Evolving Agents: Communication and Cognition

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Abstract. Computer programming of complex systems is a time consuming effort. Results are often brittle and inflexible. Evolving, self-learning flexible multi-agent systems remain a distant goal. This paper analyzes difficulties toward developing evolving systems and proposes new solutions. The new solutions are inspired by our knowledge of the human mind. The mind develops language and cognitive abilities jointly. Real-time sensor signals and language signals are integrated seamlessly, before signals are understood, at pre-conceptual level. Learning of conceptual contents of the surrounding world depends on language and vice versa. This ability for integrated communication and cognition is a foundation for evolving systems. The paper describes a mathematical technique for such integration: fuzzy dynamic logic and dual cognitive-language models. We briefly discuss relationships between the proposed mathematical technique, working of the mind, applications to understanding-based search engines and evolving multi-agent systems.

1 Cultural Evolution: Computers Vs. Nature

Computer capabilities for communication and cognition currently are developed separately, usually in different organizations. The nature does it differently. A child develops both capabilities *jointly*. We do not know if it is possible to code computers to be 'cognitive' or 'language capable', one capability separately from the other. Current engineering approaches could be invalid in principle. These considerations are prime motivations for this paper. Let us examine them in some details. Evolution of the human mind from pre-human ancestors occurred in three stages: genetic evolution, cultural evolution, and learning along with ontological development of an individual child into an adult. Cultural evolution and cognitive learning are much faster than genetic evolution. This paper concentrates on the mechanisms of cultural evolution and learning.

As physical infrastructure for communication systems and the Internet matures, the *information* services are gaining in importance. Distributed integration of sensor signals with flexible communications, with data and text data bases would be necessary for the future Sensor web, an integrated operation of multiple users and agents using sensors and communications. However, computer systems today use inflexible models and ontologies. Communication systems use fixed protocols. Contents of communications are intended for human understanding, computers do not understand contents.

Practical implementations of complex multi-agent systems with communication and cognitive abilities are based on detailed models and protocols. These systems lack the flexibility of human cognition and natural languages. They integrate signals from sensors and communication messages only at high cognitive levels of logical predicates. First, information has to be extracted from sensor signals and formulated as logical statements at the appropriately high level of abstraction. Similar language or communication messages have to be pre-processed, the relevant data extracted and formulated as logical statements at a similar level of abstraction. Integration rely on models, ontologies, and protocols, which assume shared knowledge and understanding [1]. In practice, structures of these models have to be fixed. This is also true for ontologies being developed for semantic web. They are not as flexible as "shared knowledge" necessary for understanding among people. Specific mathematical reason for this inflexibility we discuss in section 2. The resulting systems are brittle. As requirements and hardware are changing, they become obsolete.

Contrary to the brittleness of artificial fusion systems, the human mind improves with experience. We discuss in this paper that learning, adaptive, and self-evolving capabilities of the mind are closely related to the ability to integrate signals subliminally. For example, during everyday conversations, human eye gaze as well as visual processing stream and the type of conceptual information extracted from the surrounding world are affected by contents of speech, even before it is fully processed and conceptually analyzed. Similarly, speech perception is affected by concurrent cognitive processing. To some extent, we see, what we expect to see; verbal preconditioning affects cognition, and vice versa. This close, pre-conceptual integration of language and cognition is important not only in real-time perception and cognition, but also in ontogenesis, during child growing up, as well as in evolution of culture and language. Concepts used by individual minds evolve over generations in interaction among multiple agent-minds. As we attempt to develop intelligent systems, these lessons from biological systems and their evolution should be taken into account.

Developing integrated systems with language and cognition abilities might seem premature. Even considered separately, these problems are very complex and far from being solved. Our systems for recognition, tracking, and fusion using sensor data often fall far short of human abilities. Similarly, our computer communication systems lack flexibility of language. Natural language understanding remains a distant goal. Let me repeat that the only way two computers can communicate at all, is due to fixed protocols. Communications among computers are intended for human users. Computers do not understand contents of communication messages, except within narrow domains. Everyone knows frustration of searching information on the Internet; Google and Yahoo do not understand our language. But, why should we hope to achieve progress in fusing two capabilities, neither of which is at hand?

