al. 2013) stimulations.

IV Slow Cortical Potentials (SCP) are low frequency potential variations (lower than 1Hz), generated in the higher cortical layers. They are related to the state of readiness and preparation to movements or resting and mental energy demanding tasks (Birbaumer et al. 1990). People can learn to regulate SCP if they are provided with the feedback of their potentials (Hinterberger et al. 2007), thus allowing to control a BCI, even though this requires long training periods (tens or even hundreds of sessions) (Birbaumer et al. 1999).

Despite the large variety of brain activation strategies, they could be all useless for some BCI users, that could be incompatible with BCI.

1.4. *BCI Illiteracy*

The increasing interest in BCIs has risen the problem of the so-called *BCI-illiteracy*, that is the incompatibility between the user and the BCI occurring when a user is unable to attain effective control of a BCI. This makes the user-BCI compatibility another critical point. Though the term *illiteracy* is widely used by now (Vidaurre and Blankertz 2010), the word *incompatibility* would be more suitable: the failure depends on the impossibility of the subject using the BCI paradigm or on the incapability of the BCI to exploit the residual subject capacity and not on the lack of will or dedication to use the BCI by the subject. For this reason, both the machine, meaning the techniques used to decode signals, and the user should be taken in account in the design of BCI systems, though user capacity still represents the major cause of incompatibility. As argued in (Lotte et al. 2018), no signal analysis techniques would be able to recognize (decode) specific command patterns if the user is unable to produce (encode) them. For example, the subject could be: unable to receive an input from the system (stimulus, feedback or information about the state of the BCI); potentially alarmed or scared by the stimulus (Schreuder, Blankertz, and Tangermann 2010; Müller-Putz et al. 2012); unable to focus on the required mental task; unable to continuously focus on the assigned task. The inconstancy of the user mood, stress, engagement, and level of attention is also a cause of the BCI performance variability and should be taken in account (Friedrich et al. 2015; Pammer-Schindler et al. 2017). Moreover, since driving a BCI is a skill that could be learned and mastered, also the protocols used to train the user could be cause of performance degradation (Jeunet, Jahanpour, and Lotte 2016; Pillette et al. 2017).

As reported in (Ahn and Jun 2015), the strategic approaches for improving the performance or reliability of BCI systems include: fast performance predictors (based on anatomical, psychological and neurophysiological information) to avoid time-consuming BCI experiments before switching to other BCI control paradigms; approaches for user skill training or brain tuning; error correc-tion mechanisms; adaptive features extractors and classifiers to make BCI classification robust to experimental variations.

Nevertheless, as suggested by recent literature (Kübler et al. 1998; Neumann and Birbaumer 2003; Guger et al. 2003; Kübler et al. 2004; Nijboer et al. 2008; Guger et al. 2009; Allison et al. 2010; Ortner et al. 2011; Volosyak et al. 2011; Guger et al. 2012; Ahn et al. 2013; Lugo et al. 2014), a BCI paradigm which is compatible with all subjects does not exist, and there are still people for which any tried BCI paradigm resulted ineffective, thus confirming the thesis that finding alternative approaches is a necessary step. In this sense, the use of emotions for driving a BCI represents a new direction toward innovative activation protocols.

In this sense, active emotion-driven BCIs have already been proved to work (Placidi et al. 2015a; Iacoviello et al. 2015b,c; Pistoia et al. 2015; Placidi et al. 2015b). In particular, in (Placidi et al. 2015a) an innovative approach based on the self induction of the disgust produced by remembering an unpleasant odor, was proposed. The same method was also used in (Pistoia et al. 2015) to reveal consciousness in a Minimally Conscious State (MCS) patient, achieving promising results. However, it has been proved (Levy et al. 1999) that signals produced by remembering a past experienced emotion are lower than those produced by direct experience of the emotion (about 15%). Sensitivity could be improved by averaging and verification methods (Wolpaw et al. 1998) (with the risk that response of the BCI could become unacceptably long) or by using more sensitive EEG equipment (Besio et al. 2006, 2014).

2. Methods

2.1. *Basis for Emotional BCIs*

The classification of emotional and cognitive states from physiological signals, especially for EEG, has been widely studied (Picard, Vyzas, and Healey 2001; Lisetti and Nasoz 2004) and received a boost from the possible application in affective computing (Picard 1997). The knowledge of emotional state has been employed, for example, during videogames playing (Bos et al. 2010), for media content tagging and selection (Soleymani and Pantic 2013), for neuro-marketing (Vecchiato et al. 2011), for deception detection (Merzagora et al. 2006). According to the taxonomy given in (Zander and Jatzev 2009) and (Zander and Kothe 2011), those kinds of applications, named affective BCIs fall in the category of passive (or implicit) interfaces, since they continuously monitor the user mental state and adopt the machine behavior to it without requiring any active and voluntary involvement of the subject.

