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**PHENOMENOLOGY-BASED INVERSE SCATTERING FOR SENSOR
INFORMATION FUSION**

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14. ABSTRACT Fusion of sensor and communication data currently can only be performed at a late processing stage after sensor and textual information are formulated as logical statements at appropriately high level of abstraction. Contrary to this it seems, the human mind integrates sensor and language signals seamlessly, before signals are understood, at pre-conceptual level. Learning of conceptual contents of the surrounding world depends on language and vice versa. This paper uses phenomenology of the human mind and sensing processes to achieve high-level sensor fusion. We describe a phenomenology-based inverse scattering (PBIS) mathematical technique for such integration. It combines PBIS based on dynamic logic with dual cognitive-language models. The paper briefly discusses relationships between the proposed mathematical technique, working of the mind and applications to understanding-based search engines.					
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1. INTRODUCTION: COMPUTERS VS. HUMAN MIND

Current engineering approaches attempt to develop computer capabilities for language and cognition separately, usually in different organizations. 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 approaches could be invalid in principle. These considerations are prime motivations for this report. Let us examine them in some detail.

Consider a most influential JDL fusion model [1]. It is a functional model of a fusion process with several levels. In the 1999 revision, the model included five levels (from level 0 to level 4): sub-object, object, situation, impact, and refinement. Further enhancements of the model considered additional levels, e.g. [2]. Dasarathy proposed a sensor fusion model with three processing levels: the data level, the feature level, and the decision level [3]. Endsley suggested a model with three levels of mental representation needed for situation awareness: perception, comprehension, and projection [4]. This was extended by adding a “resolution” level, generating behavior to achieve the desired outcome [5]. A situational awareness framework unifying JDL and Endsley’s models was developed in [6]. Practical implementations of high-level fusion (levels 2, 3, and beyond) require development of detailed models with the appropriate degree of abstractness for every level. Natural-language type communications are considered necessary (or at least desirable) at these high levels. However, these high level fusion and communication in contemporary systems lack the flexibility of human cognition and natural languages. To achieve fusion and semantic integration at high fusion levels (level 2 or 3 and beyond), developers rely on models, ontologies, and protocols, which assume shared knowledge and understanding [7]. In practice, structures of these models have to be fixed. This is also true for ontologies being developed for semantic web. They cannot be as flexible as “shared knowledge” necessary for understanding among people. Specific mathematical reason for this inflexibility we discuss in section 2.

As the physical infrastructure for communication systems and the Internet matures, the *information* services are gaining in importance. Distributed data fusion integrated with flexible communication would be necessary for the future Sensor web, an integrated operation of multiple platforms and agents with sensors and communication capabilities. However, computer systems today are using inflexible models and ontologies. They can integrate signals from sensors with language communication messages only at a 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. Similarly, language or communication messages have to be pre-processed, the relevant data extracted and formulated as logical statements at a similar level of abstraction. 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. As we attempt to develop intelligent systems, these lessons from biological systems and their evolution should be taken into account.

Developing computer systems for fusion of language and cognition 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 the 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 the 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, and may possibly be 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 a child's inborn capabilities, enabling joint learning of language and cognition. Humans 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 the 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.

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. Contemporary linguists appreciate that language and cognition could be distinct and different abilities of the mind [see⁸ 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 [9, 10]. Cognition includes abilities to understand the surrounding world in terms of objects, their relationships (scenes and situations), relationships among relationships, and so on [11]. 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 [9,10,11,12,13,14]. 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 thinking, words and objects, phrases and situations are discussed in this paper.

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 [11,14]. Yet, mathematical methods describing cognition as processes involving concepts, instincts, emotions, memory, imagination are not well known, although significant progress in this direction was achieved [11,14,15]. 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 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 building hierarchy of high-level fusion (including levels 2, 3, and beyond) 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. Words like *mind*, *thought*, *imagination*, *emotion*, *concept* are often used colloquially in many ways, but their use in science and especially in mathematics of intelligence has not been uniquely defined and is a subject of active research and ongoing debates [14,15]. According to a dictionary [16], the mind includes conscious and unconscious processes, especially thought, perception, emotion, will, memory, and imagination, and it originates in brain. These constituent notions will be briefly discussed throughout the paper. 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 high-level fusion 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 and activates internal brain signals leading to mental and behavioral responses, which constitute the understanding of the meaning (of the objects).

Developing mathematical descriptions of the very first *recognition* step of this seemingly simple association-recognition-understanding process has not been easy, and a number of difficulties have been encountered during the past fifty years. These difficulties have been summarized under the notion of combinatorial complexity (CC) [17]. The problem was first identified in pattern recognition and classification research in the 1960s and was named “the curse of dimensionality” [18]. The following thirty years of developing adaptive statistical pattern recognition and neural network algorithms designed for self-learning led to the conclusion that these approaches often encountered *CC of learning requirements*: recognition of any object, it seemed, could be learned if “enough” training examples were used for an algorithm self-learning. The required examples had to account for all possible variations of “an object”, in all possible geometric positions and in *combinations* with other objects, sources of light, etc., leading to astronomical (and worse) numbers of required examples.

By the end of the 1960s a different paradigm became popular: logic-rule systems (or expert systems) were proposed to solve the problem of learning complexity. According to Minsky, rules were to capture the required knowledge and eliminate a need for learning [19]. Similar were the first Chomsky ideas concerning mechanisms of language grammar related to deep structure [20]; they also used mechanisms of logical rules. Rule systems work well when all aspects of the problem can be predetermined and there are no unexpected variabilities. However, rule systems in presence of unexpected variability, encountered *CC of rules*: more and more detailed sub-rules and sub-sub-rules, one contingent on another, had to be specified.