The answer was given at the beginning of the paper. The only system that we know capable of human level cognition and communication is the human mind. An individual human mind develops both capabilities in ontogenesis, during childhood, *jointly*. This is opposite to current engineering approaches, which attempt to develop these capabilities separately, usually in different scientific and engineering organizations. It is quite possible that coding a computer to acquire language and cognitive abilities similarly to the human ways is an 'easier' task, possibly, the only way to go. We do not even know if it is possible to code computers to be 'cognitive' or 'language capable', one capability separately from the other. These current approaches could be invalid in principle.

A similar argument is applicable to the 'initial' computer code, which we would like to be similar to inborn child's capabilities, enabling joint learning of language and cognition. Human evolved this capability over at least two million years. It is possible, that simulating an accelerated evolution is an 'easier' scientific and engineering approach, than 'direct coding' into a computer of the current state of human baby mind. Moreover, we do not need to have to simulate evolution of culture; computers may learn from humans in collaborative human-computer environment. Therefore, along with smart heuristic solutions, we should try to uncover natural mechanisms of evolving language and culture, and to develop mathematical descriptions for these processes.

Scientific understanding of relationships between language and cognition in the past went through several reversals. Close relationships between language and cognition encouraged equating these abilities in the past. Rule-based systems and mathematics of logic implied significant similarities between the two: Thoughts, words, and phrases, all are logical statements. The situation has changed, in part due to the fact that logic-rule systems have not been sufficiently powerful to explain cognition, nor language abilities, and in part due to improved scientific understanding (psychological, cognitive, neural, linguistic) of the mechanisms involved. Many contemporary linguists consider language and cognition to be distinct and different abilities of the mind [see[2] for further references].

Language mechanisms of our mind include abilities to acquire a large vocabulary, rules of grammar, and to use the finite set of words and rules to generate virtually infinite number of phrases and sentences [[3,4]]. Cognition includes abilities to understand the surrounding world in terms of objects, their relationships (scenes and situations), relationships among relationships, and so on [[5]]. Researchers in computational linguistics, mathematics of intelligence and neural networks, cognitive science, neuro-physiology and psychology during the last twenty years significantly advanced understanding of the mechanisms of the mind involved in learning and using language, mechanisms of perception and cognition [[3,4,5,6,7,8]]. Much less advance was achieved toward deciphering mechanisms relating linguistic competence to cognition and understanding the world. Although it seems clear that language and cognition are closely related abilities, intertwined in evolution, ontogenesis, and everyday use, still the currently understood mechanisms of language are mainly limited to relations of words to other words and phrases, but not to the objects in the surrounding world, not to cognition and thinking. Possible mathematical approaches toward integrating language and cognition, words and objects, phrases and situations are discussed in this paper. This might be a foundation for cognitive learning and mechanisms of cultural evolution.

The paper starts with a mathematical description of cognition, which still is an issue of much controversy. Among researchers in mathematical intelligence it has become appreciated, especially during the last decades that cognition is not just a chain of logical inferences [[5,8]]. Yet, mathematical methods describing cognition as processes in human mind involving concepts, instincts, emotions, memory, imagination are not well known, although significant progress in this direction was achieved [[5,8]]. A brief historical overview of this area including difficulties and controversies is given in the next two sections from mathematical, psychological, and neural standpoints. It is followed by a mathematical description of cognitive processes, including image recognition, tracking, and fusion as variations of the same basic paradigm. Then the paper discusses the ways in which the mathematical description of cognition can be combined with language, taking advantage of recent progress in computational linguistics. It touches upon novel ideas of computational semiotics relating language and cognition through signs and symbols. Approaches to understanding-based web mining and building integrated multi-agent systems are discussed.

In conclusion, I briefly touch on relationships between mathematical, psychological, and neural descriptions of cognitive processes and language as parts of the mind. It turns out that, far from being esoteric abilities far removed from engineering applications, these abilities are inseparable from a mathematical description of even simplest cognition processes. Their understanding is helpful for developing integrated multi-agent systems.

2 Theories of the Mind and Combinatorial Complexity

Understanding signals coming from sensory organs involves associating subsets of signals corresponding to particular objects with internal representations of these objects. This leads to recognition of the objects. Developing mathematical descriptions of this very first *recognition* step was not easy; a number of difficulties were encountered during the past fifty years. These difficulties were summarized under the notion of combinatorial complexity (CC) [9]. CC refers to multiple combinations of various elements in a complex system; recognition of a scene often requires concurrent recognition of its multiple elements that could be encountered in various combinations. CC is prohibitive because the number of combinations is very large: for example, consider 100 elements (not too large a number); the number of combinations of 100 elements is 100^{100}, exceeding the number of elementary particles in a Universe; no computer would ever be able to compute that many combinations.

