Towards Representation of Agents and Social Systems Using Field-Theoretical Approach

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Abstract: This multidisciplinary paper starts from a review of a wide range of theories across various disciplines in search of common field-like fundamental principles of coordination and self-organization existing on the quantum, cellular, and social levels. These studies outline universal principles, which are further employed to formulate main premises and postulates for the proposed OSIMAS (oscillation-based multi-agent system) simulation paradigm. OSIMAS design is based on neuroscience discoveries about the oscillating nature of the agents mind states and of the nonlocal field-like self-organization properties of modern information societies. OSIMAS approach considers conceptual trinity of the core models. In this paper there is presented the pervasive information field conceptual model in more details. In this way, the paper sheds new light on social systems in terms of fundamental properties of information and order. We also provide a review of some related other studies and applications of virtual field-based modeling.

Key-Words: multi-agent systems, oscillating agent, information field, self-organizing systems.

1 Introduction

The relatively broad scope of the presented research inevitably touches upon many disciplines, like quantum mechanics, neuroscience, the cognitive and social sciences, multi-agent system research, etc. Therefore, we had to provide an extended introduction.

Let's start from some fundamental observations in the micro scale, i.e. quantum physics, where we can find a great number of theoretical and empirical studies suggesting that the peculiar properties of the micro scale occur not simply on the quantum level with subatomic or atomic particles, but also in the world of large molecules [1]. For instance, some findings show that something as large as a molecule can become entangled [2,3] or that collective bioelectromagnetic oscillations cause proteins and cells to coordinate their activities [4] or that the Bose-Einstein condensate in living tissues produces the most organized light waves (i.e. biophotons) found in nature [5]. All this suggests that there are no separate laws for the large (on a biological, sociological, or cosmological scale) and for the physics of the small (on the atomic/subatomic scale), but rather universal all-embracing laws for the self-organized, multifaceted information that permeates all living and nonliving states of energy-matter [6].

The examples given above name just a few research results among many others that are forming a coherent transition from the quantum world of field-like reality to the mesoscopic world of field-like coordination in cellular biosystems. In short, the latest findings clearly indicate that different spatial scales (microscopic and mesoscopic) operate on the same spectral ladder, although in different spectral domains, see Fig. 1. Various research areas in the different spatial scales, united by the universal dimensionless concept of a multifaceted oscillation-based information field Fig. 1. For instance, the existence of biophotons and bioelectromagnetic dynamics (as contextual information distributed in fields) during vital metabolic processes expresses some field-based information locally perceived and communicated by cells [5].

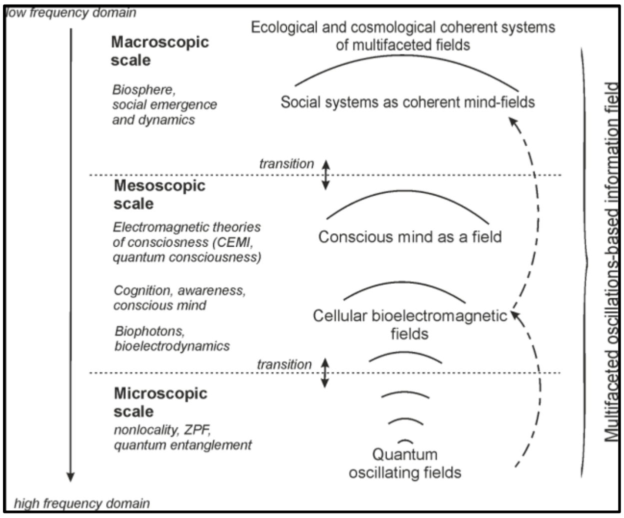

Fig. 1 Various research areas in the different spatial scales, united by the universal dimensionless concept of a multifaceted oscillation-based information field

Review of a wide range of multidisciplinary research across various disciplines in search of some common fundamental principles of coordination and self-organization on the quantum, cellular, and social levels reveals universal oscillations-based principles, which are deeply rooted in the very origin of life and in the evolution of biospheres [1,2,3,5]. It yields at least one clear claim: not only the quantum world, but also the cellular world has oscillation-based wavelike duality at the very core of its existence. Living cells not only generate but also receive and use electromagnetic fields for communication, self-preservation, and metabolism [7,8,5]. They conserve internal energy states by means of such metabolism, which realizes homeostasis, i.e. the most important characteristic of life, related to decision-making, adaptation, functional sharing, and coordination.

Hence, once we acknowledge the essential role of quantum bioelectromagnetic oscillations (field) based metabolism in cellular systems, we automatically have to recognize the same wave-like metabolism in neural cells too, e.g. field-based coherent communication between neurons in the central nervous system [9,10].

Some neuroscience studies lead to unified field models of consciousness. For instance, some researchers study the large-scale dynamics of EEG (electroencephalography), precisely describing the interference patterns of standing waves of post-synaptic potentials that may be superimposed on neurons embedded in these potential fields. As these studies indicate, changes in long-range coherence between remote cortical regions of certain frequencies during cognitive tasks support the concept of “globally dominated dynamics” [11].

Some MEG (magnetoelectric) studies show extensive cross-cerebral coherence, which led to the proposition that consciousness arises from the resonant coactivation of sensory-specific and nonsensory-specific systems that bind cerebral cortical sites to evoke a single cognitive experience [12]. At the same time, other studies are being coordinated to construct a field theory of consciousness [13,14].

We may recall here some electromagnetic field-based theories of consciousness (or so-called quantum consciousness), e.g., holonomic brain theory [15]. This theory describes processes occurring in visual neural webs (and in other sensory networks), where patches of local field potentials, described mathematically as windowed Fourier transforms or wavelets, change a space-time coordinate system into a spectral coordinate system within which the properties of our ordinary images are spread throughout the system.

We should also mention another well-known approach – the conscious electromagnetic field theory (CEMI) [16]. This electromagnetic field theory of consciousness is inherently attractive because of its natural solution to the binding problem. According to the CEMI theory, the brain generates an electromagnetic (EM) field that influences brain function through EM field-sensitive voltage-gated ion channels in neuronal membranes. The information in neurons is therefore pooled, integrated, and reflected back into neurons through the brain’s EM field and its influence on neuron firing patterns [16,17]. The CEMI theory states:

The digital information within neurons is pooled and integrated to form an electromagnetic information field. Consciousness is that component of the brains electromagnetic information field that is downloaded to motor neurons and is thereby capable of communicating its state to the outside world.