Although a huge effort was put in emotions classification, the exploitation of emotional states as voluntary input for a BCI is still moving its first steps. Driving a BCI requires that the computer presents a choice between two or more mental tasks (or states), associated with corresponding commands and the user will have to choose by using different activations. In this scenario, the BCI dependency on the stimuli is a critical aspect too. Most of the experimental designs belong to the class of stimulus-dependent paradigms and allow to implement passive BCIs. To provide really effective BCI, we should move from passive BCI to new approaches for voluntary driven, active BCI. In the emotional context, this modality could represent a more natural way to control a BCI, by using self-induced emotions, for example triggered by recalling in mind personal experiences.

The following section reviews the state of the art and recent progresses in emotions recognition, with the objective of gathering the most used approaches and techniques and setting the basis to active emotional driven BCI.

2.2. *Relevant articles on emotion recognition*

Publications dealing with emotion recognition often use very different methods regarding acquisition set-up, participants recruitment, elicitation protocols, features extraction procedures and classification algorithms. We performed an analysis of these publications considering articles of the last 10 years from peer reviewed journals and conference proceedings selected by querying Google Scholar[1], Pubmed[2], Scopus[3] and IEEE Xplore[4] databases. Inclusion criteria have been that papers provided adequate information regarding: studied emotions, acquisition device, classification methods, parameters and results (only studies reporting significant accuracy were considered). The exclusion criterion was the use of consumer-grade EEG devices (they could negatively affect the measurements due to: 1) unstable signals (Maskeliunas et al. 2016); 2) very low signal quality (Nijboer et al. 2015); 3) connection losses (Duvinage et al. 2013)). A recent review on emotion recognition from EEG signals is (Alarcao and Fonseca 2017): though it contains interesting considerations, it did not make a meta-analysis of the reported papers.

With this method, from the initial 103 articles, we have chosen 60 articles, whose findings are summarized in Table 1.

Table 1.: Summary of the selected studies on emotions recognition. Elicitation method (P = pictures, A = audio, V = video clips, R = recall, I = imagery) and number of channels (and their position in case of non-homogeneous distribution) are indicated. Last column provides the list of emotions recognition performed in the studies: emotions, or classes of emotions, compared each other are separated by "vs", while the symbol "+" indicates the construction of larger classes of emotions. The average accuracy is indicated in brackets. The following acronyms are used: HA: High Arousal, HD: High Dominance, HL: High Liking, HV: High Valence, LA: Low Arousal, LD: Low Dominance, LL: Low Liking, LV: Low Valence, MA: Medium Arousal

Ref.	**Y**	**Elicitation**	**Channels**	**Emotions Comparison (Accuracy)**
Bos (2006)	2006	P/A	3: F3-F4 dipole, Fpz monopole	LV vs HV (97.4%) or LA vs HA (94.9%)
Chanel et al. (2006)	2006	P	64 (34 used)	HA vs LA (~60%) or HA vs MA vs LA (~45%)
Schaaff (2008)	2008	P	16, (4: Fp1, Fp2, F7, F8), (3: Fz, Cz, Pz)	LV vs HV vs MV (62.1%)
Lin et al. (2008)	2008	A	32 (only 24 symmetric used)	Joy vs Anger vs Sadness vs Pleasure (92.7%)
Li et al. (2009)	2009	V	4: F4, T3, T4, P4	Happiness vs Relax (96.1%) or Relax vs Sadness (97.4%) or Happiness vs Sadness (100.0%)
Lin et al. (2009)	2009	A	32 (only 24 symmetric used)	Joy vs Pleasure vs Anger vs Sadness (92.6%)
Khalili and Moradi (2009)	2009	P	54	LV-HA vs HV-HA vs MV-LA (76.7%)
Murugappan et al. (2009)	2009	P/V	64	Anger vs Disgust vs Happiness vs Surprise vs Sadness (63.3% - 67.3%)
Chanel et al. (2009)	2009	R	64	LV-HA vs HV-HA vs MV-LA (~67%) or LV vs HV (~77%) or HV-HA vs MV-LA (~82%) or LV-HA vs MV-LA (~75%) or LA vs HA (~80%)

[1] scholar.google.com
[2] www.ncbi.nlm.nih.gov/pubmed
[3] www.scopus.com
[4] ieeexplore.ieee.org

Table 1.: Summary of emotions recognition studies.

