MultiMind: Multi-Brain Signal Fusion to Exceed the Power of a Single Brain

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Abstract

We propose a Multi-Brain (multi bio-signal) Fusion (MBF) technology, which consists in the aggregation and analysis of brain and other biometric signals collected from a number of individuals. Often performed in the context of some common stimulus, MBF aims to facilitate rapid/enhanced collective analysis and decision making, or to assess aggregate characteristics, such as a group emotional index (GEI). The wide range of potential applications may justify an ongoing, distributed program of research into the biometric correlates of conscious and unconscious human cognitive functions (practical intelligence). An example is MBF-enabled joint analysis, which would combine cues from several intelligence analysts who are examining the same visual scene in order to rapidly highlight important features that might not be salient to any individual analyst, and which might be difficult to elicit from the group by conventional means. An experiment in presented in which a GEI is obtained by aggregating the information from two people wearing EMOTIV Epoc™ 'neuroheadsets', which collect electroencephalogram (EEG) / electromyogram (EMG) signals from 14 sensors on the scalp. As subjects watch a sequence of slides with emotion-triggering content, their decoded emotions are fused to provide a group emotional response, a collective assessment of the presented information. MBF has the potential to surpass single-brain limitations by accessing and integrating more information than can be usefully shared within even small human groups by means of speech, prosody, facial expression and other nonverbal means One may speculate that the automated aggregation of signals from multiple human brains may open a path to super-human intelligence.

1. Introduction

This paper proposes multi-brain fusion (MBF) technology (patent application [1]) as a means of aggregating biometric information[1] taken from a number of individuals, with the result reflecting a meaningful characteristic of the ensemble. Automated means to seamlessly and quasi-instantly fuse the intelligence of a group on the basis of biometric information will also facilitate the integration of human and machine intelligence. This new aspect of distributed group intelligence will enhance the ability of virtual teams to analyze problems from multiple perspectives, reflecting the greater diversity of expertise that can be rapidly configured in the communication-rich distributed environments that are now commonly available. Joint decision-making from presented information is needed in many tactical situations, ranging from the rapid assessment of vulnerability threats to the immediate engagement of targets. In socio-political contexts, its broadest impact might be in the expression of votes for elections or selections.

Imagine a committee that has to make a critical decision on a complex problem in seconds only. Time constraints prevent opinion sharing and rule out a multi-criteria analysis discussion, forcing a simplification down to Yes/No type votes, best case weighted when combined. This is sub-optimal, for it neglects critical information and lacks robustness.

Conventional joint analysis and decision making processes have several bottlenecks:

(a) Communication bottlenecks – optimal joint decisions require exchange of information [2]; however, conventional (mostly verbal) communication severely limits the rate at which such information can be exchanged. Also, conventional communication is not in the position to completely and exactly convey the entire spectrum of information harbored by the human mind.

(b) Processing (single brains) bottlenecks – humans have a limited attention capacity, which severely limits the conscious perception and consequently the amount of information processed at any particular time [3, 4]. All the information, be it important or not, left at the unconscious level will be neglected. Also, humans have a limited capacity to store information and can only remember about 4-6 "chunks" in short-term memory tasks [5, 6].

(c) Aggregation methodology bottlenecks – in many instances, the time allocated for discussing everyone's perspective on the matter to be decided is minimal. In such situations, binary Yes/No individual votes may be

[1] Here 'biometric' is used in its broader sense, referring to information in human signals, as opposed to its narrow sense associated with person identification

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aggregated to obtain the final decision rapidly, yet this is known to lead to suboptimal collective decisions [3].
(d) Inaccuracies in expression/communication of internal analysis/judgments bottlenecks – even when there is time to communicate, humans tend to misrepresent the level of certainty about their individual determinations, thus severely reducing the quality of the collective decision [7].

Gathering and processing brain-collected information in electronic form is faster and potentially more relevant or complete than verbal communication. The MBF technology holds the promise to overcome the above bottlenecks and provides an optimal collective decision or assessment, even in the absence of conventional means of verbal or non-verbal communications and of consciously understood criteria and metrics. It can be used for decision-making after analyzing signals from individual brains by aggregating the results. This can be done by fusing information from multiple people. In addition, MBF may enhance the information processing quality by opening access to the subconscious perceptual information and by allowing for a coordinated utilization of higher amounts of information, including information from the short memory.