In other words, the CEMI theory argues that we experience this field-level feedback processing as consciousness[1]. Its defining feature is the ability to

[1]CEMI theory does not propose that consciousness is necessarily associated with the amplitude, phase, or

handle irreducibly complex concepts such as a face, the self, identity, words, meaning, shape, and number as holistic units[2]. All conscious thinking involves the manipulation of such irreducibly complex concepts and must involve a physical system that can process complex information holistically. According to this theory, the only physical system that can perform this function in the brain is the CEMI field[3]. It is through this mechanism that humans acquired the capacity to become conscious agents able to influence the world [18].

In sum, recent research trends in biophysics, neuroscience and related other domains are leading to increasingly complex approaches, pointing towards oscillations-based field-theoretic representations of individual and collective mental and behavioral phenomena as well [10].

According to these theories and recent experiments, consciousness is usually associated with attention and awareness, which mostly are not correlated with a pattern of neural firing per se, but with neurons that fire in synchrony [19]. Similarly, we could assume that self-organization and coherent behavior in social systems should not be correlated with the particular patterns of agents' actions (which are only the aftermaths), but with the neurophysiologically rooted synchrony of their mental activity. It paves the ground for the employment of field-based approach for the collective mind-fields simulations.

In this way, even our societies (the macro-world) can no longer be viewed as an entity separate from the quantum reality taking place in the conscious mind-fields of the individual society members [10]. Following such approach, societies can be understood as global processes emerging from the collective behavior of the coherent conscious mind-fields of individual members. Practically it can be interpreted as contextual (nonlocal) information distributed in fields, and fields – although expressing some global information – are locally perceived by agents. Therefore, some distributed social processes can be interpreted in terms of a collective mind-field and inherit some degree of field-like behavior.

In fact, this is an important claim as it offers a different worldview that opens new perspectives for modeling and simulating emergent social properties as collective mind-field effects. More details about the proposed OSIMAS (oscillation-based multi-agent system) paradigm can be found in the earlier paper [20]. In short, the empirical implications of OSIMAS approach cover wide area of possible applications. For instance, simulations of self-excitations in social mediums, propaganda wars, political tensions, contagion effects in financial markets, herd effects, innovations and opinion distributions, social clustering, synchronization of economic cycles [21], etc. In other words, novel OSIMAS paradigm potentially covers all nonlocal social phenomena, which cannot be explained using pair-to-pair communication approaches between agents.

In reality, social networks are highly heterogeneous with many links and complex interrelations. Uncoupled and indirect interactions among agents require the ability to affect and perceive a broadcasted information context [22]. Therefore, this research is looking for ways to model the information network as a virtual information field, where each network node receives pervasive (broadcasted) information field values. Such an approach is targeted to enforce indirect and uncoupled (contextual) interactions among agents in order to represent contextual broadcasted information in a form locally accessible and immediately usable by network agents [23].

The pioneering study described in the following few sections seeks to shed new light on the fact that there is a conceptually new way of understanding and simulating complex social processes taking place in an information (networking) economy [24]. However, many years will pass until novel

frequency of the brains electromagnetic field. The defining feature is rather the informational content and its ability to be communicated to motor neurons.

[2]In other words, information that is encoded by widely distributed neurons in our brain is somehow bound together to form unified conscious percepts [16].

[3]The idea that our conscious minds are some kind of field goes back at least as far as the gestalt psychologists of the early twentieth century. They emphasized the holistic nature of perception, which they claimed was more akin to fields rather than particles. Later, Karl Popper proposed that consciousness was a manifestation of some kind of overarching force field in the brain that could integrate the diverse information held in distributed neurons. Only recently has an understanding emerged that this force field is actually generated by the bioelectromagnetic activity of neurons in a form of conscious mind as an electromagnetic field.

conceptual approach will find its proper modeling and application base.

This article is organized as follows. Section 2 describes the OSIMAS paradigm by introducing main assumptions and postulates. Section 3 provides a conceptual framework for the main field-based principles and assumptions, which are intended for designing field-based pervasive contextual environments. Section 4 revises the use of information and ways to measure and visualize ordered structures in social systems. Section 5 reviews related other research approaches. Finally, section 6 summarizes with concluding major remarks.

2 The OSIMAS Paradigm: Basic Assumptions and Postulates

First, let us emphasize that, when formulating OSIMAS (oscillation-based multi-agent system) assumptions, we are looking for universalities across different spatial scales and time horizons. In essence, we are searching for pervasive fundamental laws of self-organizing information unconstrained by space and time. If, for instance, some field-like fundamental principles work in the quantum world and in cellular biophysics, we admit that similar principles manifest themselves in the mesoscopic world of social systems, too. However, the form and expression of these fundamental principles vary across different scales.

Second, when formulating basic assumptions and postulates, we want to elaborate how field-based underlying reality can be applied in modeling pervasive contextual environments in complex information-rich social networks. In other words, we formulate the bases for modeling the emergent and self-organizing features of modern information-rich social networks, where not only intangible but also tangible natural resources and even social agents themselves can be simulated as oscillating processes immersed in an all-pervasive contextual information field (PIF).

On the basis of a multidisciplinary research review (see Introduction), the OSIMAS paradigm adapts and formulates five basic assumptions:

1. There are no separate laws for the large (on a biological, sociological, or cosmological scale) and for the physics of the small (on an atomic/subatomic scale), but rather universal all-embracing laws for the self-organized multifaceted information that integrally permeates all living and nonliving states of energy-matter.
2. In the mesoscopic scale, the most complex known form of self-organized information is the human mind. In electromagnetic (EM) field-based neurophysiological approaches, the human mind can be represented as a unified EM or other field-like model of consciousness.
3. Societies can be understood as global processes emerging from the collective behavior of the conscious and subconscious mind-fields of their individual members. In this way, emergent social processes are produced by a collective mind-field and inherit some degree of coherent (synchronized) field-like behavior.
4. Societies (the macro-world) can no longer be viewed as separate from the quantum effects taking place in the conscious mind-fields of the society members. Self-organization and coherent behavior in social systems is not so much correlated with the particular patterns of agents' behavioral actions, but with the coherence and synchrony of their mental activity.
5. A core motif of social behavioral synchrony is the convergence of otherwise dissipating and self-destructive mental activity and, consequently, of the behavioral patterns of the individual members of a society. In this regard, the social coordination mechanism, or so-called social binding, involves the synchronicity mechanism between local self-organized information processes, i.e. agents. The dynamics of synchronous oscillations creates self-organized social systems.

