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A preliminary structured database for Multimodal Measurements and Elicitations of EMOtions: M^{2}E^{2}MO

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ABSTRACT

Recent studies show that emotions can be considered as different subjective processes. In this paper we describe M^{2}E^{2}MO, a new multimodal database including signals from electroencephalogram (EEG), functional near-infrared spectroscopy (fNIRS) and autonomic data recorded during emotions elicitation by means of different stimulations: visual-stimuli (International Affective Picture System, IAPS), interactional scripts (IS, brief interactional sketches) and memory stimulation on autobiographic basis (autobiographic memories, AM). M^{2}E^{2}MO has been designed to host big-data from heterogeneous sources. Although there are many databases for measuring emotions, the present study used a new measurement dataset for the recording of neurophysiological emotions pathways when they are self-generated by recalling in mind past life experiences (AM) and when external stimulations elicit them (IAPS; IS). M^{2}E^{2}MO will be made publicly available to allow neuroscientists a better insight into brain mechanisms to study new signal processing and classification strategies of emotional signals to be used for studying human-computer interfaces.

Keywords: emotional memories; emotion recognition; facial expressions of emotions; multimodality

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1. Introduction

The aim of this research is to allow study and analysis of the neurological pathways and features underlying emotions felt by human beings, in particular when emotions are elicited by external cues (in what follows, we call also them “external-induced”) or on autobiographic basis (“self-induced”). Human brain gives people the capacity for art, language, moral judgments, and rational thoughts.

It is also responsible of the subjective personality, memories, movements, and perception about the world.

Emotions play a powerful and significant role in every-day life of human beings and their study is particularly important to understand the emotion a subject is feeling and to get empathy with him, to prevent and diagnose psychosomatic disorders, to implement emotional patterns into computers and artificial intelligence equipment, and to use emotions as driving strategies for brain-computer interfaces (BCI) (Balconi, Grippa, & Vanutelli, 2015).

1.1 Lived Emotions

The most successful way to represent emotional data is the one done by the human brain, as explained by Adolphs (Adolphs, 2002). He discusses how the human brain expresses and recognizes emotional expressions from visual and auditory stimuli, correlating information from different areas. The brain correlates past experiences, movements, voices and facial expressions. The brain is also capable of integrating this multimodal information and generates a unique representation of the visual and auditory stimuli (Balconi & Carrera, 2011; Barros & Wermter, 2016). When it comes to emotions, according to the classical literature there exists a small set of discrete emotional categories labels (happiness, anger, sadness, and fear are among them) universally shared from which other emotions can be derived (Ekman, 1999). This view has been largely debated by the Circumplex Model of Affect (Russell, 1980) which categorizes emotions by their valence and arousal dimensions.

However, across a large number of studies, the basic underlying conceptual structure is found consistently. Indeed, despite the ample theoretical differences observed in previous studies, two features seem to largely affect the emotional response to external cues: arousal and valence (Balconi & Carrera, 2011; Balconi & Molteni, 2016). These two dimensions were conceptualized in different ways: as the dimensions of positive and negative affect (Watson, Wiese, Vaidya, & Tellegen, 1999), tension and energy (Eysenck, 1990), approach and withdrawal (Lang, Bradley, & Cuthbert, 1997), or valence and arousal (Russell, 1980). The valence dimension measures whether a human has negative or positive feelings, whereas the arousal dimension measures whether a human feel bored or excited. Therefore, each perceived emotional state can be depicted on a 2 dimensional plane with valence and arousal at each axis respectively (see Fig. 1).

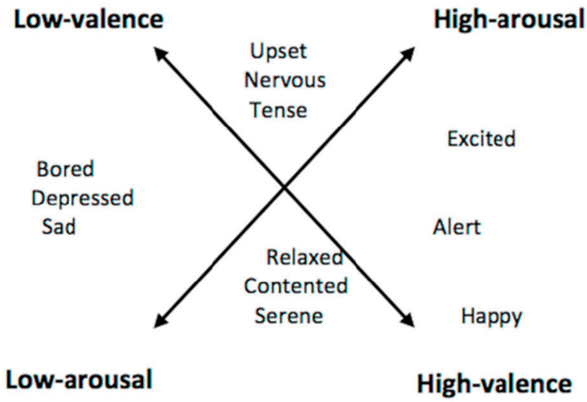

Figure 1. Valence/arousal model representation of emotions

Therefore, individuals recognize emotions as overlapping experiences and, as an emotion is experienced and communicated, cognitive interpretations are applied to identify the neurophysiological correlates in the valence/arousal systems and conceptually organize these physiological changes in relation to the eliciting stimuli and contexts, memories of past experiences, behavioral responses, and semantic representation (Balconi & Vanutelli, 2016; Balconi, Vanutelli, & Grippa, 2017; Russell, 2003).