Brain activity measurement techniques are rapidly advancing. Non-invasive brain-computer interfaces rely on Electroencephalography (EEG), which correlates brain records such as Slow Cortical Potentials (SCP) [8] [9], Sensorimotor Rhythms [10], or the P300 component of Event-related Potentials [11]. Other techniques include Magnetoencephalography (MEG) [12] and functional Magnetic Resonance Imaging (fMRI) [13]. These techniques have been successfully applied to detect brain signals that correlate with motor imagery (e.g., left vs. right finger movement [15]) or with basic emotions [18, 19]. They enable thought-controlled cursor movements on a video screen [20] or thought-controlled keyboards [21]. To date, DARPA has funded several brain-machine interface programs [22]. Such techniques have been successfully used to indicate a variety of brain states, emotions and simple commands, used for example to control game avatars or physical robots.

Despite these successful applications, current non-invasive techniques are extremely poor compared to what invasive techniques can offer, and those in turn capture only a tiny fraction of brain processes. EEG offers low associated bit rates and low spatial resolutions compared to other methods (~1 bit per second, at an accuracy of ~ 90-95% [14, 15, 16, 17]),

Yet to prove the MBF potential coming from *aggregation* of signals one can use EEG signals, and in time migrate to more powerful measurement techniques.

The paper is organized as follows – Section 2 further details the MBF methodology; Section 3 suggests applications; Section 4 presents an MBF experiment in which two subjects wearing EMOTIV Epoc™ 'neuroheadsets' [23] watch a sequence of slides with humorous content, while their decoded emotions are fused to produce a group emotional response, as a collective assessment of the presented information.

2. Aggregation of signals from multiple brains

A multi-brain aggregator (MuBrain) is able to collect brain signals from group members, analyze them, bring them together, as well as fuse/aggregate the processed signals. The main process steps are: (1) collect/filter brain signals robustly and reliably, (2) determine appropriate class/dimension projection vectors to cumulate/aggregate signals from multiple brains, (3) determine methods to make decisions, validate them based on evaluating the distances from '"truth," and improve determination efficiency by minimizing those distances. In this context, one can leverage group decision making techniques [24], in particular multi-attribute group decision making (MAGDM). Elements of a MAGDM matrix of user-provided perceived performance scores for alternative Aj, against criterion Ci (weights moderate user input), currently expressed by users through writing/typing. In MBF they could be obtained from bio-signals that reflect user's attitude toward an alternative/criterion or degree of support.

To effectively aggregate multi-brain signals, one must select the appropriate data by isolating/extracting, determining appropriate classes/dimensions, along which to cumulate/aggregate, as well as deciding the functions and methods for the fusion process. Fusion can take place at different levels:

- Fusion at data level – bio-signals from multiple subjects are fused together after suitable sampling, normalization, and artifact removal. The fusion involves arithmetic, relational, or logic operators. Statistics are then computed to obtain features associated with the spatial location (of the sensor array mounted on the head) in the time domain (e.g., average, variance, correlations/cross-correlation among different channels/subjects), in the frequency domain (e.g., power spectral density), or in the time-frequency domain (e.g. wavelet).
- Fusion at feature level – after extraction of the feature vectors from the bio-signals for each individual, the vectors are aggregated, for example, by concatenation or by using relational operators. The aggregated feature vectors will become the inputs for pattern recognition systems using neural networks, for clustering algorithms, or for template methods. For example, in a workload-aware task allocation scenario, one might use the average power spectral density in the 8-13Hz range, which is especially indicative of workload levels. In a joint perception scenario, one might concatenate the spectral

features of the P300 components of event-related potentials of each individual, and use linear discriminant analysis to detect an unexpected event.

• Fusion at decision level – the information is fused after a separate determination made on the intent/emotion/decision for each subject. Determinations can be aggregated by using weighted decision methods (voting techniques), classical inference, Bayesian inference, or the Dempster-Shafer's method. Section 4 describes a relevant example.