The OSIMAS paradigm is based on these key assumptions, which at least theoretically open up a new way for modeling and simulating emergent social properties as collective mind-field effects. To further clarify the OSIMAS paradigm, some underlying basic postulates are formulated below:

1st Postulate. Social systems can be modeled as complex informational processes comprised of semi-autonomous interdependent organizational layers, e.g. the individual, the group, and society. Social information is coded and spread via social network almost at the speed of light via broadcasting telecommunication networks. In the modern information societies information is propagated not primarily through peer-to-peer interactions between agents, but increasingly via nonlocal fields transmitted through broadcasting information channels (Internet, GSM, radio, TV, etc.).

2nd Postulate. Like all complex systems, social systems are always on the verge of internal (inner organization) and external (behavioral) chaos. They are constantly balancing between order and disorder. Therefore, social systems have the naturally inherited property of changing and adapting while searching for niches to survive in. Hence, the main feature of social systems is not the ability to stay in internal and external states of equilibrium (which are constantly changing), but rather the ability to change and adapt while searching for internal and external equilibrium.

3rd Postulate. Uncoupled and indirect interactions among social agents require the ability to affect and perceive broadcasted contextual information. Therefore, a social information network can be modeled as a pervasive information field (PIF), where each network node receives pervasive (broadcasted) information field values[4]. Such a model provides an appropriate means of enforcing indirect and uncoupled (contextual) interactions among agents. It is expressive enough to represent contextual broadcasted information in a form locally accessible and immediately usable by network agents.

4th Postulate. The simulation results of social systems behavior do not adequately reflect observable reality unless simulated models acquire the features of living systems, e.g. adaptability, self-organization, field-like inner coordination, and outer communication.

5th Postulate. The individual members of a society can be modeled as information-storing, -processing and -communicating agents in an information network society. From another perspective, information societies operate through agents, which are complex multifaceted self-organized information processes composed of mind-fields of quantum field-like processes originating in brains[5].

[4] Following the broadcasting communication technology of telecommunication systems, we assume that similar principles should be applied to simulating platforms in the social domain, too. In other words, communication between agents should operate not in the (peer-to-peer) vector-based multidimensional semantic space, but rather directly in the form of multimodal energy (spectra) emanated and absorbed over the social network. The flow of energy (and associated with it, information) in the form of fields, however, requires a somewhat different understanding of the agents role and their interaction mechanism.

[5] We do not necessarily propose that collective wave-like processes originating from the set of human brains are associated with the amplitude, phase, or frequency of the set of the human brains electromagnetic fields. The essential feature is rather the informational content and its ability to be communicated through field-like media

6th Postulate. Agents, as complex multifaceted field-like information processes, can be abstracted using the physical analogy of multifaceted field-like energy, which is commonly expressed through spectra of oscillations. In this way, an agent becomes represented in terms of a unique composition of oscillations (individual spectrum).

7th Postulate. An agents inner states can be represented in terms of organized multifaceted information that expresses itself in the form of a preserved specific energy set. The latter can be modeled by means of a specific spectrum of oscillations. The distribution of an agents oscillations over an individual spectrum, in contrast to a random distribution, carries information about the agents self-organizational features, i.e. negentropy (order). Hence, social agents are complex processes that dynamically change multifaceted inner information-energy states depending on the information received from a PIF.

8th Postulate. Artificial societies can be modeled as superimposed sets of individual spectra or, in other words, as part of the PIF. Hence, social order emerges as a coherent superposition of individual spectra (self-organizing information processes) and it can be modeled as coherent fields of information resulting from the superposition of the individual mind-fields of the members of a society.

9th Postulate. Social order, i.e. self-organized and coherent behavior in social systems, is not so much correlated with the particular patterns of agents actions, but with the synchrony of their mental activity. That multi-agent synchrony can be compared to the physical model of superposition of weakly coupled oscillators. Synchronicity is involved in the social-binding problem how information distributed among many agents generates a community. The social-binding process can be imagined as a global resonance state.

10th Postulate. The core reason for the emergence of social synchrony is related to the fundamental property of all self-organized systems, i.e. the preservation or increase of negentropy, which creates socially organized behavior.

Of course, at the current stage of common understanding these postulates cannot be self-evident as to be accepted as indisputably true. There is a long way to go before some of these postulates will find proper mathematical and experimental proof. Hence, putting mathematical notation aside, the above postulates define and delimit the realm of our deductive analysis, serving as a starting point for our reasoning.

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, where some base-line EEG tests for the chosen mind states have been provided [20,23,30,31].

In the proposed paradigm, agents can communicate, voluntarily or involuntarily, their states of mind-field to each other. In this way, they form a collective mind-field, where communication in technical terms is realized via a common medium, i.e. a pervasive information field (PIF), and is managed by the wave-like communication mechanism (WIM), see our previous research [20,23]. The next section briefly outlines the OSIMAS paradigm setup and specifically the PIF approach.

3 The Pervasive Information Field Approach

In the previous section, we formulated the major assumptions and postulates of the OSIMAS paradigm. It is also helpful to set some guidelines for the modeling framework. Hence, OSIMAS employs a conceptual trinity of models: the PIF (pervasive information field), the OAM (oscillating agent model), and the WIM (wave-like interaction mechanism); see Fig. 2.

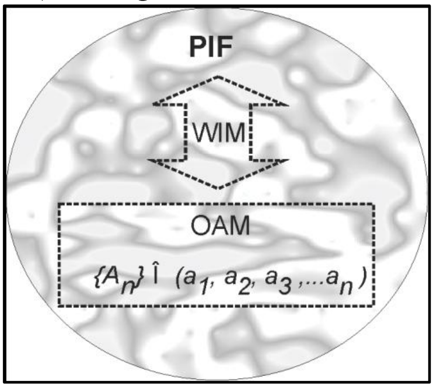

Fig. 2 The three major OSIMAS models: (i) the all-embracing pervasive information field (PIF), (ii) the oscillating agent model (OAM), which identifies each agent from a set $\{A_n\}$, and (iii) the wave-like interaction mechanism (WIM), which realizes the interaction between those agents.