Ref.	**Y**	**Elicitation**	**Channels**	**Emotions Comparison (Accuracy)**
Li and Lu (2009)	2009	P	62	Happiness vs Sadness ($\sim$ 93%)
Koelstra et al. (2010)	2010	V	32	LV vs HV (58.8%) or LA vs HA (55.7%) or LL vs HL (49.4%)
Petrantonakis and Hadjileontiadis (2010)	2010	P	4: F3-F4 dipole, Fp1, Fp2 monopole	Happiness vs Surprise vs Anger vs Fear vs Disgust vs Sadness (83.3%)
Frantzidis et al. (2010)	2010	P	19 (3: Fz, Cz, Pz)	LV-LA vs LV-HA vs HV-LA vs HV-HA (81.3%)
Lin et al. (2010)	2010	A	32	Joy vs Anger vs Sadness vs Pleasure (82.3%)
Hosseini and Khalilzadeh (2010)	2010	P	5: Fp1, Fp2, T3, T4, Pz	Calm vs Stress (82.7%)
Murugappan, Nagarajan, and Yaacob (2011)	2011	V	62 or 24	Disgust vs Happiness vs Surprise vs Fear vs Neutral (83.0%)
Nie et al. (2011)	2011	V	62 or 24	LV vs HV (87.53%)
Brown, Grundlehner, and Penders (2011)	2011	V/P	8	LV vs MV vs HV (82.0%) or HV+MV vs LV (85%)
Hosseini and Naghibi-Sistani (2011)	2011	P	5: Fp1, Fp2, T3, T4, Pz	Calm vs Stress (72.2%)
Wang, Nie, and Lu (2011)	2011	V	62	Joy vs Relax vs Sadness vs Fear (66.5%)
Koelstra et al. (2012)	2012	V	32	LV vs HV (57.6%) or LA vs HA (62.0%) or LL vs HL (55.4%)
Bastos-Filho et al. (2012)	2012	V	4: Fp1, Fp2, F3, F4	Calm vs Stress (70.1%)
Soleymani, Pantic, and Pun (2012)	2012	V	24	LV vs MV vs HV (50.5%) or LA vs MA vs HA (62.1%)
Yohanes, Ser, and Huang (2012)	2012	P	2: Fp1 vs Fp2	Happiness vs Sadness (84.67%)
Murugappan and Murugappan (2013)	2013	V	62	Disgust vs Happiness vs Surprise vs Fear vs Neutral (91.33%)
Soleymani and Pantic (2013)	2013	V	32 (14: Fp1, T7, CP1, Oz,Fp2, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, PO4)	LV vs MV vs HV (F1=0.56) or LA vs MA vs HA (F1=0.64)
Kothe, Makeig, and Onton (2013)	2013	I	124	LV vs HV (71.3%)
Yoon and Chung (2013)	2013	V	32	LV vs HV (70.9%) or LA vs HA (70.1%) or LV vs MV vs HV (55.4%) or LA vs MA vs HA (55.2%)
Duan, Zhu, and Lu (2013)	2013	V	62	LV vs HV (84.3%)
Hidalgo-Muñoz et al. (2013)	2013	P	21	LV vs HV (80.8%)
Liu et al. (2013)	2013	P	62	LV vs HV (82.7%) or LA vs HA (84.8%)

Table 1.: Summary of emotions recognition studies.

Ref.	Y	Elicitation	Channels	Emotions Comparison (Accuracy)
Koelstra and Patras (2013)	2013	V	32 (14: Cp6, Cz, Fc2, Oz, Cp1, T7, C4, Fc6, Po4, Cp2, T8, F8, Fp1, Fp2)	LV vs HV (71.5%) or LA vs HA (67.5%) or LD vs HD (67.5%)
Sohaib et al. (2013)	2013	P	6: Fp1, Fp2, C3, C4, F3, F4	LV vs MV vs HV (83.3%) or LA vs MA vs HA (83.3%)
Wang, Nie, and Lu (2014)	2014	V	128	LV vs HV (87.5%)
Valenzi et al. (2014)	2014	V	32 (8: AF3, AF4, F3, F4, F7, F8, T7, T8)	Sadness vs Disgust vs Neutral vs Amusement (97.2%)
Liu et al. (2014)	2014	P	62	LV vs HV (82.7%) or LA vs HA (84.8%)
Yaacob et al. (2014)	2014	P	8	Happiness vs Fear vs Sadness vs Calm (92.94%)
Liu and Sourina (2014) [5]	2014	V	32 (4: Fc5, F4, F7, Af3)	Satisfaction, Happiness, Surprise, Protected, Sadness, Unconcerned, Anger, Fear, recognized in groups from 2 (90.4%) to 8 (69.53%)
Zheng et al. (2014)	2014	V	62	LV vs HV (88.4%)
Jenke, Peer, and Buss (2014)	2014	P	64	Happiness vs Curiousity vs Anger vs Sadness vs Quietness (36.8%)
Hatamikia, Maghooli, and Nasrabadi (2014)	2014	V	32	LV vs HV (72.3%) or LV vs MV vs HV (61.1%) or LA vs HA (74.2%) or LA vs MA vs HA (65.2%)
Lin, Yang, and Jung (2014)	2014	A	32	LV vs HV (76.1%) or LA vs HA (74.3%)
Lee and Hsieh (2014)	2014	V	64 (19: Fp1, Fp2, F7, F8, F3, F4, Fz, C3, C4, Cz, T7, T8, P7, P8, P3, P4, Pz, O1, O2)	LV vs MV vs HV (82.0%)
Placidi et al. (2015a)	2015	R	8	Disgust vs Relax (89.3%)
Iacoviello et al. (2015b)	2015	R	8	Disgust vs Relax (95.0%)
Liu et al. (2015)	2015	V	62	Happiness vs Neutral vs Tension vs Sadness vs Disgust (93.3%)
Zheng and Lu (2015)	2015	V	62	LV vs HV (86.1%)
Chen et al. (2015)	2015	V	32	LV vs HV (67.9%) or LA vs HA (69.1%)
Vijayan, Sen, and Sudheer (2015)	2015	V	12 (7: P7, P3, PZ, PO3, O1, CP2, C4)	Happiness vs Sadness vs Excitement vs Hate (94.1%)
Placidi et al. (2016a)	2016	V	32	HV-HA vs LV-HA (>80%) or MV-LA vs LV-HA (>80%) or MV-LA vs HV-HA (>80%)
Liu et al. (2016)	2016	V	60	LV vs MV vs HV (73.0%)