The problem was first identified in pattern recognition and classification research in the 1960s and was named "the curse of dimensionality" [10]. The following forty years of developing intelligent systems faced CC in various forms. Self-learning systems encountered *CC of learning requirements*. Logic-rule AI systems [11] and the first Chomsky ideas concerning mechanisms of language grammar related to deep structure [12] encountered *CC of rules*. Model-based systems were proposed to combine advantages of adaptivity and learning with rules by utilizing adaptive models. Along similar lines were *rules and parameters* ideas of Chomsky [13]. Model-based systems encountered *computational CC* (N and NP complete algorithms). The CC became a ubiquitous feature of intelligent algorithms and seemingly, a fundamental mathematical limitation.

CC was related to the type of logic, underlying various algorithms and neural networks [9]. CC of algorithms based on logic was related to the Gödel theory: It is a finite system manifestation of the incompleteness of logic [14]. Multivalued logic and fuzzy logic were proposed to overcome limitations related to the law of excluded third [15]. Yet the mathematics of multivalued logic is no different in principle from formal logic. Fuzzy logic encountered a difficulty related to the degree of fuzziness: If too much fuzziness is specified, the solution does not achieve a needed accuracy, if too little, it becomes similar to formal logic.

Various approaches to signal and communication integration are related to mathematical methods considered above. For example, an influential and general method of Multiple Hypothesis Testing (MHT) is a model-based method. Its combinatorial complexity is widely appreciated. Combinatorial complexity prevents these mathematical methods from achieving human-like flexibility and adaptivity. In section 4 we discuss a biologically inspired mathematical technique, which overcomes CC. The biological inspirations for this approach are briefly summarized in the next section 3.

3 Mind: Instincts, Concepts, and Emotions

Among fundamental mechanisms of the mind are instincts, concepts, emotions, and control of behavior. Instincts operate like internal sensors: for example, when a sugar level in blood goes below a certain level an instinct “tells us” to eat. Concepts are like internal models of the objects and situations; this analogy is quite literal, e.g., during visual perception of an object, an internal concept-model projects an image onto the visual cortex, which is matched there to an image projected from retina (this simplified description will be refined later). Emotions are neural signals connecting instinctual and conceptual brain regions. Whereas in colloquial usage, emotions are often understood as facial expressions, higher voice pitch, exaggerated gesticulation, these are the outward signs of emotions, serving for communication. A more fundamental role of emotions within the mind system is that emotional signals evaluate concepts for the purpose of instinct satisfaction [16]. This emotional mechanism described in the next section is crucial for breaking out of the “vicious circle” of combinatorial complexity. Conceptual-emotional understanding of the world leads to actions (or behavior) in the outside world or within the mind. In this paper we describe only one type of behavior, the behavior of learning that is improving understanding and knowledge of the language and world.

4 Modeling Field Theory (MFT)

The mind involves a hierarchy of multiple levels of concept-models, from simple perceptual elements (like edges, or moving dots), to concept-models of objects, to complex scenes, etc. Modeling field theory (MFT) [5], summarized below, associates lower-level signals with higher-level concept-models; a result is an understanding of signals as concepts. The difficulties of CC described in Section 2 are avoided. It is achieved by a new type of logic, the fuzzy dynamic logic. MFT is a multi-level, hetero-hierarchical system. We start with a basic mechanism of interaction at a single level.

At each level, the output signals are concepts recognized (or formed) in input signals. Input signals are associated with concepts according to the representations-models and similarity measures at this level. In the process of association-recognition, models are adapted for better representation of the input signals; and similarity measures are adapted so that their fuzziness is matched to the model uncertainty. The initial uncertainty of models is high and so is the fuzziness of the similarity measure; in the process of learning models become more accurate and the similarity more crisp, the value of the similarity measure increases. This is a mechanism of fuzzy dynamic logic.