1.2 Emotions as Communication Signals

From a more specific behavioral and communicative perspective, emotions are the informational mechanism used by living beings to give appropriate sensorimotor answers to external cues as well as a way to assign meaning to internal and external information. This mechanism is bodily-oriented and maintains a direct relationship with environment, generating the notion of ‘emotional meaning’. Thus, introducing a functional perspective, emotions serve as identifiers and labelers of individual informational states as well as in social contexts, as intentional arrows. From this point of view, the vital role of emotions in human cognitive processes (LeDoux, 1998) represents a challenging topic in Information Communication Technology (ICT). Detecting and recognizing emotional cues is crucial to understand and respond to user's need and facilitate human-machine interaction. This may be even more important when emotional states can be the only way to communicate with the external world. The need to understand such processes is justified by the huge demand to implement machines able to assist people on several psychological and physical weaknesses, ranging from depressive states to communicative disorders, to either physical, or cognitive, or social health care assistance in daily functional activities (Esposito & Jain, 2016).

Therefore, we know that emotion regulation strategies are linked with specific emotional, physiological, cognitive and behavioral responses (Gross, Sheppes, & Urry, 2011). Specifically, the study of brain signals is a direct way to gather information about emotions directly on their physiological source and to discover their pathways. A lot of research identified brain regions performing functionally different emotional processes. Making use of the current neuroimaging techniques such as functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and magnetoencephalography (MEG), it has been possible to identify how different brain regions encode, to a certain degree, different emotional states to the extent that is has been possible to build a map of the emotional brain (Deak, 2011; Kassam, Markey, Cherkassky, Loewenstein, & Just, 2013). Neuroimaging measures are used as input to Affective Computing technologies (Frantzidis et al., 2010).

1.3 Emotion Detection by EEG, fNIRS and Autonomic Measures

In this context, emotional EEG-based technology had acquired a growing interest since it holds the promise to allow the recognition and classification of inner emotional states, meeting users expectations in terms of costs and easiness to use (differently from fMRI, PET, and MEG which are expensive and immobile) because of the availability of very fast, wireless and inexpensive EEG systems. Recent reviews underlined the utility to apply EEG measurement in emotional study. Indeed it was found to be suitable to measure changes in brain activity at early and late latencies, furnishing a complete overview of the emotional processing across-time with high temporal resolution. In fact, early and late mechanisms sequentially describe the dynamic variations of subjective response to emotional conditions and these dynamic modulations are not easily accessible by classical neuroimaging measures (Balconi & Canavesio, 2014; Balconi, Finocchiaro, & Canavesio, 2014; Balconi, Tirelli, & Frezza, 2015).

Although the good temporal resolution of EEG enables a precise evaluation of the time-course of response to the emotion perception, its low spatial resolution makes less easy to draw accurate conclusions regarding the main neural areas involved. Due to its fast temporal evolution and its representation and integration among complex, widespread neural networks, the emotional experiences should preferably be examined by means of imaging methods that offer good resolution in both temporal and spatial domains. Temporal resolution of fNIRS is high enough for measuring event-related hemodynamic responses (Elwell et al., 1993), and combined EEG/NIRS measurements allow for the complementary examination of neural as well as hemodynamic aspects of brain activation. For this reason, recently fNIRS measure was applied to study emotions in different domains (Balconi & Molteni, 2016; Koseki et al., 2013). fNIRS has been developed to be non-invasive, easy-to-use, portable, restraint-free and replicable and fNIRS is considered to impose considerably milder physical and psychological burdens than those of classical neuroimaging techniques.