These conceptual models describe an integral theoretical framework. In this paper, we elaborate mostly on the PIF model. In essence, the PIF model serves as a means for contextual information (and associated energy) storage, dynamic distribution, and organization. According to the above assumptions, contextual information is distributed in fields, and fields although expressing some global information are locally perceived by agents, who are but a self-organizing part of the same PIF.

In this way, the PIF serves as a universal medium managing all kinds of multifaceted information in the form of self-organizing fields. Hence, multifaceted information is conceptualized in the form of an all-embracing virtual field, which can be realized as a programmable abstraction, where all phenomenalogically tangible and intangible observables are represented as a set of oscillations (energy equivalents). However, for the effective implementation of spectra as a universal energy-information warehouse, we first have to transform all tangible objects-resources into their energy equivalents and then interrelate different types of energy as intangible information stored in the form of corresponding sets of spectral bands (natural frequencies).

The reasoning behind this is based on the principle of reductionism and universality as we are looking for the most fundamental means of representing a multiplicity of phenomenological forms in a single informational medium. In the OSIMAS paradigm, this medium is modeled by means of a system of oscillations. In other words, all tangible and intangible system resources are represented by means of sets of spectra of oscillations. Consequently, the PIF represents a grand total of all individual spectra.

Hence, the PIF computation is a theoretical model of information processing operations that take place in natural systems. The PIF can be treated mathematically as a multifaceted function Ψ over a bounded spatial set Ω. The value of the function Ψ is restricted to some bounded subset of real numbers $\Psi\!:\Omega \rightarrow K$ for a K-valued field. Thus, for the time-varying field we have $\Psi(k,\ t)$, where $k \in K$. In general, we assume that Ψ for each moment and space location are uniformly continuous, square-integrable, finite energy $\|\Psi\|^2 = \langle\Psi|\Psi\rangle < \infty$, of Hilbert space functions [25].

In general terms, the time-varying field Ψ(t) can be defined by field transformations and differential equations. A linear field transformation can be described by using integral operators of the type

$$\Phi\big(\Psi(k)\big) = \int_{t_1}^{t_2} K(k,t)\,\Psi(t)\,dt,$$

where Ψ - input field, Φ-output (transformed) field,

K -kernel function or nucleus of the transform. One important class of linear field transformations, as continuous mapping functions, consists of integral operators of the Hilbert-Schmidt type $\int_{\Omega}^{w} K_{ku}\ \Psi_u du$, which map input field Ψ into output field Φ over Ω.

In the presence of multiple stimuli, multilinear integral operators can be applied [25], which map one or more input fields Ψ_n into one or more output fields Φ_k

$$\Phi_k = \int_{\Omega_n}^{w} ... \int_{\Omega_2}^{w} \int_{\Omega_1}^{w} K_{ku_1 u_{2...}u_n}\ \Psi_1(u_1)\ \Psi_2(u_2) ... \ldots \Psi_n(u_n) du_1 du_2 ... du_n \quad (1)$$

Such mapping represents interference from all the stimuli, i.e. incoming fields. Let us take an example of two simple fields represented by two linear harmonic waves with the same frequency and amplitude $y_1(x, t)=2A\cos(\omega t- kx + \varphi_1)$ and $y_2(x, t)=2A\cos(\omega t - kx + \varphi_2)$. The resulting wave

$$y_{res}(x,t) = y_1(x,t) + y_2(x,t) = 2A\cos\left(\omega t - kx + \frac{\varphi_1}{2\varphi_2}\right)\cos(\Delta\varphi/2) \quad (2)$$

has a doubled amplitude, the same frequency, and a changed phase. Actually, the phase difference $\Delta\varphi$ determines the resulting wave's amplitude. In essence, the phase difference shapes the outcome, i.e. the magnitude of the resulting oscillations. This dependence holds for other types of interference too.

In fact, synchronization phenomena are directly related to the law of wave interference and consequently to the frequency and phase management mechanism, which provides a key for modeling coherent systems and self-organization processes. Indeed, according to the phase synchronization theory of chaotic systems, dynamic coherent behavior emerges as a consequence of nonlinear synchronization in complex networks. In the framework of such a frequency and phase approach, it is quite natural that synchronization processes in various systems of different nature have close similarities and can be studied by using common tools [26].

The holistic nature of social systems is rich in connections, interactions, and communications of many different kinds and complexities. In this regard, synchronization is the most fundamental phenomenon as it is a direct and widespread consequence of the interaction of multifaceted systems. There is a great deal of material on different aspects and effects of synchronization [26,27].

Fortunately, we can employ the essential contribution made by some earlier research [28], that has provided a contemporary view of synchronization as a universal phenomenon that manifests itself in the entrainment of rhythms in interacting self-sustained systems.

The second applied research phase requires the definition of quantification and the measurement of order in spectral patterns, as it represents coherence and the social-binding effects observed in real social oscillatory networks. Therefore, in the following section we shall discuss how synchronization contributes to the observed order in oscillatory networks and how coherence can be employed as a measure of order.

4 Social Systems in Terms of Information and Order

The terms information and order are found quit often in the literature about complex self-organizing systems, but often they are provided without adequate fundamental framework. Therefore, we have to make a bit clearer what we mean when using these terms in the OSIMAS paradigm and particularly in the PIF conceptual model.

First, we will begin with a brief review of the most common classical approaches. The use of the mathematical formalism of information theory may seem preferable in the social domain, but we have to be cautious, as information theory is severely limited in its scope. It was originally developed for practical needs by telecommunications engineers to investigate how the characteristics of closed systems, i.e. information channels, influence the amount of information transmitted from the source to the receiver in a given time. Consequently, the amount of transmitted information is usually measured by employing entropy S, which according to Shannon's theory [26] expresses a logarithmic measure of the density of possible states

$$S = -k\sum_{i=1}^{N} p_i ln(p_i), \quad (3)$$

where p the number of elementary complexions (the ratio of observed states to the possible number of states), k the scaling factor, p_i the probability of events i. Hence, the information content of an event is defined not by what has actually happened, but only with respect to what might have happened instead [27].