In the 1980s model-based systems became popular. They were proposed to combine advantages of adaptivity and learning with rules by utilizing adaptive models. Existing knowledge was to be encapsulated in models and unknown aspects of concrete situations were to be described by adaptive parameters. Along similar lines were *rules and parameters* ideas of Chomsky [21]. Model-based systems encountered *computational CC* (N and NP complete algorithms). The reason was that considered algorithms had to evaluate multiple combinations of elements of data and rules (models). CC is prohibitive because the number of combinations is very large: for example, consider 100 elements (not too large a number) which combinations had to be evaluated; the number of combinations of 100 elements is 100^{100} , a number comparable to the number of elementary particles in a Universe; no computer would ever be able to compute that many combinations. The CC became a ubiquitous feature of intelligent algorithms and seemingly, a fundamental mathematical limitation.

Combinatorial complexity was related to the type of logic, underlying various algorithms and neural networks [17]. Formal logic is based on the “law of excluded third,” according to which every statement is either true or false and nothing in between. Therefore, algorithms based on formal logic have to evaluate every little variation in data or internal representations as a

separate logical statement; a large number of combinations of these variations cause combinatorial complexity. In fact, combinatorial complexity of algorithms based on logic has been related to the Gödel theory: It is a finite system manifestation of the incompleteness of logic [22]. Multivalued logic and fuzzy logic were proposed to overcome limitations related to the law of excluded third [23]. 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 fusion can be related to mathematical methods considered above. For example, an influential and general method of Multiple Hypothesis Testing (MHT), and closely related Multiple Hypothesis Tracking, are model-based methods. Their combinatorial complexity is widely appreciated. MHT for tracking is often used at the object level 1. MHT using hypotheses and models of situations are often used for fusing at higher levels 2, 3 and beyond. Combinatorial complexity prevents these mathematical methods from achieving human-like flexibility and adaptivity. Yet general methods for high-level fusion overcoming CC were not developed. In presence of variability, the most difficult aspect of fusion, it seems, is fusion of signals with knowledge, or fusion of lower-level knowledge with higher-level knowledge. The reason is a need to 'fit' higher-level models to objects and situations identified at lower levels. This requires testing of multiple combinations and leads to CC. In section 4 we discuss a biologically inspired mathematical approach to fusion, which overcomes CC. The biological inspirations for this approach are briefly summarized in the next section 3.

3. MIND: CONCEPTS AND EMOTIONS

The seemingly fundamental nature of mathematical difficulties discussed above has led many to believe that classical physics cannot explain the working of the mind. Yet, I would like to emphasize another aspect of the problem: often mathematical theories of the mind were proposed before the necessary physical intuition of how the mind works was developed. Newton, as often mentioned, did not consider himself as evaluating various hypotheses about the working of the material world, he felt that he had what we call today a physical intuition about the world [24]. An intuition about the mind points to mechanisms of concepts, emotions, instincts, imagination, behavior, consciousness, and unconscious [25]. An essential role of emotions in the working of the mind was analyzed from the psychological and neural perspective by Grossberg [26], from the neuro-physiological perspective by Damasio [27], and from the learning and control perspective by the author [28,29,30]. One reason for the engineering community being slow in adopting these results is the cultural bias against emotions as a part of cognitive processes. Plato and Aristotle thought that emotions are “bad” for intelligence, this is a part of our cultural heritage (“one have to be cool to be smart”), and the founders of Artificial Intelligence repeated this truism about emotions [31]. Yet, as discussed in the next section, combining conceptual understanding with emotional evaluations is crucial for overcoming the combinatorial complexity as well as related difficulties of logic.

Let me summarize briefly and in a much simplified way several aspects of the working of the mind, which seem essential to the development of the mathematical descriptions of the mind mechanisms: instincts, concepts, emotions, behavior [32,33].

The most accessible to our consciousness mechanism of the mind is concepts: the mind operates with concepts. 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). Concept mechanism evolved for the purpose of survival, and therefore it serves for a better satisfaction of the basic instincts, which have emerged as survival mechanisms even before the mind. Instincts operate like internal sensors: for example, when a sugar level in blood goes below a certain level an instinct “tells us” to eat.

We do not read ‘instinctual sensor readings.’ Satisfaction or dissatisfaction of instincts is measured by emotions that we feel. 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. This evaluation is not according to rules or concepts (like in rule-systems of artificial intelligence), but according to a different instinctual-emotional mechanism [34]. Specific instinct and emotions related to learning [25] and their mathematical mechanisms are described in the next section. This instinctual-emotional mechanism is crucial for breaking out of the “vicious circle” of combinatorial complexity.

The results of conceptual-emotional understanding of the world are actions (or behavior) in the outside world or within the mind. In this paper we touch on only one type of behavior, the behavior of improving understanding and knowledge of language and the world. In the next section we describe a mathematical theory of a 'simple' conceptual-emotional recognition and understanding. This includes tracking and sensor fusion. As we will discuss, in addition to concepts and emotions, it involves with necessity mechanisms of intuition, imagination, conscious, and unconscious. And this process is intimately connected to an ability of the mind to form symbols and interpret signs.

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, and up the hierarchy... toward the concept-models of the meaning of life and purpose of our existence. Hence the tremendous complexity of the mind, yet relatively few basic principles of the mind organization go a long way explaining this system. Development of sensor fusion systems does not require most general and abstract models. Situational awareness, for example, requires models of situations.

