Agent-Based Nonlocal Social Systems: Neurodynamic Oscillations Approach

Darius Plikynas[1] and Saulius Masteika[1,2]

[1] Research and Development Center, Kazimieras Simonavicius University,
J. Basanaviciaus 29a, LT-03109, Vilnius, Lithuania
darius.plikynas@ksu.lt
[2] Department of Informatics, Faculty of Humanities, Vilnius University,
Muitines g. 8, LT-44280, Kaunas, Lithuania
saulius.masteika@khf.vu.lt

Abstract. This work addresses a conceptual problem – the lack of a multidisciplinary connecting paradigm, which could link fragmented research in the fields of neuroscience, artificial intelligence (AI), multi-agent systems (MAS) and social simulation domains. The need for a common multidisciplinary research framework arises essentially because these fields share a common object of investigation and simulation, i.e. individual and collective behavior. Based on the proposed conceptually novel social neuroscience paradigm (OSIMAS), we envisage social systems emerging from the coherent neurodynamical processes taking place in the individual mind-fields. For the experimental validation of the biologically inspired OSIMAS paradigm we have designed a framework of EEG based experiments. Some benchmark EEG tests for the chosen mind states have been provided in the current paper.

Keywords: oscillating agent, group neurodynamics, social neuroscience, multi-agent systems.

1 Introduction

The complexity of individual and collective human behavior permits myriad theoretical, simulational and experimental ways of investigation. This naturally deepens, but also fragments and specializes our knowledge. Therefore, this paper first strives to find a common a priori denominator as regards deductive reasoning. Only then does it offer some experimental approaches to validate the proposed nonlocal simulation aaproach. In this way, we strive to escape the loss of a general overview, and retain the necessary precision and scrutiny of investigation a posteriori. Below, in a few paragraphs, we briefly review the chosen research domains in order to emphasize some recent common trends, which in our understanding connects them all.

Lately new opportunities for multidisciplinary integration have emerged following technical neuroscience advancements in the research area of brain activity mapping. This has enabled a qualitatively new level of cognitive, behavioral and computational neuroscience (Bunge and Kahn 2009, Haan and Gunnar 2009). With the increase of

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computing power neuroscience methods have crossed the borders of individual brain and mind states research. Hardware and software, used for mapping and analyzing electromagnetic brain activations, has enabled measurements of brain states across groups in real time (Nummenmaa 2012, Lindenberger et al. 2009, Newandee et al. 1996, Grinberg-Zylberbaum and Ramos 1987). This research frontier has made room for emerging multidisciplinary research areas like field-theoretic modeling of consciousness (McFadden 2002, Vitello 2001, Travis and Orme-Johnson 1989, Travis and Arenander 2006, Thaheld 2005, Pribram 1991, Pessa and Vitello 2004, Libet 1994), social neuroscience, neuroeconomics, and group neurodynamics (Cacioppo and Decety 2011, Haan and Gunnar 2009), see Table 1.

From the other side, some perspicacious biologically–inspired simulation approaches have emerged in the areas of computational (artificial) intelligence and agent-based and multi-agent systems research (Pérez et al. 2012, Raudys 2004, Qi and Sun 2003, Nagpal and Mamei 2004). In turn, these advances have laid the foundations for simulation methods oriented towards intelligent, ubiquitous, pervasive, amorphous, organic computing (Poslad 2009, Hansmann 2003, Servat and Drogoul 2002) and field-based coordination research (Mamei and Zambonelli 2006, Paoli and Vizzari 2003, Bandini et al. 2007, Camurri 2007), see Table 1.

A closer look at applied social networks research also reveals some related approaches, which deal, in one way or another, with simulations of field-like information spreading in social networks. For instance, behaviors spread in dynamic social networks (Zhang and Wu 2012), spread of behavior in online social networks (Centola 2010), urban traffic control with coordinating fields (Camuri et al. 2007), mining social networks using wave propagation (Wang et al. 2012), network models of the diffusion of innovations (Valente 1996), a virtual field-based simulation of complex social systems (Plikynas et al. 2014, Plikynas 2010), etc.