Therefore, we can argue that the traditional interpretation of entropy as an information measure in the case of biological or social domains has two basic limitations:

1) it neglects the fundamental fact that organisms are not closed systems their organizational structures embrace many horizontal and vertical

channels of internal and external communication, extending beyond the physical boundaries of the organism or social agent itself;
2) it does not account for the proper meaning and multifac eted aspects of information manifested in ordered structures and behavioral patterns.

Bearing in mind these limitations of classical information theory, let us investigate how classical thermodynamics and statistical mechanics deal with the concepts of entropy and information respectively. In the former case, the concept of entropy is defined phenomenologically by the second law of thermodynamics, which states that the entropy of an isolated system always increases or remains constant. This means that the total entropy of any system will not decrease unless the entropy of some other system is increased or, in other words, higher order in one system means less order in another [21]. Hence, in a system isolated from its environment, the entropy of that system will tend not to decrease [29].

In this way, by applying the universal law of conservation of energy we could infer that there is a law of conservation of information in an isolated system, too. According to this analogy, the total amount of information in an isolated system should remain constant over time, as information can neither be created nor destroyed, but it can be transformed from one form to another. But according to the second law of thermodynamics, the entropy of an isolated system always increases or remains constant. Thus, entropy measures the process of constant or diminishing information (order) in an isolated system. Therefore, we infer that this apparent contradiction can be resolved by admitting that the term isolated system is only a useful abstraction as all systems in terms of all pervasive information are open, i.e. holistic in their essential nature.

Meanwhile, in statistical mechanics entropy is a measure of the number of ways in which a system can be arranged, often taken to be a measure of disorder (the higher the entropy, the higher the disorder). This definition describes entropy as being proportional to the logarithm of the number of possible microscopic configurations of the individual atoms or molecules in the system (microstates), which can give rise to the observed macroscopic state (macrostate) of the system [30], see Eq. 3.

Hence, as we see, according to thermodynamics and statistical mechanics, the most general interpretation of entropy results in a measure of uncertainty about a system or, in other words, disorder. In fact, such a measure has the opposite meaning to the order observed in the inner structures and behavior of living systems as well as societies. Therefore, this provides clear incentives for living systems to employ another measure, which is called negentropy. This term was first used by Erwin Schrodinger [31]. He introduced the concept of negative entropy for a living system as entropy that it exports to keep its own entropy low. In this way, negentropy is understood as a measure of the distance D of the entropy state S of the investigated system to the white noise state S_{max}

$$D(p_x) = S(r_x) - S(p_x) = S_{max} - SS(p_x) = \int p_x(u) log p_x(u) du, \qquad (4)$$

where $S(r_x)$ -the entropy of the Gaussian white noise distribution r_x with the same mean and variance as of the investigated systems distribution p_x; $S(p_x)$ - the entropy of the investigated system. When an investigated system's state differs from the Gaussian white noise distribution, then negentropy $d(p_x) > 0$, and when it is equal to a random distribution, then negentropy $d(p_x) = 0$ In the first case, we have some degree of order, and in the second case, there is no order at all.

This makes perfect sense as a random variable with a Gaussian white noise distribution would need the maximum length of data to be exactly described. If p_x is less random, then something about it is known beforehand, i.e. it contains less unknown information, and accordingly it needs less length of data to be described. In other words, negentropy measures something which is known about a system's state. In this way, negentropy serves as a measure of order.

It is apparent that unlike engineering (where negentropy takes the form of digital information and is quantized in bits), social and biological systems are much more complex self-organizing processes and require a more sophisticated approach. Consequently, two important questions arise:
(i) what can be known about the ordered states of social systems?
(ii) what kind of quantification method can be applied to measure order in such ordered states?

These two fundamental questions are directly related to the qualitative and quantitative assessments of order respectively. Looking for the answer to the first question, we should first recall our basic OSIMAS and PIF assumptions (see previous sections):

- *social order, modeled as a coherent field of information, results from the superposition of the individual mind-fields (self-organizing* *information processes) of the members of a society, represented as sets of natural (resonant) oscillations;*

- *agents, as complex multifaceted field-like information processes, resemble a physical analogy of potential field-like energy, stored in the form of natural oscillations, which is commonly expressed through spectra of oscillations; in this way, an agent becomes represented in terms of a unique composition of resonant oscillations, i.e. an individual spectrum;*
- *societies, however, can be modeled as a superimposition of agent-based individual spectra; consequently, social order emerges as a coherent global field based upon superimposed sets of resonant individual oscillations.*

In our case, the distribution pattern of single-agent A_j natural resonant oscillations (an individual spectrum) for the time moment t, described as the spectral density $\Phi^{Aj}(\omega)$ of its energy distribution over a range of frequencies, in contrast to a random distribution $\Phi^{R}(\omega)$, carries 1) quantitative knowledge about the spectral energy distribution patterns leading to particular behavioral patterns $\Phi^{Aj}(\omega) \rightarrow B^{Aj}$, and 2) formative (qualitative) knowledge about ordered patterns.

In accordance with OSIMAS assumptions, social behavior emerges, and then individual spectral density patterns interfere, producing coherent behavior in social systems. This process has some specific synchronicity effects basically related to:

1) the superposition of an agents individual resonant (natural) oscillations, which form common resonant patterns in the social mind-field;

2) the feedback loop; then the social mind-field influences and adjusts individual mind-fields by creating the social binding process (that is, individual mind-fields accommodate themselves to the social mind-field, which generates a coherent social community).

We infer that the driving force behind both synchronization effects is programmed into the individual and social optimization (binding) processes. For instance, the individual and social optimization processes can be optimized to search for (i) synergy effects, (ii) internal energy[6] minimization effects, (iii) emerging self-organization and complexity effects.

All these effects, in one way or another, are related to negentropy and, therefore, indicate various aspects of the order observed in social systems.