4. PHENOMENOLOGY-BASED INVERSE SCATTERING (PBIS)

Phenomenology-based inverse scattering [35] is implemented in this paper using modeling field theory (MFT), summarized below. It is a biologically inspired multi-level intelligent system. MFT architecture is based on the phenomenology of human mind. In addition, specific models within MFT use phenomenology of the appropriate sensing processes. At each level MFT associates lower-level signals with higher-level concept-models (representations, ontologies, scattering models), resulting in understanding of signals, while overcoming the difficulties of CC [11,33]. CC is overcome by using a new type of logic, fuzzy dynamic logic. Modeling field theory is a hetero-hierarchical system. We first describe a basic structure of interaction between two adjacent hierarchical levels of signals; sometimes, it will be more convenient to talk about these two signal-levels as an input to and output from a (single) processing-level.

At each level, input comes either from sensors (at the lowest level), or from a lower level; output signals are concepts recognized (or formed) in input signals. Input signals \mathbf{X} are associated with (or recognized, or grouped into) 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 mechanism is called fuzzy dynamic logic, or dynamic logic for short.

4.1 INTERNAL MODELS, LEARNING, AND SIMILARITY

During the learning process, new associations of input signals with concept-models are formed resulting in evolution of new concepts. Input signals are denoted $\{\mathbf{X}(n)\}$, $n = 1, \dots, N$; concept-models $\{\mathbf{M}_h(n)\}$, $h = 1, \dots, H$, predict values of signals $\mathbf{X}(n)$ expected from object (or situation) h ; each model depends on its parameters $\{\mathbf{P}_h\}$, $\mathbf{M}_h(\mathbf{P}_h, n)$. 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 [36]. Learning process attempts to “match” these top-down and bottom-up activations by selecting “best” models and their parameters. Mathematically, learning increases a similarity measure between the sets of models and signals, $L(\{\mathbf{X}(n)\}, \{\mathbf{M}_h(n)\})$. A biological interpretation is that similarity maximization is the instinct for knowledge, for improving correspondence between the concept-models and the world. The similarity measure is a function of model parameters and associations between the input signals and concepts-models. It is constructed in such a way that any of a large number of objects can be recognized. Correspondingly, a similarity measure is designed so that it treats each concept-model as an alternative for each subset of signals

$$L(\{\mathbf{X}\}, \{\mathbf{M}\}) = \prod_{n \in N} \sum_{h \in H} r(h) l(\mathbf{X}(n) | \mathbf{M}_h(n)). \quad (1)$$

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 $\mathbf{M}_h(n)$, and all possible combinations of signals and models are accounted for in this expression. Parameters $r(h)$ are proportional to the number of signals $\{n\}$ associated with the model h (in statistics they are called priors). Although, (1) contains a product over individual signal samples, n , signal samples are not assumed statistically independent. Inter-dependence is defined by models \mathbf{M} . Note, (1) contains a large number of combinations of models and signals, all possible signal-model associations, a total of H^N items. This is a cause for combinatorial complexity of many algorithms discussed in section 2.

In the process of learning, concept-models are constantly modified. From time to time a system forms a new concept, while retaining an old one as well; alternatively, old concepts are sometimes merged. Formation of new concepts and merging of old ones require a modification of the similarity measure (1); the reason is that more models always result in a better fit between the models and data. This is a well-known problem, it can be addressed by reducing (1) using a “penalty function”, $p(N,M)$ that grows with the number of models M , and this growth is steeper for a smaller amount of data N . For example, an asymptotically unbiased maximum likelihood estimation leads to multiplicative $p(N,M) = \exp(-N_{\text{par}}/2)$, where N_{par} is a total number of adaptive parameters in all models (this penalty function is known as Akaike Information Criterion, see [11] for further discussion and references).

4.2 FUZZY DYNAMIC LOGIC AND MFT

The learning process consists in estimating model parameters \mathbf{P}_h and associating subsets of signals with concepts by maximizing the similarity (1). Fuzzy dynamic logic [11,37,38,39] is an iterative process, which solves this problem without combinatorial complexity as follows. The iterations start with any arbitrary values of the unknown parameters \mathbf{P}_h . The next step is to compute fuzzy association variables $f(h|n)$

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

These variables give a measure of correspondence between signal $\mathbf{X}(n)$ and model \mathbf{M}_h relative to all other models, h' . A mechanism of concept formation and learning, a dynamics of the modeling fields is defined as follows,

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

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

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-object n . Steps (2), (3) and (4) are repeated iteratively, until convergence, which is measured by parameter changes falling below a predefined threshold. As already mentioned, in the MF internal dynamics, similarity measures are adapted so that their fuzziness is matched to the

model uncertainty. Mathematically, this can be accomplished in several ways, depending on the specific parameterization of the conditional partial similarity measures, $l(n|h)$; for example, they can be defined as Gaussian functions,

$$l(n|h) = (2\pi)^{-d/2} (\det \mathbf{C}_h)^{-1/2} \exp\{-0.5(\mathbf{X}(n) - \mathbf{M}_h(n))^T \mathbf{C}_h^{-1} (\mathbf{X}(n) - \mathbf{M}_h(n))\}. \quad (5)$$

Here, d is the dimensionality of the vectors \mathbf{X} and \mathbf{M} , and \mathbf{C}_h is a covariance. The dynamics of fuzziness of the MF similarity measures is defined as

$$\mathbf{C}_h = \sum_n f(h|n) (\mathbf{X}(n) - \mathbf{M}_h(n))(\mathbf{X}(n) - \mathbf{M}_h(n))^T / N_h. \quad (6)$$

Initially, models do not match data; any data sample n fits equally poorly any model h , and association variables, $f(h|n)$, take homogeneous values across the data, associating all concept-models h with all input signals n . Correspondingly, covariances are large, encompassing all the data. As matching improves, covariances become smaller, and the association variables, $f(h|n)$, tend to high values 1 for some subsets of signals and models and zero for others; thus certain concepts get associated with certain subsets of signals (objects are recognized and concepts formed). The following theorem was proven [11].