[5] One experiment over three has been considered, due the hardware exclusion criterion

Table 1.: Summary of emotions recognition studies.

Ref.	**Y**	**Elicitation**	**Channels**	**Emotions Comparison (Accuracy)**
Li et al. (2016)	2016	V	62	LV vs HV (88.4%)
Ackermann et al. (2016)	2016	V	32	LV-HA-HD vs HA-LD vs LA (*sim* 50%)
Al-Qammaz, Ahmad, and Yusof (2016)	2016	V	32	LV vs MV vs HV (49.2%) or LA vs MA vs HA (54.8%)
Velchev et al. (2016)	2016	V	32 (Valence: Oz, P04, CP1, FC6, Cz, T8 - Arousal: CP6, Cz, Fz, FC2)	3, 5 or 7 classes for Arousal (79.8%, 65.5%, 39.1%) and Valence (75.4%, 58.0%, 28.6%)
Ang, Yeongi, and Ser (2017)	2017	P	3: FP1, FP2, Cz	Happiness vs Sadness (81.8%)
Zheng, Zhu, and Lu (2017)	2017	V	32 - 62	LV-LA vs LV-HA vs HV-LA vs HV-HA (69.7%) or LV vs MV vs HV (91.1%)
Chai et al. (2017)	2017	V	62	LV vs MV vs HV (85.6%)
Yin et al. (2017)	2017	V	32	LV vs HV (78.8%) or LA vs HA (78.7%)
Singh and Singh (2017)	2017	P	10 (3: Fz, Cz, Pz)	LV vs HV (82.1%) or LA vs HA (80.2%) or LV-LA vs LV-HA vs HV-LA vs HV-HA (68.2%)

The reviewed articles used a variety of elicitation strategies: pictures, sounds, music, autobiographic memories and multi-media sources (mainly fragments of movies, commercials or music videoclips, often pre-rated or pre-classified by groups of unknown volunteers). Experiments were often conducted by using public datasets of stimuli (Lang, Bradley, and Culthbert 2008; Bradley and Lang 1999; Langner et al. 2010) or signals (Koelstra et al. 2012; Soleymani et al. 2012; Duan, Zhu, and Lu 2013). Signal classification and recognition were attained with really different and hardly comparable algorithms, though most of them used support vector machines, combined with features reduction strategies, in particular principal component analysis.

3. Results

3.1. *Most Recognized Emotions*

A useful concept in the recognition of emotions is the model used to represent them. The representation model, indeed, influences the separation in classes. There exist discrete models that represent emotions as separate entities (Ekman 1992a,b; Panksepp 2004), dimensional models, represented by continuos 2D Valence-Arousal (VA) orthogonal axes, proposed by Russel (Russell 1980; Posne, Russell, and Peterson 2005) or its 3D extension (Valence-Arousal-Dominance (VAD)) (Mehrabian 1995) or a hybrid 3D conical model, proposed by Plutchik (Plutchik 2001), in which the vertical dimension represents the intensity and the circular arrangement corresponds to the similiraty between emotions. Table 1 shows the emotions treated in each paper and represented in the model used by the Authors.

In what follows, we extrapolated their content by using the discrete model to analyze the most recognized emotions, and we analyzed the most activated brain regions by emotional processes, focusing on the discrete emotions case too.

In order to summarize the presence and the occurence of emotions in the considered publications, Figure 2 shows a discrete representation in the Valence-Arousal plane. Intensity and the font size are proportional to the occurrence of each emotion in the considered studies. Groups of equivalent or very close emotions were joined into a single element to fit the Russel positioning model. The