In quantitative terms, self-organizing order (negentropy) can be quantized as the difference D_n between the non-infinite flat white noise power distribution spectra described by the maximum entropy S_{max} and the given power distribution spectra described by the entropy Sdivided by the norm S_{max}

$$D_n = \frac{D}{S_{max}} = \frac{S_{max} - S}{S_{max}}, \tag{5}$$

where D_n denotes normalized negentropy. In two extreme cases in which $S \rightarrow S_{max}$, we get $D_n = 0$, which indicates zero quanta of order in a given system, and in another extreme in which $S \rightarrow 0$, we get $D_n = 1$, which indicates the maximum possible quanta of order in a given system. Therefore, D_n serves as a relative measure of order, which can be used to compare different systems. Other, more sophisticated measures of order can be applied, too, e.g. chaotic invariants, phase space reconstruction, etc [28].

It is important to notice, that order arises because of characteristic processes. For instance, in the case of living systems, there are complexes of continuous self-organizing processes $P_{S\rightarrow D}$ (where $P_{S\rightarrow D} \in (p_1, p_2, \ldots p_n)$, which are able to process inward and outward entropy and produce order, i.e. negentropy D

$$[P_{S\rightarrow D}(S)]_t = [P_{S\rightarrow D}(S_{in} + S_{out})]_t \rightarrow D_t = [D_{st} + D_{bh}]_t \ , \tag{6}$$

where D sustains vital internal structures D_{st} and

[6] In thermodynamics, the free energy (free energy is a state function) is the internal energy of a system minus the amount of energy that cannot be used to perform work (it is given by the entropy multiplied by the temperature of the system). Likewise, for social systems the qualitative aspect of free energy can be understood as the internal energy (described by the spectral density in the PIF model) of a social system minus the amount of energy that cannot be used to perform social work (background white noise spectral density). The definition of social work depends on the specific simulation case, when an individual agent's behavior (the spectral pattern described by the OAM) is bonded (resonating) with some social activities (global spectral patterns).

behavioral patterns D_{bh} respectively. This can be achieved only through the constant transformation of entropy into negentropy. Otherwise, after some time the second thermodynamic law of increasing entropy transforms negentropy back to entropy $[P_{D \to S}]_t$. In general, the dynamics of a local ordered state can be described in the following way:

$$if \frac{d(P_{S\to D})_t}{dt} + \frac{d(P_{D\to S})_t}{dt} = \begin{cases} > 0, & \text{then order increases } x < 0, \\ 0, & \text{then order persist } x = 0, \\ < 0, & \text{then order increases } x > 0. \end{cases} \quad (7)$$

The increase of negentropy in a local system does not violate the second law of thermodynamics as it is compensated for by the equivalent increase of entropy in the surrounding open system, i.e.

$P_{S\to D} + P_{D\to S} \to 0.$

Actually, this relationship confirms the earlier mentioned assumption that ordered structures emerging in initially uniform noise power distribution spectra neither create nor destroy information.

In order to find a quantification measure for negentropy in the form of a coherent distribution of natural frequencies, we have to specify Eq. 5, which estimates negentropy as the difference D_n between non-infinite flat white noise energy distribution spectra described by the maximum entropy S_{max} and given energy distribution spectra described by entropy S divided by the norm S_{max}. In our case, when we deal with the frequency domain, S_{max} and S take an equivalent form of energy spectral density distributions represented as flat white noise energy spectral density $\Phi^{R}(\omega)$ and $\Phi^{R+Aj}(\omega)$ respectively.

Energy spectral density (ESD) is a positive real function $\Phi(\omega)$ of a frequency variable associated with a stationary stochastic process which is commonly expressed in energy per hertz [30]. ESD is often simply called the spectrum, and it is expressed as a square of the magnitude of the continuous Fourier transform of the time dependent signal $f(t)$

$$\Phi(\omega) = \left\| \frac{1}{2\pi} \int_{-\infty}^{+\infty} f(t) e^{-i\omega t}\, dt \right\|^2 \quad (8)$$

Hence, according to Eq. 8 and Eq. 5 we can specify negentropy D_n by integrating the normalized difference between the ESD of flat white noise $\Phi^{R}(\omega)$ and the ordered process (i.e. agent) $\Phi^{R+Aj}(\omega)$ as follows:

$$D_n^{ESD} = \int \frac{\Phi^R(\omega) - \Phi^{R+A_j}(\omega)}{\Phi^R(\omega)} d\omega. \quad (9)$$

In Eq. 9, we integrated the distance in energetic terms between flat white noise and the agent-based individual (ordered) spectra bands $\Phi^{Aj}(\omega)$. The latter spectra bands, i.e. the distribution of the agents natural frequencies, are embodied in the flat white noise $\Phi^{R}(\omega)$:

$$\Phi^{R+A_j}(\omega) = \Phi^R(\omega) + \Phi^{A_j}(\omega) \quad (10)$$

here, $\Phi^{R}(\omega)$ -means background white noise and $\Phi^{Aj}(\omega)$ -means individual A_j agent-based spectrum bands. In fact, Eq. 10 denotes the individual spectrum embodied in the background white noise spectrum. Therefore, in Eq. 9 we integrate the normalized individual spectra bands which are left after subtracting the flat white noise. In this way, we obtain the measurement of negentropy $D_n^{ESD_{A_j}}$ for the individual ordered process, e.g. agent A_j, which gives

$$D_n^{ESD_{A_j}} \to 0,\ then\ \Phi^R(\omega) - \Phi^{R+A_j}(\omega) \to 0, \quad (11)$$

i.e. the individual distribution of natural frequencies, which diminishes and merges with the background noise. This actually happens, depending on the measurement of distance d to the agent location, see Fig. 3.

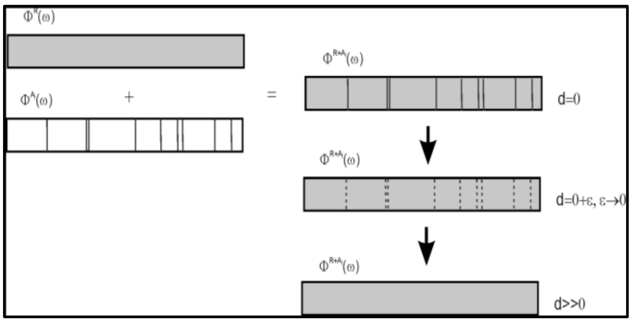

Fig. 3 The background at white noise spectrum $\Phi^R(\omega)$, individual (agent-based) spectrum bands $\Phi^{Aj}(\omega)$, and the common spectrum $\Phi^{R+Aj}(\omega)$ dependence on the measurement of distance d to the agents location.