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

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 sensor data. Despite a combinatorially large number of items in (1), the computational complexity of the MF method is relatively low, it is linear in N and could be implemented by a physical system (like computer or brain). These equations describe a loop system, which is illustrated in the block-diagram in Fig. 1. The MFT / dynamic logic loop sustains its operations on its own; the loop is not closed in that there are input signals into the loop and output concepts from the loop. This theorem is proved by demonstrating that similarity (1) increases at each iteration step, eqs. (3) and (4). A biological interpretation of these equations is that they satisfy the instinct for knowledge, therefore they are positive emotions. MFT adapting to data according to dynamic logic, ‘enjoys’ the learning process.

Comment. A definition (5) of conditional partial similarities using Gaussian functions can be considered a basis for the following probabilistic interpretation: a model $\mathbf{M}_h(\mathbf{P}_h, n)$ is a conditional statistical expectation of signals from object h described by parameters \mathbf{P}_h . A similarity measure (1) is a total likelihood. Let me emphasize that such an interpretation could be valid if for some values of the parameters, the models are accurate (that is, models actually *are* conditional statistical expectation). If models are approximate in a non-statistical sense, other similarity measures could be more preferable mathematically, like mutual information in the models about the data [11]. I’d also like to emphasize that unlike usual “Gaussian assumption,” MFT structure is quite general, it *does not assume that the signal distribution is Gaussian*, but only the conditional deviations between models and signals are, this likelihood can represent any statistical distribution [11].

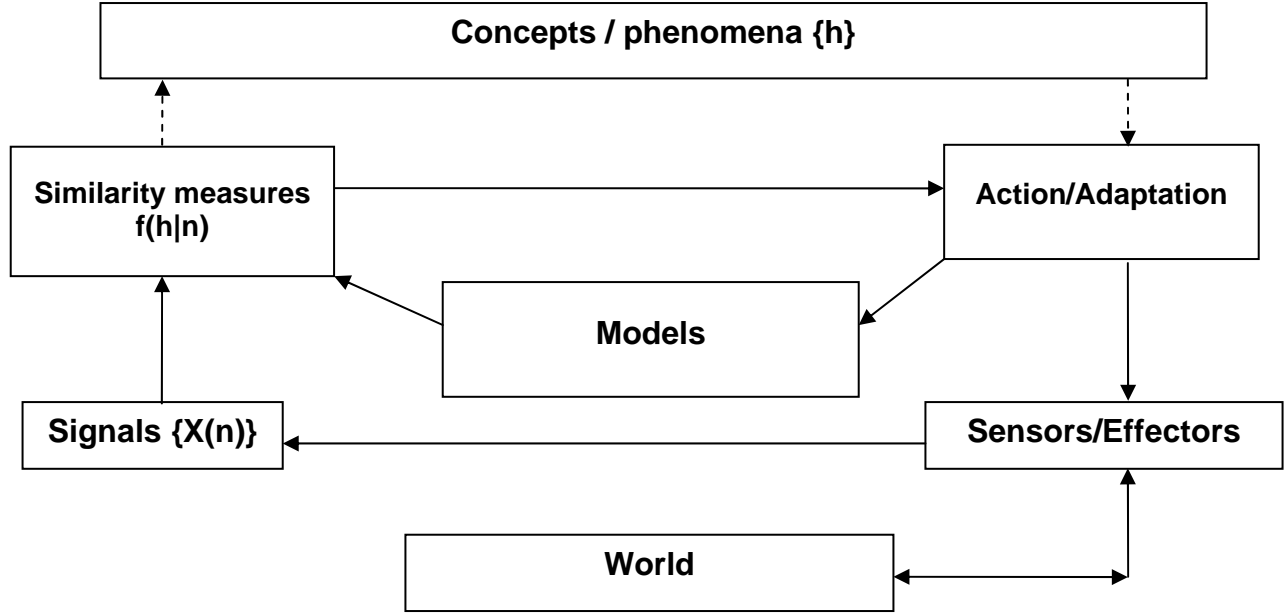


Fig.1. For a single level of MFT, input signals are unstructured data $\{X(n)\}$ and output signals are recognized or formed concepts $\{h\}$ with high values of similarity measures. The MFT equations (2) through (6) describe a continuous loop operation involving input signals, similarity measures, models, and actions of the model adaptation (the inner loop in this figure). Biologically, a similarity measure corresponds to the knowledge instinct and its changes to emotions.