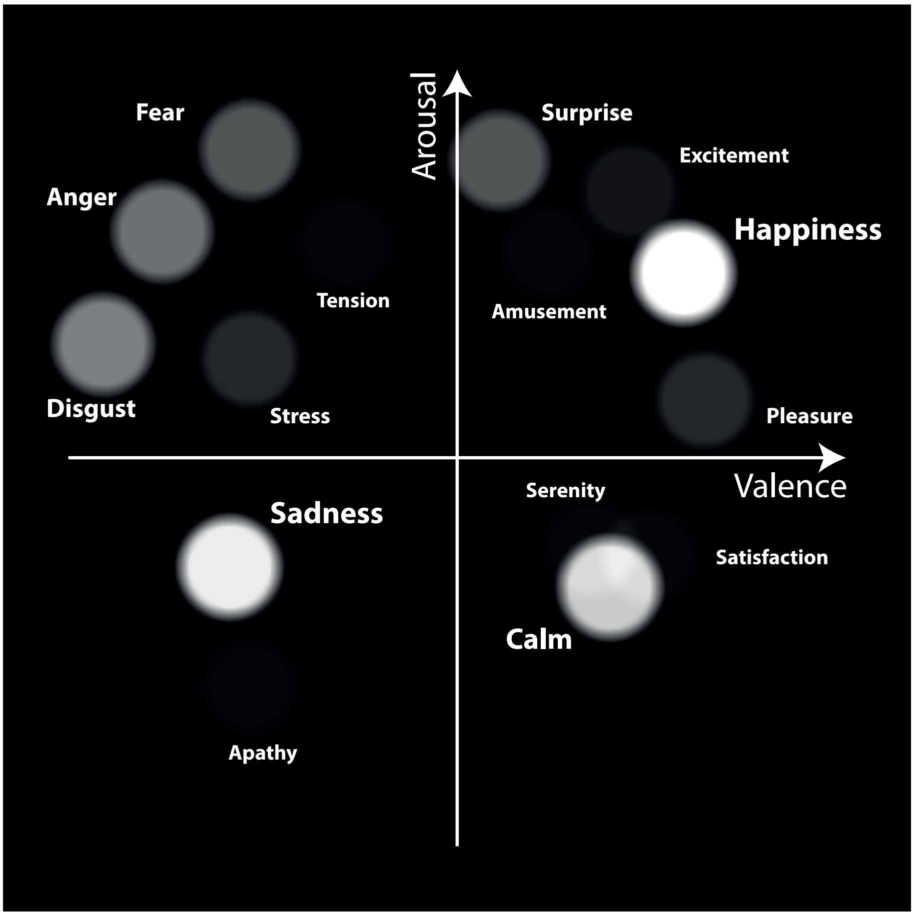

Figure 2. Representation of the recognized emotions and their occurrence in the considered papers. Circles are used to merge very close emotions in the continuous models into a single region. Intensity and font size are proportional to the frequency of occurrence of each emotion (greater occurrences correspond to brighter circles and greater fonts).

advantage of using the representation of Figure 2 is twofold. First, it serves to generalize into a common scheme what in different papers was represented with different models: the usage of circles allows to merges intervals in the continuous models into the circle having the name of the central emotion, thus avoiding dispersion. Second, it serves to represent, through circle brightness and font size, the number of papers dealing with the given group of emotions falling inside each circle. Happiness, sadness and calm were the most recurrent, often used as representative of their respective quadrants: High Valence-High Arousal (HVHA), Low Valence-Low Arousal (LVLA), High Valence-Low Arousal (HVLA). On the contrary, in the Low Valence-High Arousal (LVHA) sector, a predominant emotion was not identifiable, since disgust, anger and fear were almost equally frequent. Moreover, the upper part of Figure 2 (corresponding to high arousal) was more explored than the lower part both in terms of emotions variety and occurrence. This reflects the fact that most of the emotions, in particular those with short persistence and elicitable by fast stimuli (easier to be reproduced in experimental setting), are characterized by high arousal. Conversely, low arousal is common between persistent emotional states like gloom, fatigue and depression. Moreover, arousal was responsible for stronger differences in signals patterns.

An interesting aspect is that a relevant group of the examined emotions corresponded to those that Plutchik indicated as basic (Plutchik 2001), which can be combined to express the total language of emotions: disgust, anger, fear, surprise, excitement, joy, sadness, calm. Figure 2 gives a quantitative perception of the recognized emotions, but does not provide any information about