As in the electromagnetic field case, individual field intensities can decrease according to the d^2 or similar negative power law, where $d$represents the distance from the emanating source

$$D_n^{ESD_{A_j}}(d) \cong kD_n^{ESD_{A_j}} \Big/ d^2 , \qquad (12)$$

where the k coefficient is adjusted to the measurement scale. A somewhat opposite effect in appearance and in nature takes place when some agents spectral density patterns interfere, producing common spectral bands which act further as attraction centers for the rest of the population. In this way, the social binding process emerges, i.e. stronger common spectral bands work as attractors for individual agents. In this process, individual agents are transformed so that they can better fit into the common spectral patterns, see Fig. 4.

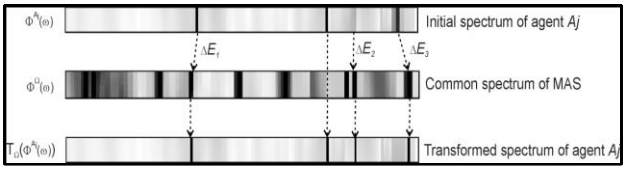

Fig. 4 An illustration of the process of social binding, when a multi-agent systems (MAS) common spectral pattern $\Phi^{\Omega}(\omega)$ (see the middle spectrum) works as an attractor for the individual (agent-based) spectral pattern $\Phi^{Aj}(\omega)$ (see the upper spectrum), producing the transformed individual spectral pattern $T_{\Omega}(\Phi^{Aj}(\omega))$ (see the lower spectrum).

In this way, the transformation function T_{Ω} may be interpreted as a social harmonization function that makes a social system more coherent. This is the case when, through harmonization, a systems global state influences the microstates on the agents level. On the systems level, however, the harmonization function T_{Ω} is counterbalanced by the deharmonization function T_R, which is produced by the fluctuating microstates on the agents level. The interaction of these two functions produces complex, constantly self-organizing social behavior, which can be characterized by the negentropy [21].

$$T_{\Omega} + T_R \rightarrow D_n \qquad (16)$$

In fact, when these two levels (micro and macro) interact with each other, they are restricted only by the boundary conditions of self-preservation, which were hard-wired during biological evolution so that micro systems (agents) do not destroy the macro system and the macro system does not destroy the underlying micro systems [1, 29]. This cooperation mediated by coherence and synchronization constantly searches for new niches of coexistence in order to increase overall negentropy. As we have mentioned earlier, the social binding process of coherent behavior for self-organizing systems is driven by the fundamental law of increasing negentropy, which is realized for a spectrally represented population of agents through the principles of spectral coherence and synchronicity.

More details about OSIMAS paradigm in terms of fundamental design, experimental validation setup and related simulations are provided in our earlier papers [20,23,30,31]. Below we briefly mention few related other research approaches.

5 Related Other Research

The major area of virtual field-based social simulations and applications is related to emerging research in social-networking, agent-oriented and multi-agent systems (MAS). Feld-based modeling is usually applied in the nature inspired studies while searching for the better simulation results of very complex, large and highly dynamic physical, biological and even social networks. Unfortunately, these studies mostly employ field-based coordination approach as technical solution without deeper conceptual understanding of the fundamental nature of such an approach. In this sense, OSIMAS provides at least some fundamental background and reasoning for the field-based coordination applications in the social domain.

For instance, in social-networking research, because of its large scale and complexity, often attempts are being made to simulate social networks using wave propagation processes. Some of these applications deal with message-broadcasting and rumor-spreading problems [32], other applications deal with behaviors spread in dynamic social networks [33,34] or with the diffusion of innovations [35], etc. For instance, in this latter approach the authors capture the effect of clusters and long links on the expected number of final adopters. They found that the expected number of final adopters in networks with highly clustered sub-communities and short-range links can be less effective than in networks with a smaller degree of clustering and with long links (nonlocal interaction). Basically, all these social-networking approaches employ graphs theory using nodes and connections to represent links between agents and social networks in general. Hence, in social-networking research nonlocal interactions are mostly realized through random connections between pairs of distant agents. In fact, this is an intermediate solution toward a virtual field-type representation of information diffusion.

In the last decade, a number of other field-based approaches have been introduced, like Gradient Routing (GRAD), Directed Diffusion, Co-Fields at the TOTA Programming Model [20], CONRO [36], etc. In fact, almost all of these methods are employed for various technological or robotic applications, and very few of them, like MMASS, Agent-Based Computational Demography (ABCD), or Agent-Based Computational Economics [37], are suitable for programmable simulations of social phenomena.

Let us take a closer look at one particularly interesting proposal in that direction, i.e. the Multilayered Multi-Agent Situated System (MMASS), which defines a formal and computational framework by relying on a layered environmental abstraction [38]. MMASS is related to the simulation of artificial societies and social phenomena for which the physical layers of the environment are also virtual spatial abstractions. In essence, MMASS specifies and manages a field emission-diffusion-perception mechanism, i.e. asynchronous and at-a-distance interaction among agents. In fact, different forms of interaction are possible within MMASS: a synchronous reaction between spatially adjacent agents and an asynchronous and at-a-distance interaction through a field emission-diffusion-perception mechanism. Fields are emitted by agents according to their type and state, and they are propagated throughout the spatial structure of the environment according to their diffusion function, reaching and being eventually perceived by other spatially distant agents [39]. Differences in sensitivity to fields, in capabilities, and in behaviors characterize agents of different types[7]. The MMASS simulation platform has been applied in various modeling cases like crowd behavior, adaptive pedestrian behavior for the preservation of group cohesion, websites as context-aware agents environments, awareness in collaborative ubiquitous environments, etc [40,39]. In fact, MMASS corresponds well to the OSIMAS paradigm in terms of its information diffusion mechanism. However, it uses graph theory and does not seek to model the deeper, i.e. oscillatory, nature of agents themselves.