3. Potential security-related applications

Several application areas and scenarios potentially benefiting from MBF technology:

1. Autonomous joint decision making, seamless, optimal and robust (fig. 1) based on multi-perspective group intelligence. Time constraints often prohibit sharing positions/views (e.g., rapid threat assessment scenarios) MBF is expected outperform Yes/No voting combined by majority voting, a form of majority voting, which might neglect critical information and lacks robustness. A specific case is emotion-weighted voting. Decision makers can be remote.

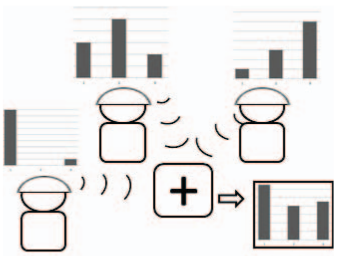

Fig. 1 MBF for joint decision making

2. Aggregated multi-perspective modeling is an improved modeling of aggregation of partial models (fig. 2). This scenario is well exemplified by the story of "Six blind people and the elephant," where each blind person touches a different part of the elephant and describes it as quite a different being. The MBT technology has the potential to create a more complete image from bits and pieces generated by the capabilities of each individual.

3. Joint analysis, based on group emotional intelligence. When watching the same video, various people notice or focus on different aspects. The MBF technology could automatically fuse their perceptions in real-time, and effectively enable perceptions on more than 4-6 "memory chunks," which is the upper limit of the short memory capacity for individual beings [5, 6].

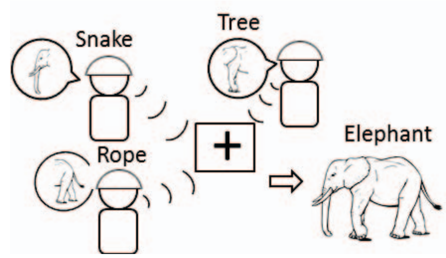

Fig. 2 Joint modeling from aggregation of partial models.

4. The characterization of group emotions is related to joint analysis. It allows obtaining a collective emotional index, or Group Emotional Index (GEI). Section 3 describes a representative experiment.

5. High-confidence, stress-aware task allocation with multiple humans in the loop.

6. Training or operating in environments requiring rapid reactions or feedback. The instructor may override wrong commands of the pilot trainee, may flag dangers/alarms, and may provide real-time feedback .

7. Joint/shared control of vehicles using more drivers or of robots. This can be single or multi-modal.

Some special characteristics of machine aggregated emotion/intelligence are:

a. Numbers – can extend multi-dimensional voting to any size group in social contexts (potential large scale participation)

b. Location – can be theoretically anywhere; it could be planet-scale emotion sharing.

c. Access – it might provide richer information for joint decision making (higher level of optimization), by exploiting subconscious information, like subconscious perceptual information.

Beyond fusing information from the human brain, one can extend the MBF model to fusing signals from biological systems in general, to achieve for example a symbiosis of living systems (heterogeneous living systems of the same type, or heterogeneous system in general). Thus one can fuse signals from a cat and an eagle while a rat enters their sensorial field. The point here is to illustrate different sensorial modalities to enhance the joint system perception beyond the capability of a single component.

Furthermore, one could make joint decisions by combining the inputs from computers and biological system, which would provide a joint/symbiotic Man-Machine Intelligence. Aggregation would not be at signal level, but at a higher level, like features level. An intelligence analysis example for the detection of an individual in a crowd consists of aggregating the result of a face tracking algorithm (or behavior classification) and the result of a human analyst looking for a certain face, individual or behavior.

Fig 3. Symbiotic intelligence of diverse living systems and symbiotic intelligence of man-machine, or, more general, of bio-artificial systems

4. Group emotion characterization

This section describes an experiment in which the information originating in signals from two subjects wearing EMOTIV Epoc™ headsets is aggregated. The headsets collect electrical signals from the scalp (EEG/EMG) via 14 channels, give access both to row data and to processed data, classified as expression and states. In the experimental setting, the subjects watch a sequence of 25 PowerPoint slides with cartoon-like drawing of humorous content. Their decoded emotions are fused to indicate a group emotional response, as a collective assessment of the presented information.