Dynamic fuzziness control. An essential part of dynamic logic is a match between fuzziness of similarity measures and uncertainty in model parameters. Initial parameter values could be wrong, correspondingly, initial values of covariances should be large. The subsequent dynamics of fuzziness is automatically given by (6). Accurate estimation of covariances matrixes by (6) requires a sufficient amount of data. If the amount of data is not sufficient for accurate estimation of covariances, the following regularization procedure is recommended. Define an initial large value of covariances, C_{1h} , corresponding to initial errors in parameter values, and define the final smallest possible value for covariances, C_{0h} , according to sensor errors (or other known sources of errors. Modify (6) as follows,

$$C_h = C_{1h} \exp(-\beta \cdot it) + C_{0h} + \hat{C}_h. \quad (7)$$

Here, it is the iteration number, β defines the speed of fuzziness reduction, which should be matched to the speed of convergence, and \hat{C} is expression (6).

Summary of the DL convergence. During an adaptation process initial fuzzy and uncertain models (internal structures of the MF system) 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 input signals. An example of this process is discussed next.

Syntax, semantics and inference rules. The *syntax* of dynamic logic (the structure of its statements in terms of its elements) is given by the structure of similarity measure (1). The hierarchical aspect of syntax is given by the MFT hierarchical structure, and this is discussed later. MFT architecture also defines interactions and relations among models, which is also an aspect of the syntax of dynamic logic. Another aspect of dynamic logic syntax is the internal structure of models; any types of models can be used (analytic, numeric, logical rules, probabilistic, fuzzy, etc.), making it a general type structure. The *semantics* (the meanings) of dynamic logic have the following aspects: every signal obtains its meaning as a part of the model it belongs to (i.e., the model it has a high similarity with). For example, pixels associated with the model “chair” acquire the meanings of “chair.” Similarly, every model obtains its meaning as a part of a higher-level model in the hierarchy. This is the cognitive or knowledge-related meaning, it pertains to the structure of knowledge and is independent from any utilitarian use; for this reason it is called aesthetic as different from utilitarian (this designation is further discussed in more details in section 6). Similarity values give the strength of associations, they evaluate the certainty of knowledge. Changes in the similarity values are aesthetic emotions. They contain the aesthetic emotional aspect of semantics. The semantic field (a set of signals or models with similar meanings) is defined by signals (or models) associated with the same higher-level model. The utilitarian aspect of semantics is contained in relationships between cognitive models and behavioral (action) models. For example, a cognitive model “chair” is connected to behavioral model “sit.” Mathematical structures of utilitarian semantics are not discussed in this paper. The *inference rules* of dynamic logic specify how new statements are derived from previously known statements, these are given by eqs. (2) through (7). An important feature of these rules is the reduction of fuzziness and uncertainty during learning, as illustrated in an example in the next section.

4.3 IMAGE RECOGNITION, TRACKING AND SENSOR FUSION

Consider recognition of objects in images, a level 0 to level 1 type problem, in a complex case, when object signals are below clutter or noise. An information-type similarity measure is appropriate for this case [^{11,40}],

$$L(\{X\},\{M\}) = \prod_{n \in N} \left[\sum_{h \in H} r(h) l(X(\mathbf{n}) | M_h(\mathbf{P}_h, \mathbf{n})) \right]^{X(\mathbf{n})}; \quad (8)$$

Here, \mathbf{n} is a two-dimensional index enumerating image pixels, and $X(\mathbf{n})$ is an absolute value of the image intensity in pixel \mathbf{n} . In certain cases this similarity measure can be interpreted as mutual information in models $\{ M_h(\mathbf{P}_h, \mathbf{n}) \}$ about image $\{ X(\mathbf{n}) \}$. DL equation (2) does not change, in equations (3, 4), $f(h|n)$ is changed into $X(\mathbf{n})f(h|\mathbf{n})$, and N stands for the entire power in the image, $N = \sum X(\mathbf{n})$. As described in [⁴⁰], we define models accounting for image intensity as follows. First, an object pixel-model is defined, $\mathbf{Y}_h(\mathbf{P}_h, k)$, this is a set of image pixels for $k = 1 \dots K$. Then image intensity models are defined as

$$M_h(\mathbf{P}_h, \mathbf{n}) = \sum_k I(\mathbf{P}_h, k) G(\mathbf{n} | \mathbf{Y}_h(\mathbf{P}_h, k)). \quad (9)$$

Here, $I(\mathbf{P}_h, k)$ specify the model pixel intensities and Gaussian functions are used for smooth intensity distributions. The model is relatively insensitive to the number of pixels k in (9); it should be selected so that the object shape is adequately represented; also since the computational complexity is proportional to the number of pixels in the models, it should not be excessive. Convergence properties depend on the number of the model parameters, \mathbf{P}_h , rather than on the number of pixels k used in this model.

Figure 2 shows an example of using this technique for finding objects below noise in an image. This is a difficult problem because detection and model estimation have to be accomplished concurrently. A brute force fitting of multiple hypotheses to the data would lead to combinatorial complexity (10^{30} to 10^{40} computer operations, vs. 10^8 operations in our example). Because of this combinatorial complexity, detection usually requires high signal to noise ratio, so that detection can be performed separately from estimation. In this example the improvement in terms of signal to noise ratio is about two orders of magnitude.