Table 1. Emerging field-theoretic research approaches in various domains and scales of self-organization

Research domains	**Emerging field-theoretic research approaches**	
	Individual level	***Social level***
Neuroscience	Consciousness as coherent electromagnetic field (e. g. represented by the Δ, θ, α, β, γ brain waves)	• Social neuroscience • Neuroeconomics • Group neurodynamics
AI/MAS	Artificial intelligent agent	• Field-based coordination • Intelligent ubiquitous • Pervasive/amorphous computing
Social networks	Social networking agent	Social mediums as excitatory systems, distributed cognition, etc

In sum, research trends in neuroscience, AI/MAS and social networks are leading to increasingly complex approaches, pointing towards oscillations or field-theoretic representations of individual and collective mental and behavioral phenomena as well. Hence, the major value of this paper is derived from our earlier proposed Oscillation-Based Multi-Agent System (OSIMAS) social simulation paradigm (Plikynas et al. 2014), which links above mentioned emerging research domains via stylized neurodynamic oscillations-based representation of human mind[1] and society (as collective mind) states as well.

Major conceptual implications of the paradigm presented here essentially provide field-theoretic ways of modeling and simulating individual and collective mind states. Major practical implications of the OSIMAS paradigm are targeted to the applied simulations of some real social phenomena[2] using agent-based and multi-agent systems (ABS and MAS respectively) research. However, it is a long way from the theory presented here to its practical applications, which are of most importance. Hence below, in a few paragraphs, we introduce how the conceptual ideas presented here can find their way in ABS and MAS applications.

This article is organized as follows. In the Section 2, we explain nonlocal approach in the agent based social modeling. Section 3 provides empirical premises of the EEG experimental setup and some results. Finally, section 4 concludes.

2 Local vs. Nonlocal Agent Based Social Modeling

Current ABS and MAS applications are famous for their construction based on the so-called ‘bottom to top’ principle, which in essence is explicitly agent-centric, with pair-based communication protocols between separate agents. Such models are used for the simulation of local pair-to-pair interactions, which are similar to cellular automata models, except that more sophisticated communication protocols and some intelligent decision algorithms are usually employed (Perez et al. 2012).

Nevertheless, in order to achieve substantial progress in the simulation of complex social phenomena, such models are usually enriched with some ‘top to bottom’ construction principles like the belief-desire-intention (BDI) approach, agent selection criteria, higher emotional states, altruism, a credit/fines system, added noise in the inputs and outputs, confines for learning speed and acceleration, etc. These principles are applied from some meta-level – in other words, a nonlocal organizational level – which cannot be deduced from the simple agent properties. In this way, the pure ‘bottom to top’ self-organization principle is lost. This obviously shows that explicit information encoded solely in the properties of individual agents is not enough for the

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[1] Some electroencephalographic (EEG) experimental evidences provided in the sections below lead to an idea of interpreting human basic behavioral patterns in terms of mind states, which can be characterized by a unique electromagnetic power spectral density distributions (Alecu 2011, McFadden 2002, Plikynas et al. 2014).

[2] Like previously mentioned modeling of contextual (implicit) information spread in social networks, network models of the diffusion of innovations, models of self-excitatory wave propagation in social media, etc.

simulation of complex social agent-based systems, as social agents are not so individual after all. They are open systems influenced by the external, i.e. not only local but also regional and global environments at large (Raudys 2004).

In one way or another, this nonlocal (or ‘implicit’) self-organizational level is introduced artificially, following observed social behavioral patterns (Qi and Sun 2003). For instance, in communication theory and practice it is well known that tacit (informal, officially unrecorded) information like emotional ‘atmosphere’, working environment, moods, mimicry, gestures, media stories, weather conditions, etc. prevail in social organizations, which all profoundly influence human decisions and social wellbeing in general on an unconscious level (Lam 2000). This unconscious (implicit) level of self-organization is working in a form of contextual (nonlocal) information shared by all.

The closest empirical confirmations come from the fundamental sciences, e.g. quantum nonlocality phenomenon, which refers to the quantum mechanical predictions of many-systems measurement correlations for the entangled quantum states (Oppenheim and Wehner 2010). The issue has also been raised that we may have to differentiate between two different types of nonlocality: one related to quantum mechanics and the other to what is termed ‘biological nonlocality’ (Thaheld 2005).

To date, very few experiments that attempt to explore the possibility of a quantum physics–biology interrelationship have been conducted. The first experiment utilized pairs of human subjects in Faraday cages, where just one of the pair was subjected to photo stimulation, and possible electroencephalographic (EEG) correlations between human brains were investigated (Grinberg-Zylberbaum et al. 1994). Later experiments, building upon this pioneering research, continue to corroborate the findings with increasing experimental and statistical sophistication [Standish et al. 2004, Radin 2004].