Finally, autonomic measures are useful to integrate previous central measures. Indeed systemic blood pressure (BP), heart rate (HR), and skin conductance level and response (SCL; SCR) were considered potential biological markers of emotions, simultaneously with EEG and NIRS measurements. The indubitable vantage of acquiring both the autonomic and the central activities stands is the possibility to better elucidate the reciprocal interplay of the two compartments. Moreover, facial EMG activity in the zygomaticus major and corrugator supercilii muscle regions were considered as predictive markers of emotional behavior, able to characterize the facial autonomic response to emotional cues (Fridlund & Cacioppo, 1986).

1.4 Elicitation of Emotional Patterns: Experiences and Memories

For eliciting individual's emotional states there exists various techniques. They are primarily elicited by watching pictures and movies with highly emotional contents. Westermann, Spies, Stahl, & Hesse (1996) tested 11 emotional elicitation methods and watching movies proved to be the best procedure to induce positive or negative emotional states. To this aim, scholars proposed several affective video-clips databases (Balconi, Brambilla, & Falbo, 2009; Chambel, Oliveira, & Martins, 2011) [among many others]. On the other hand, also databases of pictures and sounds with high emotional contents were developed to induce emotive states (Balconi & Pozzoli, 2005). Among the most exploited databases of audio and visual stimuli for emotion elicitation it is worth to mention the International Affective Digitized Sounds (IADS) (Bradley & Lang, 2007) and the International Affective Picture System (IAPS) (Lang, Bradley, & Cuthbert, 2008).

Emotions can be also produced by recalling in mind past experiences: this mechanism has been recently proposed as a strategy to drive a BCI autonomously, without any external intervention or elicitation. Self-generated emotional states are elicited asking participants to re-experience positive or negative personal life episodes as well as personal life episode marked by panel of emotions (like sadness, happiness, anger, fear or disgust (Damasio et al., 2000; Kassam et al., 2013).

Relationships between stimuli and emotional state and expressions have been extensively studied by psychologists and neuropsychologists. Nevertheless, algorithmic affect recognition remains an arduous and difficult task since human emotion elicitation involves multiple competencies, including behavioral responses, psychological and cognitive abilities. To allow robust examinations and avoid biases and artifacts, it is particularly important to study data from people with different characteristics and collected by different modalities and by using different stimulations, that is to include a huge number of examinations from several subjects in structured databases.

Databases containing stimuli media as well as emotional expressions through different modalities have been proposed in recent years (Abadi et al., 2015; Fanelli, Gall, Romsdorfer, Weise, & Van Gool, 2010; Grimm, Kroschel, & Narayanan, 2008; Gunes & Piccardi, 2006; Katsigiannis & Ramzan, 2018; Koelstra et al., 2012; Soleymani, Lichtenauer, Pun, & Pantic, 2012) and used for affect recognition using pattern recognition methods on signals coming from multiple modalities. The main characteristics of the previously listed databases is that they lack in generalization, both in elicitation strategies and in measurement modalities, that is they are concentrated on specific signal classification strategies and on the obtained results with classification. For this reason, the previous databases contain just data strictly necessary for the objective of the studies for which they are collected (elicitation strategies, measurement modalities, measurement equipment, and the number of studied subjects are limited). As structured, since they are very useful to perform comparison between different data processing and classification strategies on the same data, it is impossible to perform transversal studies, comparison between results from different imaging modalities on the same subjects, or between different activation strategies.

Therefore, given the importance of emotions and their possibly variable pathways, the present study is aimed at designing a structured multimodal database, M^{2}E^{2}MO, to host multimodal brain signals from emotions elicited by multimodal strategies. Specifically, no-relational databases are designed to deal with Big Data (De Mauro, Greco, & Grimaldi, 2016). Big Data are referred to information that grow and move too fast and are too heterogeneous to be handled by traditional technologies. The idea is to use the concepts of unstructured data and scalability by avoiding the table form of rows and columns of relational databases in favor of specialized frameworks to store dynamic and heterogeneous data, such those recorded by EEG, fNIRS and autonomic information during different stimulations: visual-stimuli (IAPS), scripts (IS) and mnemonic stimulation on autobiographic basis (AM). In what follows, the design of M^2E^2MO is presented and some examples of queries to access data are proposed and discussed.