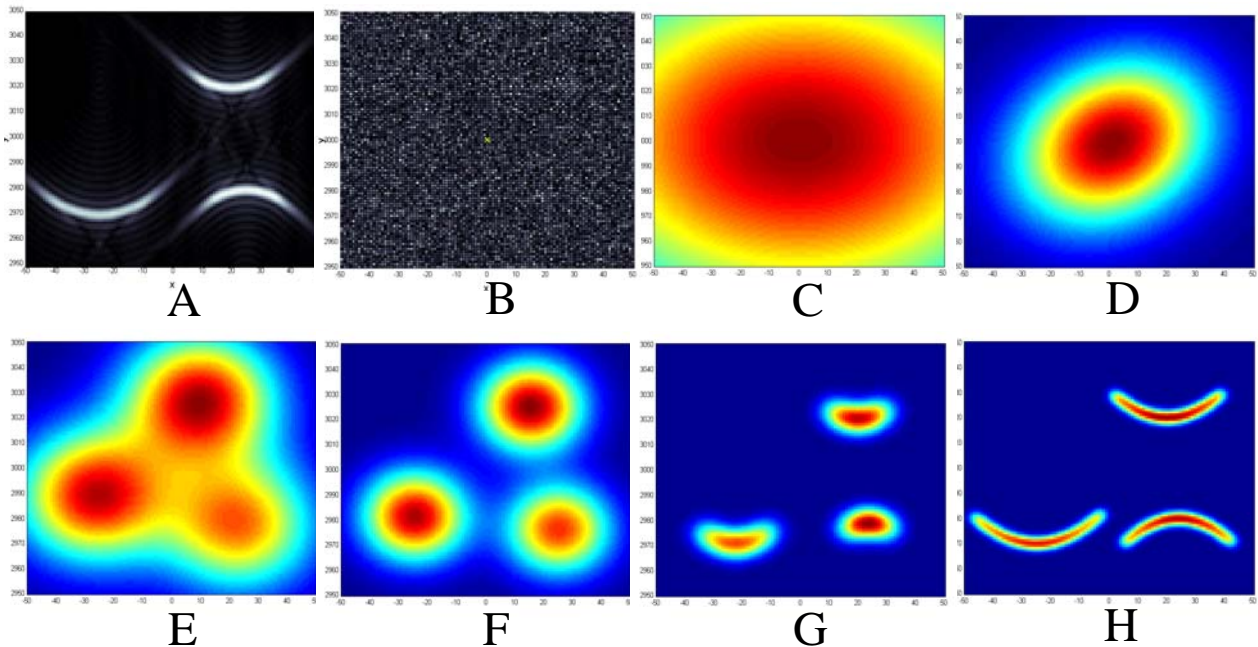


Fig.2. Finding ‘smile’ and ‘frown’ patterns in noise, an example of dynamic logic operation: (a) true ‘smile’ and ‘frown’ patterns shown without noise; (b) actual image available for recognition (signal is below noise, signal-to-noise ratio is between -2dB and -0.7dB); (c) an initial fuzzy model, the 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 [41].

In this example there are three parabolic-shape ‘smile’ and ‘frown’ objects buried in the noise. Several types of models are used to describe the data: 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. 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. 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.

MFT described above can be used for target tracking with appropriately defined models. Consider a case of pre-detected data, that is, sensor data are first compared against a small threshold. In this case data usually are a set of coordinates in time, so that every data point n is also characterized by its acquisition time, t_n , $\mathbf{X}(n, t_n)$. This problem is difficult if in addition to object signals, data also contain a large number of clutter data points; also several objects might be present. In these complex cases target detection and track estimation have to be performed concurrently (this joint problem is sometimes called ‘track-before-detect’). Like in the previous case of image recognition, signals amplitude does not convey sufficient information about target presence. The source of information is the consistency of target motion, and MFT exploits it by using the track model. Appropriate information about expected target trajectories therefore are necessary. For linear target motion (constant velocity), the linear model is

$$\mathbf{M}_h(\mathbf{P}_h, n, t_n) = \mathbf{x}_h + \mathbf{v}_h (t_n - t_0). \quad (10)$$

Here \mathbf{x}_h is the target h position at time t_0 , and \mathbf{v}_h is the target velocity. More complicated models can be used as needed [^{42,43}], for example, Keplerian models should be used for satellites. If the model is accurate, MFT performs the maximum likelihood estimation of the model parameters and therefore often attains or comes close to the best possible performance as given by the Cramer-Rao Bound (CRB) for the joint tracking and detection [⁴⁴].

Spatial dimensions of sensor data might be less than that of the model. For example, optical sensors measure 2-dimensional angular coordinates (of target and clutter signals), whereas the requirement may include estimation of 3-dimensional coordinates in (x, y, z) . Modification of the above model for this case is straightforward, angular positions should be expressed as functions of 3-dimensional coordinates. Another aspect of the problem is whether 2-dimensional data contain sufficient information for estimating 3-dimensional model. This is usually possible for tracking objects on Keplerian trajectories over an extended period of time. Sometimes it is possible for other types of motion. A general answer to the question if the track data contain sufficient information for model estimation and target detection can be answered using the joint tracking and detection CRB [⁴⁴]. An interesting and practically important situation of tracking in three dimensions with optical sensors includes sensor fusion, when two or more sensors are used for tracking.