Experiments which revealed evidence of correlated functional magnetic resonance imaging (fMRI) signals between human brains have also been conducted (Wackermann et al. 2004). These correlations occurred while one subject was being photostimulated and the other subject underwent an fMRI scan. Research is also ongoing at the University of Milan (Pizzi et al. 2004, Thaheld 2005) utilizing pairs of 2 cm diameter basins containing human neurons on printed circuit boards inside Faraday cages placed 20 cm apart. Laser stimulation of just one of the basins reveals consistent waveform autocorrelations between the stimulated and unstimulated basins[3].

All of these experiments, when taken together, seem to be pointing us in an unusual direction by implying that biological entanglement and nonlocality effects take place between human brains (Travis and Orme-Johnson 1989, Orme-Johnson and Oates 2009). These findings direct us to the idea that contextual implicit information is distributed in fields, and that fields – although expressing some global information – are locally (unconsciously) perceived by agents. It also leads us to the totally novel

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[3] Researchers at the University of Milan state, “Despite [the fact that] at this level of understanding it is impossible to tell if the origin of this non-locality is a genuine quantum effect, our experimental data seem to strongly suggest that biological systems present non-local properties not explainable by classical models” (Pizzi et al. 2004).

understanding of agents as an oscillating entity, which is capable of absorbing and emitting contextual fields (Plikynas 2010, Plikynas et al. 2014).

The current ABS and MAS have been unable to incorporate this huge amount of informal (contextual) information. This is due to the associated complexity and informal information intangibility, and the lack of a foundational theory that could create a conceptual framework for the incorporation of implicit information in a more natural way. Hence, there is a need to expand prevailing ABS/MAS conceptual frameworks in such a way that nonlocal (contextual) interaction and exchange of information could be incorporated.

Hence, the idea is to incorporate implicit information in the form of nonlocal (contextual) information, which, as in the case of natural laws (e.g. the laws of gravity, entropy, symmetry, energy conservation, etc.), would affect an entire system of social agents at once. Following such an analogy with natural laws, we assume that explicit local activities of social agents can be similarly influenced by implicit (contextual or nonlocal) social information. This could influence entire system of agents in a form of social laws (Reimers 2011). Each agent would respond to this contextual (nonlocal) information in a different way depending on individual characteristics.

Therefore, we should introduce local MAS_L and nonlocal MAS_N layers of self-organization in the prospective ABS/MAS simulation platforms:

$$MAS = (1-\eta)MAS_L + \eta MAS_N, \tag{1}$$

Where $0 \leq \eta \geq 1$denotes the degree of nonlocality:

$\eta \Rightarrow 0$, then $MAS = MAS_L$,

$\eta \Rightarrow 1$, then $MAS = MAS_N$.

In this way, we expand the concept of the ABS/MAS through nonlocal levels of self-organization. Thus, starting with $\eta \rightarrow 0$, self-organization could be observed (i) at the local single-agent level; (ii) on the intermediate scale $0<\eta<1$ it could be observed in coherent groups and organizations of agents; and (iii) on the global scale ($\eta \rightarrow 1$) it could be observed in coherent societies of agents.

The theory naturally follows from real life observations, where agents interact locally (interchanging information with neighbors), but also are affected by the nonlocal states of the whole system (e.g. traditions, cultures, fashions, national mentalities, political situations, economical/financial situations, etc.). Here the term ‘nonlocality’, which we borrowed from quantum physics, could have many social interpretations, but we prefer to understand it as Jung’s archetypes of the collective unconscious, which can be thought of as laws of nature in terms of structures of consciousness (Laszlo 1959).

In fact, recent advancements of brain imaging techniques allow to measure and differentiate human mind states (Bunge and Kahn 2009, Haan and Gunnar 2009). Hence, new niches are opening up for the group-wide brain activations research, which allows to model and simulate individual and nonlocal, i.e. collective mind states (Nummenmaa 2012, Lindenberger et al. 2009, Newandee et al. 1996, Grinberg-Zylberbaum and Ramos 1987). Following this line of thought, we designed for the experimental validation a framework of EEG based experiments. Some benchmark EEG tests for the chosen mind states have been provided in the current paper below.