Input signals $\{\mathbf{X}(n)\}$ are enumerated by n = 1,… N; concept-models h = 1,… H, are characterized by the models (representations) $\{\mathbf{M}_h(n)\}$ of the signals $\mathbf{X}(n)$; each model depends on its parameters $\{\mathbf{S}_h\}$, $\mathbf{M}_h(\mathbf{S}_h,n)$. In a highly simplified description of a visual cortex, n enumerates the visual cortex neurons, $\mathbf{X}(n)$ are the "bottom-up" activation levels of these neurons coming from the retina through visual nerve, and $\mathbf{M}_h(n)$ are the "top-down" activation levels (or priming) of the visual cortex neurons from previously learned object-models[17]. Cognition process attempts to "match" top-down and bottom-up activations by selecting "best" models and their parameters. Computationally, it increases a similarity measure between the sets of models and signals, $L(\{\mathbf{X}(n)\},\{\mathbf{M}_h(n)\})$ [[5]].

$$L(\{\mathbf{X}\},\{\mathbf{M}\}) = \prod_{n \in N} \sum_{h \in H} r(h)\, l(\mathbf{X}(n) \mid \mathbf{M}_h(n)); \tag{1}$$

here, $l(\mathbf{X}(n)|\mathbf{M}_h(n))$ (or simply $l(n|h)$) is a conditional partial similarity between one signal $\mathbf{X}(n)$ and one model $\mathbf{M}_h(n)$; (1) accounts for all possible combinations of signals and models. Parameters r(h) are proportional to the number of signals {n} associated with the model h. Maximization of similarity has the following psychological and neurobiological interpretation: it is an instinctual behavior that evolved with the purpose of understanding the world, it is *instinct for knowledge*.

Note, that (1) contains a large number of combinations of models and signals, a total of H^N items; this was a cause for the combinatorial complexity of the past algorithms discussed in section 2. MFT solves this problem using the mechanism of fuzzy dynamic logic (DL) [[5,18]]. The DL iteration's consist of two steps: first compute fuzzy association variables f(h|n), then improve parameters

$$f(h|n) = r(h)\, l(n|h) \,/ \sum_{h' \in H} r(h')\, l(n|h'). \tag{2}$$

$$\mathbf{S}_h = (1-\alpha)\, \mathbf{S}_h + \alpha \sum_n f(h|n)[\partial \ln l(n|h)/\partial \mathbf{M}_h]\partial \mathbf{M}'_h/\partial \mathbf{S}_h, \tag{3}$$

$$r(h) = N_h / N; \quad N_h = \sum_n f(h|n); \tag{4}$$

Here, parameter α determines the iteration step and speed of convergence of the MF system; N_h can be interpreted as a number of signals $\mathbf{X}(n)$ associated with or coming from a concept-model n. After step (3, 4) the iterations returns to step (2) and continues until changes in parameters become negligible and similarity (1) stop increasing). The following theorem was proven [[5]].

Theorem. Equations (2) through (6) define a convergent dynamic system MF with stationary states given by $\max_{\{\mathbf{S}_h\}} L$.

In plain language this means that the above equations indeed result in concept-models in the "mind" of the MFT system, which are most similar [in terms of similarity (1)] to the sensory data. Despite a combinatorially large number of items in (1), a computational complexity of the MF method is relatively low, it is linear in N. This theorem is proved by demonstrating that similarity (1) increases at each iteration

[5]. Psychological and neurobiological interpretation of this fact is that instinct for knowledge is satisfied with each iteration; MFT system 'enjoys' the process of convergence to better knowledge.

Summary of the MF convergence: during an adaptation process, initial fuzzy and uncertain models are associated with structures in the input signals, fuzzy models are getting more definite and crisp. The type, shape and number of models are selected so that the internal representation within the system is similar to input signals: the MF concept-models represent structure-objects in the signals. Computations describing this process are given by fuzzy dynamic logic eqs. (2, 3, 4). It is illustrated in Fig. 1 for recognition of 'smiles' and 'frowns' in the background of a strong noise. In terms of the mind, it describes an elementary cognition process involving instincts, imagination, emotions and concepts, but before discussing this cognitive-psychological interpretations, lets us briefly look into integrating this process with language.