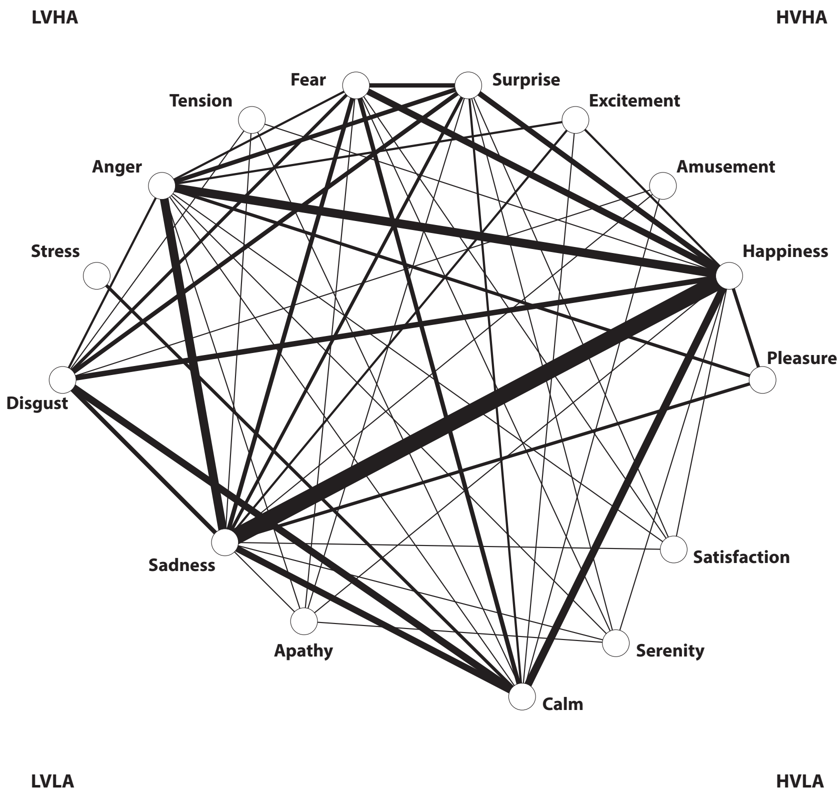

Figure 3. Classification graph. Edges joined successful recognition between emotional pairs. Edge thickness is proportional to the number of studies dealing with the recognition of the pair.

jointly recognized emotions. Figure 3 represents this information through a graph model: emotions (nodes) are linked by edges only if a reciprocal classification has occurred. In case of multiclass experiments, an edge between each pair was added. The edge thickness represents its weight that is proportional to the number of occurrences: it could be considered a metrics of reproducibility. Most connected emotions resulted to be: sadness (13), happiness (12), anger (11) and calm (9). Happiness/sadness was the most frequently discriminated pair, being examined 15 times. Happiness/anger, anger/sadness, happiness/calm and disgust/calm pairs were also common (above 6 times). It is important to note that the most connected emotions represent the most recurrent and the most examined in reference papers, which does not mean that they are the most easily recognizable but, probably, that they are the most frequently felt by human beings. By considering complex emotional states a combination of basic emotions (Plutchik 2001), we can verify the status of basic emotions recognition from Figure 3. Figure 4 shows the subgraph corresponding to basic emotions: since significant progresses have been made in emotion recognition, a substantial step toward reliability in recognition would be graph completion and weight increment on all edges.

3.2. *Brain activation areas*

Beside the choice of emotions and the process used to classify them, it is fundamentals to understand their brain activation patterns. The knowledge of the most involved brain's areas in emotional processes is the key for developing ergonomic interfaces (by using just necessary EEG channels) and reducing discomfort for the user. This has been done by combining experimental results from the considered papers where a subset of the used channels was described as the most involved in the emotional processes (some of the selected articles did not indicate a subset of channels: in that case

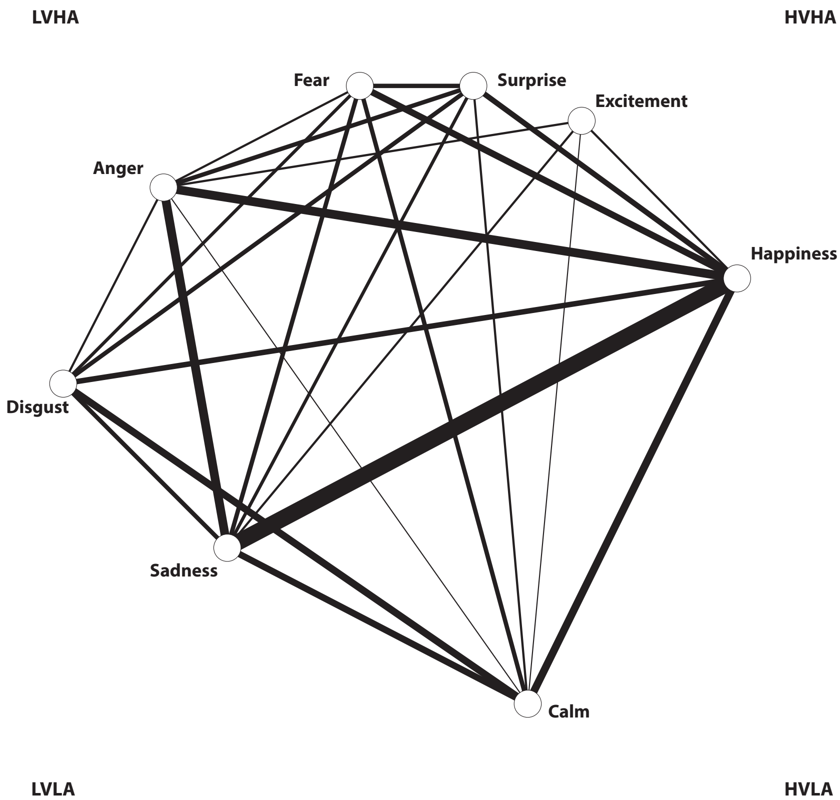

Figure 4. Basic emotions subgraph.

we have considered that all the measured channels were equally involved and considered). Figure 5 shows the positions of the most relevant areas in emotion recognition, obtained by considering the occurrence of each channel in the selected articles.