Space-dependent forms of communication (at-a-distance interaction) comparable to MMASS are pheromone-based models such as those adopted by Swarm (and other simulation platforms that are based on it, like Ascape, Repast, and Mason). Swarm-based platforms generally provide an explicit representation of the environment in which agents are placed and of the mechanisms for the diffusion of signals [42]. However, this diffusion mechanism is not well documented, and even though it allows a certain degree of configurability (e.g. through the definition of the constants regulating signal diffusion and evaporation), it does not allow the definition of specific diffusion functions. Swarm and other similar approaches[8]may thus represent a possible solution for specific field-based simulations, but it would require a huge effort to designand implement more general spatial structures and diffusion mechanisms [39].

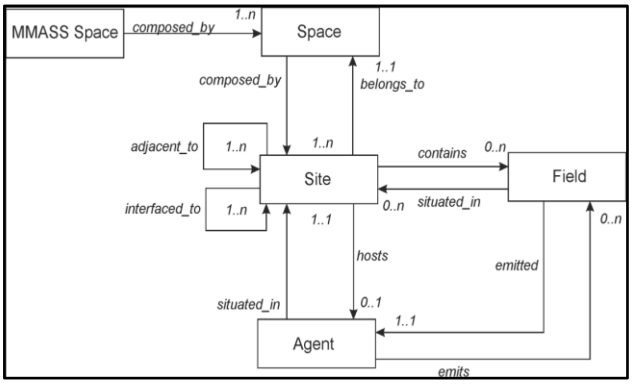

Fig. 4 MMASS model elements and relationships among them [38].

Recently, the Co-Fields model has been proposed within the area of agent coordination, and it provides a novel interaction method for agents

[7]The MMASS simulation platform also supports the implementation of applications based on the situated cellular agents (SCA) model [41], which is a particular class of MMASS characterized by a single-layered agent environment and specific constraints on field definition. In fact, the adapted CA approach has been employed in one of our applications too [30].

[8]For instance, stigmergy, as a form of self-organization, is a mechanism of indirect coordination between agents or actions. The principle is that the trace left in an environment by an action stimulates the performance of the next action by the same or a different agent. In that way, subsequent actions tend to reinforce and build on one another, leading to the spontaneous emergence of coherent, apparently systematic activity. This result produces complex, seemingly intelligent structures without the need for any planning, control, or even direct communication between the agents.

through an explicit description of agent context [22]. In essence, Co-Fields propose an interaction model inspired by the way masses and particles in our universe move and self-organize according to contextual information represented by gravitational and electromagnetic fields. The key idea is to have actions driven by computational force fields, generated by the components themselves or by some infrastructures, and propagated across the environment. Hence, agents are simply driven by abstract computational force fields generated either by agents or by the environment. Agents, driven in their activities by such fields, create globally coordinated behaviors, for instance, in the case of urban traffic control with Co-Fields [43]. Although this model still does not offer a complete engineering methodology, it can provide a unifying abstraction for self-organizing intelligent systems. Despite this drawback, the content-based information access in TOTA middleware, which implements the Co-Fields approach in distributed environments, represents an interesting and strong support for the implementation of field-based distributed applications.

Another potential area of application is in the emerging domain of pervasive computing [44], e.g. in the cases of amorphous [45] and ubiquitous [46] computing. There is fast-growing empirical research about the gradual development of context-aware pervasive computing environments, and it will create yet another area for virtual field-based communication approaches.

In short, as following chapters disclose, comparing with the other related research, our approach presents a major breakthrough related to the connection between the central oscillating agent model (OAM) and what recently neuroscience has proven about the coherently oscillating nature of human mind states (i.e. EEG-recorded mind-fields). In other words, to validate the OSIMAS premises, we designed not only a theoretical but also an experimental validation framework.

Following this line of thought, we have also proposed to interpret social order in terms of oscillatory processes emerging from the collective coherent behavior of the conscious and subconscious mind-fields of individual members of a society. In this way, emergent social processes can be interpreted as collective mind-fields that inherit some degree of coherent (synchronized) field-like behavior. On the basis of such reasoning, a social information network can be understood as a virtual information field, where each network node (agent) receives pervasive (broadcasted) information field values. Such an approach is targeted to enforce indirect and uncoupled (contextual) interactions among agents in order to represent contextual broadcasted information in a form locally accessible and immediately usable by network agents.

6 Concluding Remarks

The work-in-progress report presented here is part of a larger project intended for the development of an OSIMAS (oscillation-based multi-agent system) paradigm, i.e. a virtual field-based agent-oriented social simulation platform. In this paper, we provide the conceptual premises of this novel paradigm, which is based on the exploration of various disciplines and theories in search of universal scale-free and field-like principles valid in complex self-organizing systems.

According to the proposed pervasive information field model, contextual information is distributed in virtual fields, and fields although expressing some global information are locally perceived by agents. In fact, we have fundamentally revised the terms and meaning of information and order in a social context. Moreover, our analyses strongly support negentropy-based measures of social order. Our proposed measures of order are mainly focused on measuring the coherence of oscillatory networks.

One of the major breakthroughs in our work is related to discovering the connection between the conceptual oscillating agent model (OAM) and what neuroscience has proven the coherently oscillating nature of human mind states (i.e. EEG-recorded mind-fields). Following this line of thought, we have also proposed to interpret social order in terms of oscillatory processes emerging from the collective coherent behavior of the conscious and subconscious mind-fields of individual members of a society. In this way, emergent social processes can be interpreted as collective mind-fields that inherit some degree of coherent (synchronized) field-like behavior. On the basis of such reasoning, a social information network can be understood as a virtual information field, where each network node (agent) receives pervasive (broadcasted) information field values. Such an approach is targeted to enforce indirect and uncoupled (contextual) interactions among agents in order to represent con-textual broadcasted information in a form locally accessible and immediately usable by network agents.

Hence, this conceptual paper is proposed in the context of a larger scheme of multi-agent systems (MAS) simulation research, i.e. in the framework of the multidisciplinary OSIMAS paradigm [20,23,30,31], which aims to model social agents as oscillatory systems (see http:\osimas.ksu.lt). Our online virtual lab for the interactive testing and modeling of the proposed COEEM models is available at http://vlab.vva.lt/ (login as Guest, password: guest555).

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

Acknowledgments

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