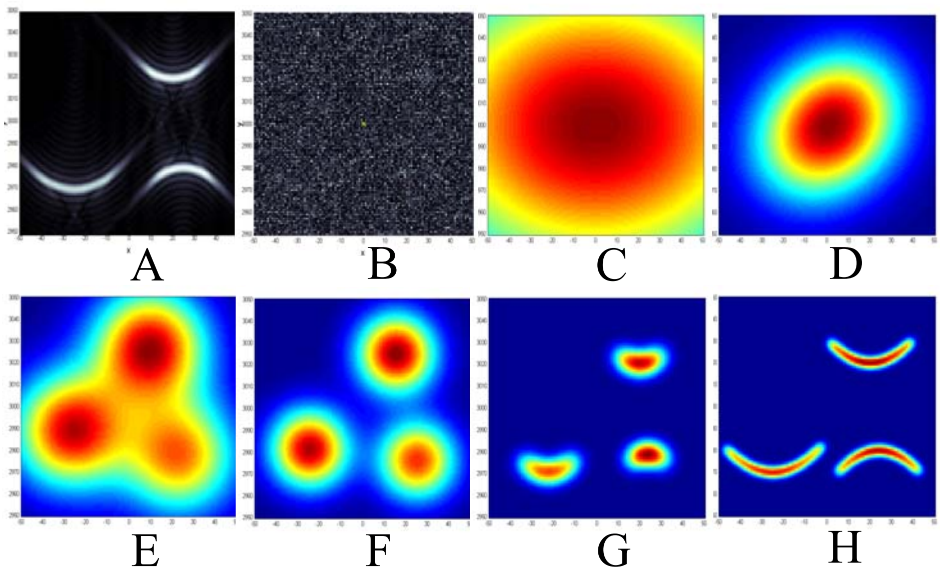

Fig.1. Finding 'smile' and 'frown' patterns in noise, an example of dynamic logic operation: (a) true 'smile' and 'frown' patterns shown without noise; (b) actual image available for recognition (signal is below noise, signal-to-noise ratio is between –2dB and –0.7dB); (c) an initial fuzzy model, the fuzziness corresponds to uncertainty of knowledge; (d) through (h) show improved models at various iteration stages (total of 22 iterations). At stage (d) the algorithm tried to fit the data with more than one model and decided, that it needs three models to 'understand' the content of the data. There are three types of models: one uniform model describing noise (it is not shown) and a variable number of blob-models and parabolic models, which number, location and curvature are estimated from the data. Until about stage (g) the algorithm 'thought' in terms of simple blob models, at (g) and beyond, the algorithm decided that it needs more complex parabolic models to describe the data. Iterations stopped at (h), when similarity (1) stopped increasing. This example is discussed in more details in [19].

By using concept-models with multiple sensor modalities, a MFT system can integrate signals from multiple sensors, while adapting and improving internal concept-models. Similarly, MFT can be used to integrate all sources of information, in particular, cognition and language. This requires linguistic MFT models, which can be developed using known linguistic structures [3,4,6,7,20]. Here, I briefly outline an approach to the development of MFT linguistic models.

Let us discuss the development of models of phrases from words for the purpose of text understanding. The input data, $\mathbf{X}(n)$, in this "phrase-level" MF system, are word strings, for simplicity, of a fixed length, S, $\mathbf{X}(n) = \{ w_{n+1}, w_{n+2} \ldots w_{n+S} \}$. Here w_n are words from a given dictionary of size K, $W = \{w_1, w_2 \ldots w_K\}$, and n is the word position in a body of texts. A simple phrase model is a subset of words from the dictionary, without any order or rules of grammar (computational linguists call it 'bag' model),

$$\mathbf{M}_h(\mathbf{S}_h,n) = \{w_{h,1}, w_{h,2} \ldots w_{h,S}\}; \tag{6}$$

the parameters of this model are its words, $\mathbf{M}_h(\mathbf{S}_h,n) = \mathbf{S}_h = \{w_{h,1}, w_{h,2} \ldots w_{h,S}\}$. Language learning in this simplified context consists in defining models-concepts-phrases best characterizing the given body of texts in terms of a similarity measure. Extension of DL to language was considered in [21]. It can be applied to bag models and to other known structures of natural languages, such as noun and verb phrases, tree structures, etc. [3,4,6,7,20,22,23]. This accomplishes the goal of the language acquisition project without combinatorial complexity. This technique can be applied to the development of understanding-based web search engines. A hierarchical language-MFT is developed with higher levels of the hierarchy extending 'above' phrases to learning the contents of paragraphs, pages, documents.

Integration of language and cognition in MFT is attained by characterizing objects and situations in the world with two types of models, cognitive and language models; so that in eqs. (1) through (4) $\mathbf{M}_h(n) = \{\mathbf{M1}_{h1}(n), \mathbf{M2}_{h2}(n)\}$, $\mathbf{M1}$ for cognitive and $\mathbf{M2}$ for language models. Indexes h1 and h2 innumerate cognitive and language models; but it is not necessary to consider combinations of h1 and h2, because initially all models are same, fuzzy blobs, just placeholders for future knowledge. The above equations describe a single agent with a MFT-mind.