The resulting distribution shows that temporal, frontal and right parietal resulted the main used (active) regions, while occipital lobe was often excluded. This could be also due to the fact that the visual component was often employed for stimulation and for synchronization and occipital channeles could produce a bias. The activation map was consistent with literature findings (LeDoux 2000; Critchley et al. 2004; Stark et al. 2007; Deak 2011) and the role of frontal dynamic in the emotional processes (Reznik and Allen 2017), both for the recognition of a single emotion and between different emotions. In order to highlight the role of different brain regions for different emotions, we separated the contribution of discrete emotions too. Figure 6 shows the most relevant areas for the 8 basic emotions separately. Frontal area was involved in most of the emotions processes but different basic emotions use quite different activation patterns: this could be really useful for recognizing emotions each other. In fact, although the activation of the same area does not exclude the possibility of recognizing different emotional states (if occurring with different modalities), surely the activation of different areas ensures the effective recognition between different emotional states.

4. Discussion

Despite the hardness in performing a comparative analysis between the selected articles (due to the heterogeneity of signal activation protocols, used EEG equipments and signal processing/classification strategies), we collected information about most studied emotions, focusing on the recurrence of successful recognitions between emotional pairs. This allowed us to verify that all

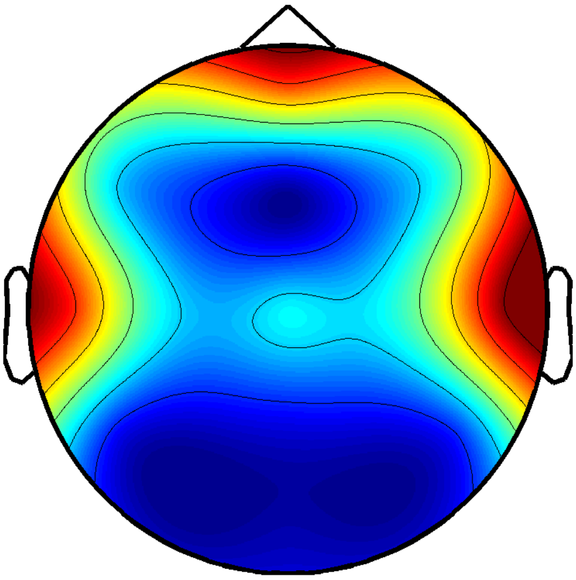

Figure 5. Most activated brain regions in emotions recognition: the image has been obtained by summing the contributes of all the considered studies regarding channels positioning and activity.

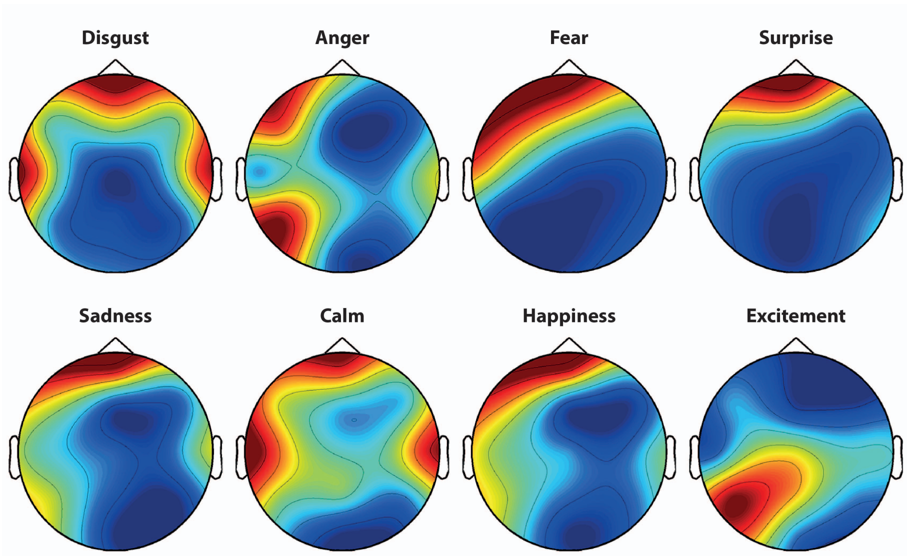

Figure 6. Most relevant areas for each basic emotion.

the basic emotions were recognized but with a prevalence for sadness, calm, happiness, anger and disgust. In particular, the graph of the basic emotion (Figure 4) is almost complete. Furthermore, we summarized data about relevant channels that most frequently occurred in emotion recognition.

We obtained spatial activation maps for emotions and more specifically, for discrete emotions and for each of the 8 basic emotions. This allows us to propose an "essential" EEG system for emotions recognition, meaning that one can build a BCI by concentrating the channels arrangement in the relevant areas of the scalp, thus gaining in terms of ergonomics. These results could represent a good step toward the comprehension and mapping of the emotional mechanisms.