3 Empirical Premises and EEG Experimental Setup

While formulating our experimental framework, we faced some challenging fundamental questions - like how to bring human interaction, occurring in a complex social environment, under the scrutiny of laboratory testing and how to identify human interaction itself, i.e. what are the most basic social communication artifacts to measure? Obviously, human external behavior shows only the tip of the iceberg and can only vaguely represent the states of individual and collective mind-fields. Hence, we had to look for more fundamental, i.e. brain waves activation artifacts, which lead to various external behavioral patterns.

Because of the immense complexity of such a research framework, we identified and cross-correlated various mental states of temporally separated individuals in terms of their characteristic brain wave patterns (delta [1-4 Hz], theta [4-8 Hz], alpha [8-12 Hz], beta [13-30 Hz], and gamma [30-70 Hz] frequency ranges), which were recorded using EEG (electroencephalograph) methods. In this way, we defined mind-field states in terms of the EEG spectra for different people and mind states. The main purpose of the proposed experimental EEG framework was to find out whether brain wave patterns, i.e. EEG-recorded mind-fields, can demonstrate mutually correlated features (Plikynas et al. 2014). Hence, the main experimental hypothesis consisted of two parts - H0(1) and H0(2), see Fig. 1 for an illustration of experimental research stages.

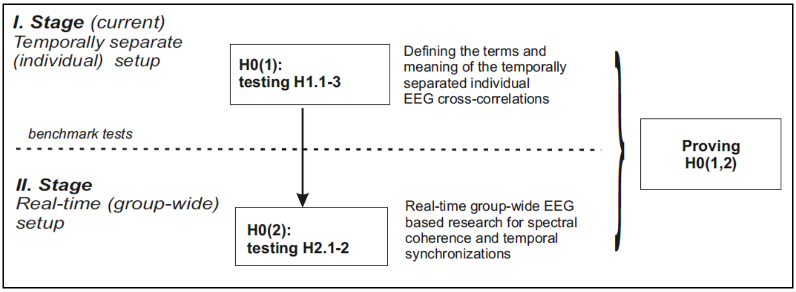


Fig. 1. Experimental research stages and series of tests

In this short paper, we mostly discuss hypothesis *H0*:

> *H0.1*: EEG recordings of different consciousness states for different individuals have the fewest cross-correlations and thus have less similar spectral patterns.
> *H0.2*: Temporally separate EEG recordings of the same consciousness states for different individuals have statistically significant cross-correlations and have more similar spectral patterns.

Hence, we were looking for the cross-correlations of brain wave signals for temporally separate individuals in the same mind states (like meditation, meditation with noise, counting with noise, thinking, thinking with noise). Saving up space, we will illustrate just few results below, see Fig. 2.

Thus, a more detailed analysis of the EEG-recorded differences (see diagrams A, B, C, and D in Fig. 2) between the meditation and thinking states has revealed results, which well correspond with other observations (Travis and Arenander 2006, Newandee et al. 1996):

1. In the meditation state, the *Δ* (delta) frequency range dominates
2. In the thinking state the *α* frequency range is dominant.
3. In the meditating and thinking states, the *Θ* and *β* frequency ranges are activated considerably less than the *Δ* and *α* ranges respectively.
4. For experienced meditators, the topological distribution of activated brain zones on the surface of the skull is almost identical in the *Δ, Θ*, and *α* ranges.