A MFT agent can be used in a particular application alone or as a part of collaborative multi-agent environment. A single MFT agent can utilize complex adaptive models, and can learn from data and signals. Several applications of this type were developed [5,22]. The more specific the models are, the less data will be required for learning. A different evolutionary approach can start with simple models and develop complex models and abilities as a result of evolution of a multi-agent MFT system. Multiple agents can learn from their environment along with communicating among themselves or within a collaborative environment with human. First steps toward the development of evolving systems with cognitive and communicating multiple agents with a MFT mind are described in [24,25].

An integrated MFT system learns similarly to human, in parallel in three realms: (1) language and cognitive models are learned jointly, when language data are present in association with perception signals, like during mother talking to a baby: "this is a car" (perception-models and word-models), and like during more complicated conversations: “Look at Peter and Ann, they are in love” (cognitive-models and phrase-models); (2) language models are learned independently from cognition, when language data are encountered for the first time with no association with perception and cognition (most of language learning during the age 2 to 7); (3) similarly, cognitive models are learned independently from language, when perception signal data are encountered for the first time without association with linguistic data. In (2) and (3) above it is important to emphasize that cognitive and language learning enhance each other. The original, inborn models are fuzzy structures equally and poorly matching any sensory or language data. In the process of learning fuzziness decreases, crisp models get associated with specific situations and phrases, and cognitive models always remain associated with language models. Due to the integrated (cognitive, language)-model structures, association between language and cognition begins at a “pre-conceptual” fuzzy level, inaccessible to consciousness. Similarly a child learns a large number of language models, which association with real life is very fuzzy; throughout later life they facilitate learning of corresponding cognitive models; similarly, cognitive (say visual) models facilitate learning of language models; eventually h1 and h2, cognitive and language models are properly associated (that is similar across the system, so that people and computers understand each other).

5 Conclusion

At the beginning of this paper I summarized some justifications for following biological examples in engineering system design. Still, often one can hear a question: Why does an engineer need to know about concepts and emotions? After mathematical equations are derived, why not just use them for developing computer code, why should an engineer be concerned with interpretations of these equations in terms of instincts and emotions? This question is profound and an answer can be found in history of science and engineering. Newtonian laws can be written in few lines, but an engineering manager cannot hand these few lines to a young engineer and ask to design an airplane or rocket. Similarly, Maxwell’s equations contain the main principles of radar and communication, but radars and communication systems cannot be built without knowledge of electromagnetic phenomenology. For the same reason, MFT and dynamic logic equations need to be supplemented by understanding phenomenology of the mind signal processing to be efficiently applied to design of high level fusion systems. For this reason in conclusion of this paper we summarize the main aspects of working of the mind as described by the equations given in this paper.

Equations in section 4 describe elementary processes of perception or cognition, in which a number of model-concepts compete for incoming signals, model-concepts are modified and new ones are formed, and eventually, more or less definite connections [high values of $f(h|n)$, close to 1] are established among signal subsets on the one hand and some model-concepts on the other, accomplishing perception and cognition.

A salient mathematical property of this process is the correspondence between uncertainty in models and fuzziness in associations $f(h|n)$. In perception, as long as model parameters do not correspond to actual objects, there is no match between models and signals; many models poorly match many objects, and associations remain fuzzy (between 0 and 1). Eventually, one model (h') wins a competition for a subset {n'} of input signals **X**(n). In other words, a subset of data is recognized as a specific object (concept). Upon convergence, the entire set of input signals {n} is divided into subsets, each associated with one model-object, uncertainties become small, and fuzzy concept-models become crisp concepts. The general mathematical laws of cognition and perception are similar and constitute a basic principle of the mind organization. Kant was the first one to propose that the mind functioning involves three basic abilities: Pure Reason (concept-models), Judgment (emotional measure of correspondence between models and input signals), and Practical Reason (behavior; we only considered here the behavior of adaptation and learning) [26,27,28]. We now briefly discuss relationships between the MFT theory and concepts of mind originated in psychology, philosophy, linguistics, aesthetics, neuro-physiology, neural networks, artificial intelligence, pattern recognition, and intelligent systems.

A thought-process or cognition involves a number of sub-processes and attributes, including internal representations and their manipulation, attention, memory, concept formation, knowledge, generalization, recognition, understanding, meaning, prediction, imagination, intuition, emotion, decisions, reasoning, goals, behavior, conscious and unconscious [5,8]. We discuss how these processes are described by MFT.