2. Experimental protocols and data structures

2.1 Experimental protocols

2.1.1 Stimulus material

Stimuli datasets were organized into three datasets, related to each emotion eliciting task, taking into account the following parameters.

1) IAPS was composed by 125 stimuli selected from the International Affective Picture System (IAPS) (Bradley & Lang, 2007). They were selected based on two categories (high/low arousal; positive/negative valence). Arousal and valence rating for each picture was modified in a successive validation study (Balconi et al., 2009). All pictures were divided into five categories according to the two dimensions of valence and arousal (Rv = Range valence; Mv = Mean valence; SDv = Standard Deviation valence; Ra = Range arousal, etc.) on 9-point Likert scale:

- Positive/high arousal (Rv = 6,16 - 8,10, Mv = 7,23, SDv = 1,54; Ra = 5,60 - 7,35, Ma = 6,49, SDa = 1,37)
- Positive/low arousal (Rv = 6,17 - 8,28, Mv = 7,20, SDv = 0,50; Ra = 2,51 - 4,92, Ma = 3,49, SDa = 0,50)
- Negative/high arousal (Rv = 1,46 - 3,95, Mv = 2,51, SDv = 0,79; Ra = 5,77 - 7,35, Ma = 6,44, SDa = 0,49)
- Negative/low arousal (Rv = 2,55 - 4,25, Mv = 3,46, SDv = 0,56; Ra = 2,95 - 4,95, Ma = 4,01, SDa = 0,38)
- Neutral (Rv = 4,22 - 5,85, Mv = 4,87, SDv = 0,51; Ra = 3,46 - 5,34, Ma = 4,45, SDa = 0,46).

2) IS was firstly created and selected based on two categories (high/low arousal; positive/negative valence). Specifically, this task consisted of a collection of affective pictures portraying real interpersonal situations

of common interactions between two or more people (Balconi & Vanutelli, 2016). Indeed, 125 pictures representing positive, negative and neutral interaction situations with high/low arousing power were selected. Positive valence pictures depicted cozy situations; negative pictures represented uncomfortable situations; finally, neutral pictures described individuals interactions without emotional connotation. Pictures were similar each other for perceptual and cognitive features. All pictures were divided into five categories according to the two dimensions of valence and arousal on 9-point Likert scale:

- Positive/high arousal (Rv = 6,33 - 8,64, Mv = 7,29, SDv = 2,08; Ra = 4,68 - 7,80, Ma = 5,84, SDa = 1,81)
- Positive/low arousal (Rv = 6,05 - 8,03, Mv = 7,09, SDv = 0,56; Ra = 3,66 - 7,20, Ma = 4,49, SDa = 0,84)
- Negative/high arousal (Rv = 1,80 - 5,70, Mv = 2,82, SDv = 0,99; Ra = 4,20 - 7,09, Ma = 6,17, SDa = 1,37)
- Negative/low arousal (Rv = 1,95 - 4,50, Mv = 3,12, SDv = 1,18; Ra = 2,95 - 6,30 Ma = 4,81, SDa = 0,67)
- Neutral (Rv = 4,58 - 6,60, Mv = 5,36, SDv = 1,19; Ra = 2,77 - 5,90, Ma = 3,93, SDa = 0,79).

3) AM was firstly created and selected based on valence category (positive/negative/neutral valence). AM task planning requested three different steps. The first one consisted in the free recall based on past autobiographical events of different values: positive, negative and neutral. To free autobiographical recall, participants were asked to perform a semi-structured interview that was administered by an expert researcher. The recall of positive, negative and neutral autobiographical memories occurred freely, with the only pointing by providing specific information in relation to each event (e.g. event characteristics: duration over a day, in a specific moment and place of participant's life). The second step involved the collection of autobiographical memories previously produced by each subject to be codified by expert judges. They transpose the autobiographical memories in sentences through a specific algorithm for encoding of memories into linguistic code (brief utterances - bu - memory inducing) capable of eliciting positive, negative and neutral emotional responses related to participant's past autobiographical events. Homogeneity for grammatical and structural features of sentences was verified (linguistic code composed by: subject + verb + direct object) Specifically, 25 positive, 25 negative and 25 neutral sentences were

created ad hoc for each participant. Bu were recorded by experimenter.