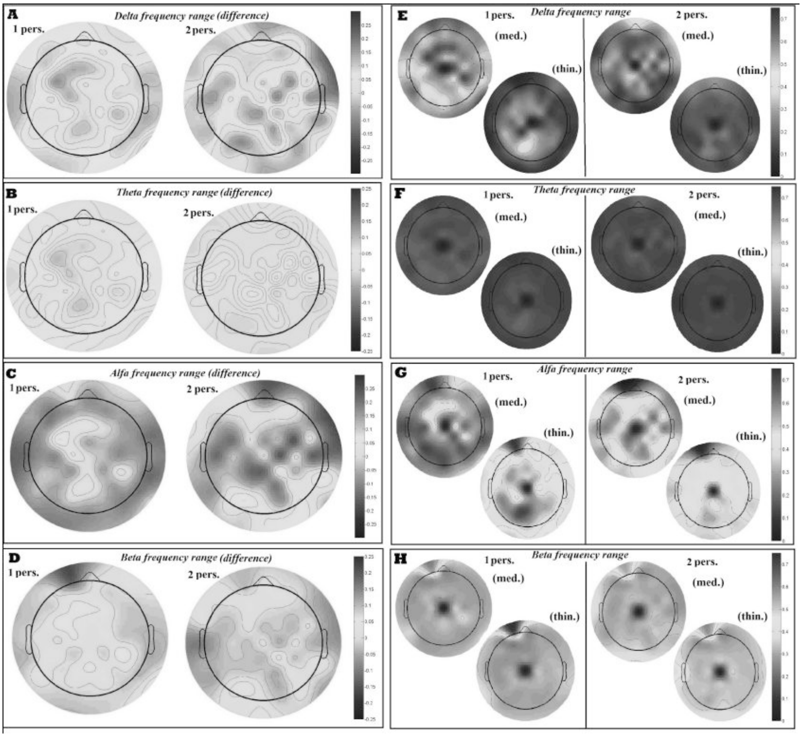
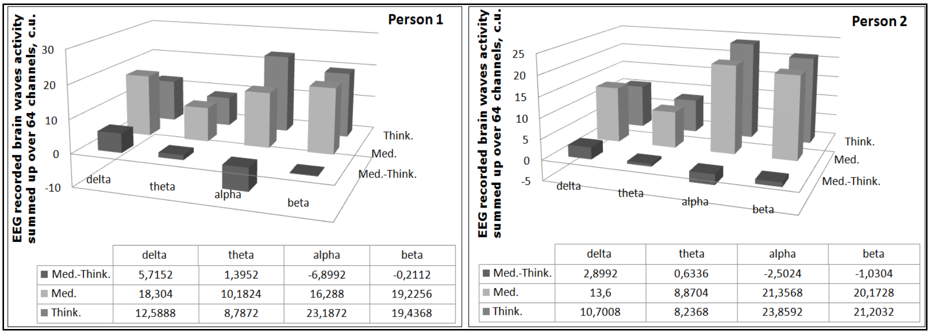


Fig. 2. Differences in the EEG-recorded electric field potentials between meditation and thinking states for experienced meditators in the Δ, Θ, α, and β frequency ranges (diagrams A, B, C, and D respectively). EEG diagrams E, F, G and H show actual activations of the corresponding mental states for the chosen frequency ranges. All power spectra are normalized (c.u.).

It is important to discuss in more detail an experimental observation regarding the inverse activation of different frequency ranges in the same brain areas depending on the mental states, see diagrams A and C in Fig. 2. In fact, this observation can be inferred from the OSIMAS paradigm (Plikynas et al. 2014), where different mental states are perceived as part of one and the same multivariate mental field composed of a set of dominant frequencies which are called natural resonant frequencies in the OSIMAS paradigm (biological system stores free energy in these superimposed spectral bands). Apart from any mathematical calculations, we argue that the theoretically inferred dominant frequencies of the mind-field correspond to the experimentally observed *Δ, Θ, α* and *β* brain waves.

Moreover, the OSIMAS paradigm envisages that various combinations of activated dominant frequencies in the common mind-field will yield unique mental states. As a matter of fact, experimental data for the meditation and thinking states validate exactly this assumption. We observe an equivalent spectral energy redistribution over frequency ranges for mental states like meditation vs. thinking, as these two states are opposite in nature. We can see this spectral energy redistribution effect especially clearly for the *Δ* (diagram A) and *α* (diagram C) ranges. In fact, our experimental results for the meditation and thinking states indicate exactly such a redistribution of energy in the spectral ranges *Δ, Θ, α* and *β*, see Fig. 3.



	delta	theta	alpha	beta
■ Med.-Think.	5,7152	1,3952	-6,8992	-0,2112
■ Med.	18,304	10,1824	16,288	19,2256
■ Think.	12,5888	8,7872	23,1872	19,4368

	delta	theta	alpha	beta
■ Med.-Think.	2,8992	0,6336	-2,5024	-1,0304
■ Med.	13,6	8,8704	21,3568	20,1728
■ Think.	10,7008	8,2368	23,8592	21,2032

Fig. 3. EEG-recorded brain-wave activity (c. u.) added up in all frequency ranges for 64 channels in the meditation and thinking states. The difference in activations for the appropriate frequency ranges is denoted as Med.-Thin.