The above results could very useful for the design of an active emotion-based BCI (as discussed above, passive elicitation is too "intrusive" to be used, especially in people affected by heavy neurological disorders). In fact, first they allowed to restrict the attention to a subset of well studied emotions whose well-defined brain activation patterns and specific features have been understood and defined. Second, they allowed to concentrate on a subset of particularly active EEG channels which serves to reduce encumbrance and nuisance of the EEG headset and to contribute to a better ergonomic and ecological BCI system. The paradigm of the potential BCI, that uses the previously defined most recognized emotions and most active brain regions, could be based on a graphic interface to show a series of symbols on a computer screen. In the case of a binary BCI (if just only one emotion is recognized with respect to a relaxing state) (Placidi et al. 2016b), the system could allow the communication though a software that continuously loops through the rows and the columns of the matrix by enlightening each of them for a fixed time. Cells could contain alphanumeric characters, symbols or commands. The strategy of choice of a proposal would be based on the association between an activation task (recalling in mind a specific emotion) to the selection and the relaxing state to its rejection, through a classification algorithm: the activation task is interpreted as “YES” or “SELECT”, the latter as “NO” or “REJECT”. The system passes through all the rows of the matrix, and the user has to focus on the first state (“YES”) when the row containing the desired symbol is illuminated, on the second state (“NO”) otherwise. After the choice of a row (the classification strategy indicated a “selection”), the system sequentially proposes symbols contained in it and the user has to activate on the desired cell using the same mechanism. For a multiple classes BCI (based on multiple emotional states), the graphic user interface could change its role by allowing a free selection between a set of static symbols, each of them associated to a different emotion (to select a symbol it could be necessary to remember the corresponding emotional state). The selection of a symbol would be direct (in this case, a cyclic software to pass over a symbol would not be necessary) and multiple matrices of symbols could be nested and arranged in a tree structure: from a root, it could be possible to navigate through branches to reach a leaf containing the desired symbol. In this way, the BCI could be made more efficient than binary.

However, before their usage in active emotion-driven BCI, further explorations need to be conduced regarding the proposal of standardized activation protocols, more sensitive EEG sys-tems, complete and uniform data collection from self-induced emotions, and specific classifica-tion/ recognition strategies. Particular attention should be paid in the elicitation protocol: in our analysis, several stimuli have been taken into account, but different emotional sources could lead in slightly different activation patterns. For future developments of active emotion-driven BCI, the elicitation protocol should consist on remembering lived experiences to generate emotions.

Another aspect to be investigated would be the nature of the EEG signals allowing to remem-bered emotions. In fact, the mental processes used to recall in mind an emotional state could produce brain patterns different by that produced by the directly felt emotion and weaker signals. Finally, most of the papers analyzed therein afforded the problem of recognizing different emotions, not really to recognize each of them with respect to each other (as reported in Table I). For these reasons, a special effort should be dedicated to study and test both specific signal preprocessing strategies, to improve the quality of weak EEG signals produced be remembering emotions, and a general classification strategy capable of recognizing all the considered emotions each-other in the same time.

Finally, data collected from the self-induced basic emotions, from a sufficiently high set of uniformly spaced channels (at least 64) should be analyzed to produce a complete version of the graph of Figure 4 and the corresponding Figures 5, and 6 (in fact it is not obvious that the brain acti-vation patterns for self-induced emotions will remain the same with respect to those obtained for externally elicited emotions). In this way, all the self-induced basic emotions would be recognizable and could be used, in combination with the minimum set of common channels to implement and drive an active BCI, in order to overcome BCI-illiteracy.

5. Conclusions

Novel mental tasks to drive a BCI are fundamental to offer new chances to overcome BCI-illiteracy. The present study performed a meta-analytic review on recent progresses in the recognition of emotions in the perspective of using them as voluntary, stimulus-independent, commands for BCI systems.

The amount of articles dealing with emotion recognition by EEG signals has become very huge in the last years due to the interest arising from the comprehension of the brain activation mechanisms due to emotions. From an initial set of 103 articles regarding this subject, obtained by querying online databases, we selected those where: reliable EEG acquisition system were used to collect data; adequate description of the considered experiments were provided; relevant results in terms of classification accuracy were obtained. The resulting set was composed by 60 articles. We concentrated our attention on the most recognized emotions and on the brain regions that were most active in the emotional process. In particular we found that the sector of the valence-arousal diagram corresponding to high arousal was more explored than the low arousal sector both in terms of emotions variety and occurrence in the studies. A relevant group of examined emotional states matched the basic emotions set: disgust, anger, fear, surprise, excitement, happiness, sadness, calm. We performed a further analysis regarding the most involved brain regions in the recognition of emotions and we obtained a restricted group of areas (temporal, frontal and right parietal). A similar set was also extracted for the particular case of discrete emotions recognition. The obtained results represented the basis for future developments of an active emotions driven BCI and for beating BCI-illiteracy. However, future explorations have to be done regarding: 1) standardized activation protocols for autonomous (self) elicitation of emotions; 2) uniform data collection form; 3) specific multi-emotions classification strategies; 4) individuation of specific "signatures" (brain activation patterns and features) of emotions capable of recognizing emotions from each-other.

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Disclosure

The authors declare that they have no competing interests.

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