The third step provided the guided recall based on listening to bu after a fixed time interval from the first step (about five days). Bu were reproduced in an auditory format for the emotional memories elicitation. All Bu were divided into three categories according to the dimension of valence and arousal (Rv = Range valence; Mv = Mean valence; SDv = Standard Deviation valence; Ra = Range arousal, etc.). Valence and arousal were evaluated on 9-point Likert scale by subjects based on their autobiographical past memories:

- Positive (Rv = 4,44 - 7,64, Mv = 6,25, SDv = 1,08; Ra = 4,08 - 8,04, Ma = 5,90, SDa = 1,59)
- Negative (Rv = 2,36 - 5,40, Mv = 3,89, SDv = 1,09; Ra = 4,36 - 6,72, Ma = 5,29, SDa = 0,84)
- Neutral (Rv = 3,56 - 6,16, Mv = 4,94, SDv = 0,97; Ra = 3,60 - 6,64, Ma = 4,74, SDa = 1,08).

2.2 Procedural features

The stimuli for IAPS were administered by a computer placed in front of the subject at a distance of 80 cm. E-Prime V. 2.0 (Psychology Software Tools) was used for pictures presentation. The number of pictures was the same for each category according to the two dimensions of valence and arousal. Images were presented in a randomized order for a fixed interval of time, followed by the presentation of an interstimulus (black screen) of fixed duration. To prevent subjects fatigue, pictures presentation was divided into 5 blocks of 25 images. After the presentation of each picture subjective ratings were obtained with the SAM (Self-Assessment Manikin), using a 9-point version (Bradley & Lang, 1994; Bradley & Lang, 1999).

The stimuli for IS were administered with the same modalities of IAPS. The number of the interational sketches were the same for each category according to valence and arousal dimension (5 categories). Pictures' presentation followed the same modality of IAPS. Each image presentation was followed by rating evaluation with SAM.

The stimuli for AM were administered by a computer placed in front of the subject at a distance of 80 cm. E-Prime 2.0 software was used for AM stimuli presentation. The number of sentences was the same for each valence category (25 positive, 25 negative and 25 neutral). The stimuli were administered in the auditory format. The presentation of the sentences was randomized, with a fixed interstimulus time interval. Each Bu presentation was followed by rating evaluation with SAM.

2.3 Data acquisition

For each of stimuli datasets in response to each elicitation task, three orders of measures were collected, by using respectively EEG, fNIRS and autonomic measures.

EEG measures were collected with a 32-channel DC amplifier (SYNAMPS system) and acquisition software (NEUROSCAN 4.2, V-AMP: Brain Products, München, Germany. Truscan: Deymed Diagnostic, Hronov, Czech) during three tasks execution. For the electroencephalographic activity recording, an ElectroCap with Ag/AgCl electrodes was used from active scalp sites referred to the earlobes (10/20 system of electrode placement) (Klem, Luders, Jasper, & Elger, 1958). Two EOG electrodes were placed on the eyes external site.

A sampling rate of 1000 Hz was used for data acquiring, with a frequency band of 0.01 to 50 Hz and the impedance of electrodes recording was below 5 kΩ. Specifically, prefrontal, frontal, central, tempo-parietal and occipital cerebral activity was recorded.

fNIRS measures were collected by NIRScout System (NIRx Medical Technologies, LLC. Los Angeles, California) using 16 optodes (8 light sources/emitters and 8 detectors) positioned over the prefrontal, frontal and fronto-central brain areas. A distance of 30 mm for neighboring optodes was maintained between sources and detectors and a two wave-lengths near-infrared light (760 and 850 nm) was used. For optodes placement on participant's head/scalp a NIRS–EEG (electroencephalography) compatible cup according to the international 10/5 system was used. NIRStar Acquisition Software allowed to record transformations in oxygenated hemoglobin (O2Hb) and deoxygenated hemoglobin (HHb) concentration from a 120-s resting baseline.