The highly fluctuating nature of the EEG signals makes it difficult to compare them for different individuals and mind states. Therefore, we have created a visual analysis tool. Some of the results of the numerical and visualized local electric field dynamics of the EEG signals studied and of their differences for various mental states and frequency ranges are presented at our web address http://osimas-eeg.vva.lt/. Here are presented individual and group-wide EEG estimates for various mind states and frequency ranges, see illustration in Fig. 4.

Such a visualization of brain wave dynamics is very helpful for the recognition of group synchronization patterns for different persons, mind states, and frequency ranges. For the sake of clarity, we have added smaller head-maps that show direct differences in brain wave activation patterns (for the mind state chosen) between pairs of people, e.g. for persons I-IV, I-II, III-IV, etc. If brain wave activations for the pair of people chosen are dissimilar, the corresponding differences between activations produce a color and intensity-rich activation pattern in the difference head-map.

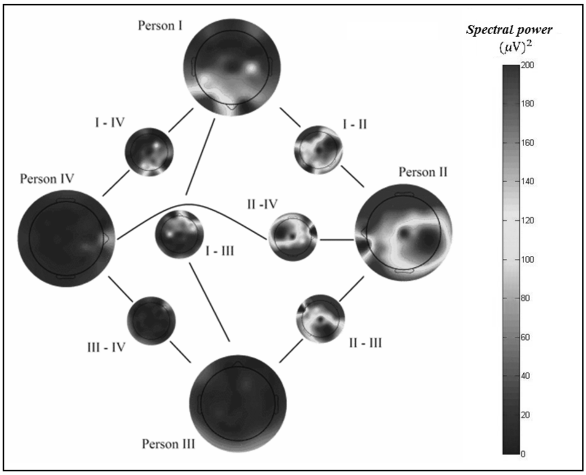


Fig. 4. Spectral power activation of brain wave dynamics for 4 persons in chosen mind state and spectral range. Smaller diagrams and connecting lines indicate spectral power differences between respective persons.

This approach helps greatly to distinguish similar brain activations when both activation patterns are very different and tend to have rapidly changing dynamics. In fact, our proposed group-wide mind-field visualization approach extends well-known brain-imaging techniques (BIT). Therefore, we named it the group-wide mind-field imaging method - GMIM.

4 Concluding Remarks

Major contribution of this paper comes from the provided conceptual and experimental framework of nonlocal field-based social simulation approach. In the presented conceptual framework, we envisage human society as a complex system of neurodynamically entangled mind-fields that together form a superposed and multifaceted collective mind-field. In this way, instead of a mechanistic pair-to-pair based communication approach, we provide a vision of social processes as collective mind-field effects emerging from the coherent field-like behavior of individual mind-fields. In other words, we propose to envisage societies as wave-like nonlocal processes emerging from the coherent behavior of the conscious and subconscious mind-fields of the individual members of a society.

Such a paradigmatic shift fosters new ways of designing nonlocal models of emergent systems of agents and complex social phenomena as well. We argue that simulation systems based on our proposed conceptual framework will make it possible to study the collective mind-field basis of social distributed cognition and interaction in terms of two- or multi-person neuroscience - an approach that could shift the focus of traditional social communication research from basic sensory functions in individual subjects toward the study of interconnected mind-fields. In this way, novel nonlocal modeling approaches could emerge in fast growing social research domains like social neuroscience, team neurodynamics, neuroeconomics, etc.

In this work-in-progress study, we have formulated an experimental framework to prove or disprove OSIMAS assumptions in terms of individual and group-wide neurodynamic processes of the temporal and spatial synchronizations and cross-correlations of EEG-recorded brain wave patterns. These base-line tests were designed to define the terms and meaning of individual and group-wide brain wave cross-correlations in various mind states and frequency ranges.

In short, our experimental findings show that each specific mental state has a characteristic spectral mind-field fingerprint in terms of the total activation distribution in the Δ,Θ,α and β frequency ranges. Hence, obtained experimental results confirmed our main experimental hypothesis: temporally separated people doing the same mental activities demonstrate a significant increase of cross-correlations in their brain wave patterns. So, neuroscience-based experimental findings have not disproved the major OSIMAS assumptions concerning the oscillatory field-like nature of mental states and consciousness in general.

Like all pioneering studies, proposed novel research framework needs thorough further investigation and statistical validation. This work-in-progress, however, provides some clear outlines with explanatory sources and initial testing for further fundamental, experimental and simulation-oriented investigation.

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