A "minimal" subset of these processes, *an elementary thought-process*, has to involve mechanisms for afferent and efferent signals [8], in other words, bottom-up and top-down signals. According to Carpenter and Grossberg [29] every recognition and concept formation process involves a "resonance" between these two types of signals. In MFT, at every level in a hierarchy the afferent signals are represented by the input signal field **X**, and the efferent signals are represented by the modeling fields $\mathbf{M}_h$; resonances correspond to high similarity values l(n|h) for some subsets of {n} that are "recognized" as concepts (or objects). The mechanism leading to the resonances between incoming signals and internal representations is given by equations in section 4.

A description of the workings of the mind as given by the MFT dynamics was first provided by Aristotle [30], describing cognition as a learning process in which an a priori form-as-potentiality (fuzzy model) meets matter (sensory signals) and becomes a form-as-actuality (a logical concept). Jung suggested that conscious concepts are developed by the mind based on genetically inherited structures, archetypes, which are inaccessible to consciousness [31] and Grossberg [8] suggested that only signals and models attaining a resonant state (that is, signals matching models) reach consciousness. Fuzzy uncertain models are less accessible to consciousness, whereas more crisp and certain models are better accessible to consciousness.

Recognizing objects in the environment and understanding their meaning is so important for human evolutionary success that an instinct has evolved for learning and improving concept-models. This instinct (for knowledge and learning) is described in MFT by maximization of similarity between the models and the world, eq. (1). Emotions related to satisfaction-dissatisfaction of this instinct we perceive as harmony-disharmony (between our understanding of how things ought to be and how they actually are in the surrounding world). Since Kant [27], emotions that are not related directly to bodily needs are called aesthetic emotions. Aesthetic emotions in

MFT correspond to changes in the knowledge instinct (1). The mathematical basis for the theorem in section 4 can be interpreted psychologically: during dynamic logic iterations the aesthetic emotion is always positive. MFT system ‘enjoys’ learning.

Signs and symbols are essential for the workings of the human mind, as well as for accumulation and transmission of knowledge in human culture. They are also used extensively in intelligent and multi-level fusion systems. Scientific theories of signs and symbols, however, are not well developed, and even the exact meaning of these words is often confused. According to [32], “symbol” is the most misused word. We use this word in trivial cases referring, say, to traffic signs and in the most profound cases of cultural and religious symbols. In mathematics and in “Symbolic AI” there is no difference between signs and symbols. Both are considered to be notations, arbitrary non-adaptive entities with axiomatically fixed meaning. This non-differentiation is a “hangover” from an old superstition that logic describes mind, a direction in mathematics and logical philosophy that can be traced through the works of Frege, Hilbert, Russell, to its bitter end in Gödel theory, and its revival during the 1960s and 1970s in artificial intelligence. Profound use of the word “symbol” in general culture, according to Jung, is related to symbols being psychological processes of sign interpretation. Jung emphasized that symbol-processes connect the conscious and unconscious [31]. Pribram wrote of symbols as adaptive, context-sensitive signals in the brain, whereas signs he identified with less adaptive and relatively context-insensitive neural signals [33]. Deacon [32] thought that the essence of the human symbolic ability is two interacting parallel hierarchies, like described in section 4 hierarchy of cognitive models and a hierarchy of sign (language) models; he called it symbolic reference.

Combining mathematical developments in sections 4 with the above discussion, we reach the following conclusion for consistent meanings of signs and symbols. The essence of a sign is that it is an arbitrary notation, which can be interpreted by our mind or by an intelligent system to refer to something else, to an object or situation. Symbols are psychological processes of sign interpretation, they are equivalent to elementary thought processes, and they integrate unconscious (fuzzy models) with conscious (crisp models). A simple symbol process is mathematically described by a single MFT level, like in section 4. A complex symbol-process of cognition of culturally important concepts may take hundreds of years in human societies and many generations of MFT agents; it may involve multiple levels of MFT or the mind hierarchy. Future sensor-webs will be designed using this biological knowledge. They will participate in human-computer collaborative networks. They will evolve through generations of agents. They will integrate the learning of language with the learning of complex cognitive concepts. They will integrate communication with sensor signal processing, and instead of quick obsolescence, their performance will improve with time and experience by accumulating knowledge similar to human cultures.

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