MFT is equally applicable to identifying objects, tracks, and situations in signals from a single sensor or multiple sensors (sensor fusion). Again, one needs to use models, appropriate for each sensor. Let us introduce an index $s = 1 \dots S$, enumerating sensors. Instead of single sensor

signals $\{ \mathbf{X}(n) \}$, we now deal with multiple sensor signals, $\{ \mathbf{X}(s,n) \}$. Here, n enumerates data from each sensor separately, and it is appropriate to use notation n_s . To simplify notations, we will omit this sub-index. It is important to remember that there is no a priori association among data from different sensors; although n always stands for n_s , these are independent indexes and no association among sensors is assumed. MFT for sensor fusion requires development of models, which predict signals from multiple sensors; instead of $\mathbf{M}_h(\mathbf{P}_h, n)$ we have to use $\mathbf{M}_h(\mathbf{P}_h, s, n)$. For example, when tracking objects on linear tracks, the same model (10) (in 3-dimensions) is used for each objects, but a next step is required, the model for each sensor, $\mathbf{M}_h(\mathbf{P}_h, s, n)$ should be computed from (10) by using appropriate coordinate transformation for each sensor. Except for this trivial additional step, the previous formulation is applicable. Defining similarity by analogy with likelihood, as in (1), according to the basic law of probability,

$$L(\{\mathbf{X}\}, \{\mathbf{M}\}) = \prod_{s \in S} \prod_{n \in N} \sum_{h \in H} r(h) l(\mathbf{X}(s,n) | \mathbf{M}_h(s,n)); \quad (11)$$

Correspondingly, the only change in equations (2, 3, 4) is a substitution of index n by s, n . Association variables, $f(h|s,n)$, which previously associated models with signals, now associate models with signals from multiple sensors. Applications of this theory to the problem of joint navigation and sensor fusion of sensors from multiple UAVs are considered in [45]. I'd emphasize that this formulation, if required, solves the joint problem of concurrent fusion, tracking, navigation, and detection, along with association among data and sensors.

4.4 HIGH LEVEL FUSION

High level fusion requires the development of multilevel architecture and high-level models. High-level models for situational awareness have been discussed in literature, for example [46]. Future research will have to combine these type models with lower level models described above. Here we define a general architecture for multi-level MFT [15]. The previous sub-sections described a single processing level in a multi-level MFT system. Input signals to each level are activations of the lower level models. At each level output signals are activations of the models recognized at this level:

$$a(h) = \sum_n f(n|h). \quad (12)$$

Output signals from the previous level become input signals for the next level. In general, a higher level in a multilevel system provides a feedback input into a lower level. For example, sensitivities of retinal ganglion cells depend on the objects and situations recognized higher up in the visual cortex; or, a gaze is directed based on which objects are recognized in the field of view. Similar mechanisms can be implemented in multi-level MFT. Fig. 3 illustrate such a multi-level MFT system.

Each loop of operations shown at each level in the above figure involves multiple concept-models, $h = 1, \dots, H$. To some extent these multiple model-loops are independent, yet some models interact when they are associated with the same input signals. Each concept-model

is an intelligent agent; at its own level it competes with other agent-models for evidence in data. It sends its activation signal to the higher level. It may activate behavioral models (allocate processing and sensor resources, etc, and generate behavior directed into the outside world – processes not contained within the above equations). Each model-agent can activate adaptation mechanism; each model-agent possesses a degree of autonomy and is interacting with other agents. Thus MFT is an intelligent system composed of multiple adaptive intelligent agents. Each agent, interacts with the similarity measure and evokes behavioral response; it is a continuous loop of operations, interacting with other agents from time to time; an agent is "dormant" until activated by a high similarity value. When activated, it is adapted to the signals and other agents, so that the similarity increases. A subset of data in input signals may activate several concepts-agents, in this way data provide evidence for the presence of various objects (or situations). Agents compete with each other for evidence (matching to signals), while adapting to the new signals.

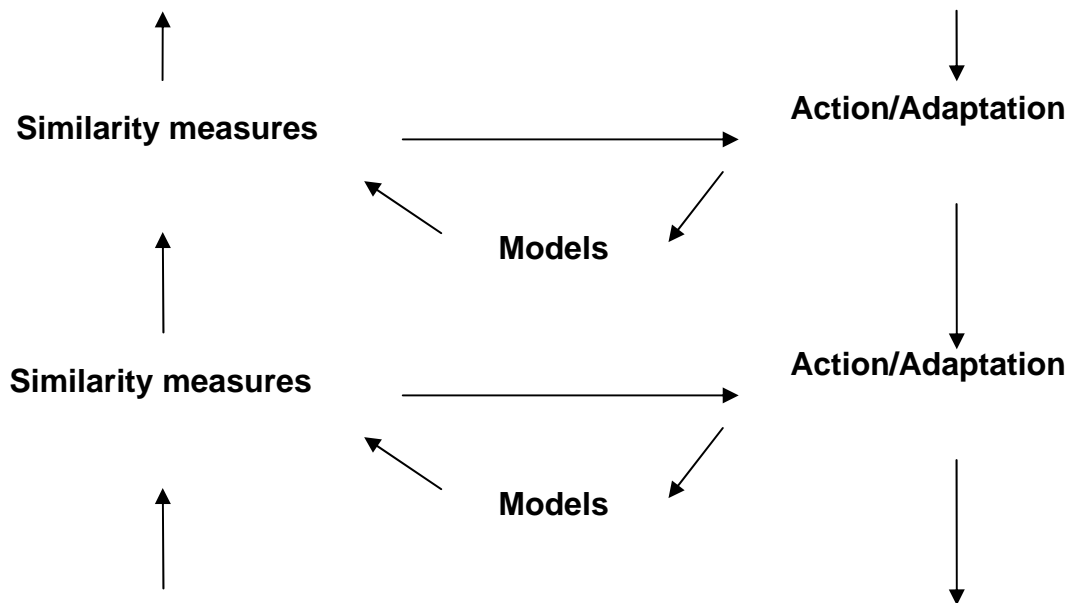


Fig.3. Multilevel organization of the MFT system. High levels of similarity measures correspond to concept-models recognized at a given level in the hierarchy; these are the input signals to the next, higher level. Also concept-models affect behavior (actions). Models at a higher level are more general than models at a lower level, like situational awareness models vs. track models.