Autonomic measures were collected with Biofeedback 2000x-pert system with radio module MULTI (Schuhfried GmbH, Mödling, Austria) positioned on the participant hand. The system, from a sensor attached to the volar surface of the middle section of the forefinger of the non-dominant hand was able to measure pheripheral parameters, such as: skin conductance response and level (SCR and SCL) in μS and heart rate (HR) in beats per minute (bpm). For the recording of SCL an EDA1 gold electrode, employing current voltage measurement of a 2 kHz sampling rate was used. For SCR, instead, a measurement resolution of 12Ns and a sampling rate of 20 Hz was used. HR measurement was allowed by infrared absorption principle. Finally, facial EMG activity in the zygomaticus major and corrugator supercilii muscle regions were recorded during the execution of the three tasks. The electrodes were positioned over the corrugator and zygomatic muscles in accordance with psycho-physiological recording guidelines (Fridlund & Cacioppo, 1986).

2.4 Data structures

EEG, fNIRS and Autonomic data, for each subject and for each examination, are contained into separated files. For the EEG modality, data are stored into one single EDF+ format file (Kemp, Värri, Rosa, Nielsen, & Gade, 1992; Kemp & Olivan, 2003), one of the most used international standard greatly implemented in most of the EEG equipment all around the world.

The EDF+ file is organized in two sections: header and data records. The header is in US-ASCII format and itself divided in two subsections. The first subsection contains information regarding the measurement setup, such as a subject id, date and time of measurement, the number of registered signals, etc. The second subsection includes information regarding the specific EEG channel, such as its label, channel dynamics (intended as ranges of amplitude values), etc. Between the channels there are also "Annotations", a specific space reserved for codes identifying the stimulus administered to the subject at a given time instant during registration.

In the data records section, data are stored in binary format and organized into blocks. The number of blocks is defined into the Header by the field "Number of Data Records". Each block contains the sampling data coming by a given channel (including Annotations).

Regarding data registered by the fNIRS equipment, 6 different files are generated in "Plain Text" format: 4 header files (having extension .txt, .evt, .hdr, and .set, respectively) and 2 files containing data (having extensions .wl1 and wl2, respectively).

The .set file contains the gain setting table. The file .evt contains the event records and the .txt file contains information regarding the configuration setup of the system. Finally, the .hdr file contains information regarding other parameters, such as ImagingParameters, Paradigm, ExperimentNotes, GainSettings, Markers etc. Regarding the data files, .wl1 and .wl2, they contains data registered at different wavelenghts: the first contains data registered at 760nm and the second at 830nm or at 850 nm. For fNIRS data, such file format is strictly dependent on the experimental equipment, since a standard for fNRIS data has not yet been defined.

Finally, Autonomic data are stored into one single file in Microsoft Excel format. The file contains data in tabular form, organized in columns (time is along the rows). The first column contains the time instant during which the measurement is collected and the last column contains the markers. Middle columns contain specific autonomic parameters, a column for each parameter.

During each experimental session, data registration is continuous without interruption between trials (a trial is a set of signals, one for each channel, occurring between consecutive events) indicated by markers.

2.5. The Design of M^2E^2MO

The proposed database has been imagined as association between each elicitation protocol and the corresponding measurement modalities used to monitor it. The design of M^2E^2MO is reported in Fig. 2.

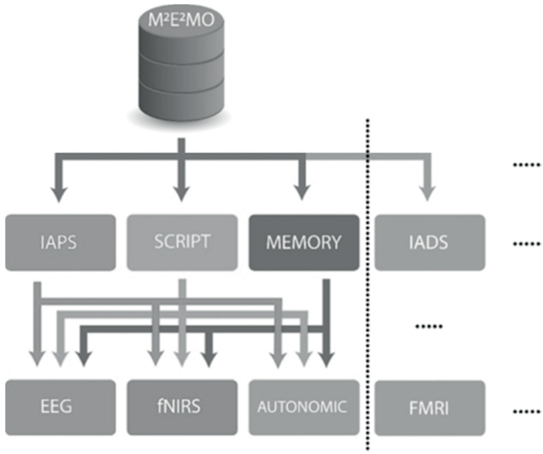

Figure 2. Database design: the first three protocols and measurement modalities are those actually measured and included into the database. Those to the right of the vertical dashed line can be added to the database with reduced effort

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