The recognition of face expressions is built into the EMOTIV toolkit. The built-in decoding of classes of signals for expressions of ‘’Neutral,” “Smile” and “Laugh,” is used with degrees of intensity associated to them. For example, it correlates “Laugh” and “0.7” (70%), a fraction number between 0 and 1, as an indicator of how strong the laugh was. The applications determine how humorous a set of images are to the subjects to which they were presented. The slides have been seen by two subjects who sat next to each other, wearing EMOTIV headsets. (Experiments in which subjects do now see eachother are also planned). The bio-signals have been collected and aggregated by software running on a laptop.

A set of fuzzy rules was used to perform a joint assessment of the presented information. The rules were of the type: “If only one of the two subjects is smiling then image is So-So” or “If both are smiling than image is Funny.” In fact, the rules were of IF-THEN type: “IF User1 is Smiling AND User2 is Laughing THEN the image was Quite Funny.” Those rules are summarized in Table 1, while the convention for the output decoding is in Table 2.

The conjunction AND in the IF-THEN rule can be interpreted in various ways. In this example the rules were considered to describe a fuzzy system, and the conjunction AND was taken as a MIN of the two numbers. PRODUCT and AVERAGE can also be used, in a different setting. Thus, the output was calculated as a minimum of the two inputs, O=MIN (I1, I2) where I1 and I2 are numbers in the [0,1] domain, indicating a degree or intensity of class membership.

Table 1. Rule table for aggregation/fusion of 2 inputs.

	Neutral	Smile	Laugh
Neutral	Neutral	So-So	Funny
Smile	So-So	Funny	Quite Funny
Laugh	Funny	Quite Funny	Really Funny

Table 2. Convention for decoding of the output

Output: Joint evaluation	Class relative Intensity/ degree	Added term	Overall/ absolute intensity
Really Funny	0.0-1.0	+3.0	3.0-4.0
Quite Funny	0.0-1.0	+2.0	2.0-3.0
Funny	0.0-1.0	+1.0	1.0-2.0
So-So	0.0-1.0	+0.0	0.0-1.0
Neutral	0.0-1.0		0

To assign numerical indices to joined outputs (an overall evaluation of how humorous a slide was), an ordering system was created in such a way that a continuous augmentation is possible. For example, a “1.0” for So-So Funny has as a “0.0” for “Funny” at the other end. To obtain the overall intensity, the relative position in a class has to be added to the max scale of the previous class, as shown in Fig. 4.

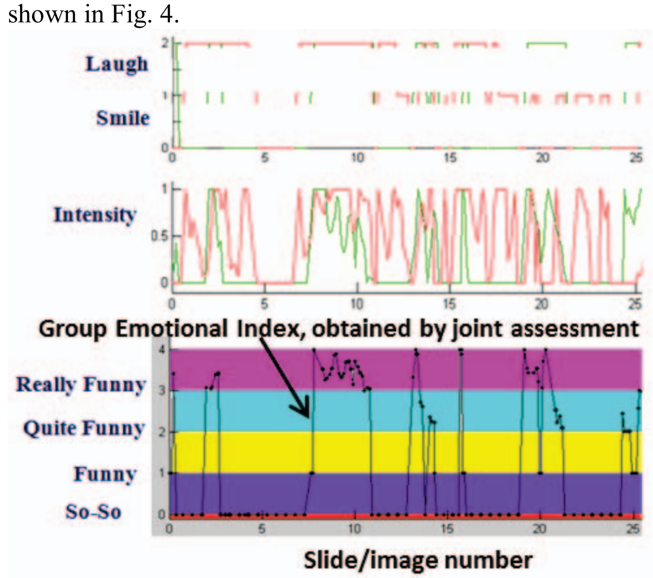

Figure 4: “Smile” and “Laugh” classes (top) and intensities in those classes (middle) for the two subjects (red and green). At the bottom, an aggregated emotional assessment is represented for several classes. The absolute scale of intensity is a measure of “how funny” each of the presented slides was.

5. Summary and conclusion

The paper introduces the concept of Multi-Brain Fusion (MBF) technology and it sketches, at high level, a methodology to generate super-intelligence (i.e. beyond human-level intelligence) by fusing the power of multiple human brains, or by fusing the power of the human brain with machine intelligence.

A series of applications was suggested. An experiment shows how emotional responses of two humans were aggregated. The brain signals are collected with EMOTIV neuroheadsets, and fused in a joint/aggregated emotional index, GEI

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