5. INTEGRATING LANGUAGE AND SENSOR SIGNALS

High level sensor fusion requires integration of communications and sensors. A number of MFT models have been developed for various sensors, and used for sensor fusion and for recognition of simple situations [11]. 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 language and sensing. This requires the development of language MFT models.

5.1 LANGUAGE MODELS

Mathematical techniques previously considered for describing language ability suffer from combinatorial complexity for the same reason that cognitive models considered previously. For example, Solomonoff's methodology [47] is combinatorial in computational complexity because of its relying on formal logic. Chomsky's original ideas of Universal grammar [20] also relied on logical rules; his second proposal [21] relied on parametric models. Similarly combinatorially complex are logical tree structures considered by Pinker [10]. Here, we consider a non-combinatorial mathematical description of language learning and usage based on an extension of MFT. We argue that symbolic abilities require joint working of language and cognition, in other words, understanding of sensory data, and communication about this understanding. Language, like MFT is a hierarchical system, it involves sounds, phonemes, words, phrases, sentences, grammar... and each level operates with its own models. Development of these levels at each level is a research project, which is added by a number of already described linguistic models [9,10,12,48]. Here I discuss an approach to the development of models of phrases from words. This can be used for text understanding; for example, it could be used for an understanding-based search engine. The input data, $\mathbf{X}(n)$, in this "phrase-level" MF language system, are word strings, for simplicity, of a fixed length, P , $\mathbf{X}(n) = \{w_{n+1}, w_{n+2} \dots w_{n+P}\}$. Here w_n are words from a given dictionary of size K , $\mathbf{W} = \{w_1, w_2 \dots w_K\}$, and n is the word position in a body of texts. A simple phrase model is "a bag of word" [49,50,51], that is, a model is a subset of words from a dictionary, without any order or rules of grammar,

$$\mathbf{M}_h(\mathbf{P}_h, n) = \{w_{h,1}, w_{h,2} \dots w_{h,P}\}; \quad (13)$$

the parameters of this model are its words, $\mathbf{M}_h(\mathbf{P}_h, n) = \mathbf{P}_h = \{w_{h,1}, w_{h,2} \dots w_{h,P}\}$. The language acquisition project in this simplified context consists in defining models-concepts-phrases best characterizing the given body of texts in terms of a similarity measure.

Conditional partial similarities between a string of text, $\mathbf{X}(n)$, and a model \mathbf{M}_h could be defined by a proportion of the matches between the two sets, $\mathbf{X}(n)$ and \mathbf{M}_h , $l(n|h) = |\mathbf{X}(n) \cap \mathbf{M}_h| / P$. Thus similarity (1) is defined and it could be maximized over the unknown parameters of the system, $\{\mathbf{P}_h\}$, that is, over the word contents of phrases. This would result in learning models-concepts-phrases, accomplishing the goal of the language acquisition project. The difficulty of the above approach is that the dynamics of MFT cannot be used for the similarity maximization, in particular, (3) requires evaluating derivatives, which requires a smooth dependence of models

on their parameters. Without dynamic logic of MFT, the computational complexity of this language acquisition project becomes combinatorial $\sim K^{(H*N*P)}$, this is a prohibitively large number. In the following section we extend dynamic logic to this type of models, specified as sets of qualitative variables.

5.2 DYNAMIC LOGIC OF QUALITATIVE SETS

Developing dynamic logic procedures for qualitative sets, like phrase bag models, represents a principled step beyond procedures considered above. It is generally important for developing multilevel models, because input signals at higher levels are qualitative variables, concepts, recognized at lower levels; and higher-level models are sets of such variables. ‘Fitting’ uncertain situational-awareness models to uncertain data often leads to combinatorial complexity of high-level joint learning and fusion. Within the MFT formulation this combinatorial complexity is related to a need to maximize a similarity measure of type (1) over the content of qualitative set models. If this maximization were attempted by ‘brute force’ combinatorics, it would lead to a combinatorial complexity. It is a consequence of “logic-type” similarity measure, which treats every potential phrase-model (every combination of words) as a separate logical statement. The problem can be solved by using dynamic fuzzy phrase-contents, as follows. First, define fuzzy conditional partial similarity measures,

$$l(n|h) = (2\pi\sigma_h^2)^{-S/2} \exp\{-0.5 \sum_p e(n,h,p)^2 / \sigma_h^2\}, \quad (14)$$

where $e(n,h,s)$ is a distance (measured in the numbers of words) between the middle of the word sequence $\mathbf{X}(n)$, that is $n+P/2$, and the closest occurrence of the word $w_{h,p}$; the sum here is over words belonging to the phrase-model h . In practical implementations, the search for the nearest word can be limited by $\pm 3\sigma_h$ words, and $e(n,h,p)$ falling outside this range can be substituted by a $(3\sigma_h+1)$. The dynamics of fuzziness of this similarity measure is given by a modification of (6),

$$\sigma_h^2 = \sum_n f(h|n) \sum_p e(n,h,p)^2 / N_h. \quad (15)$$

Second, define fuzzy phrase-contents, that is a degree of the word $w_{h,p}$ “belonging” to a model-phrase h , $\phi(p|h)$; this is a function of the average distance of the word $w_{h,p}$ from the phrase-model, $\varepsilon(p,h)$

$$\varepsilon(h,p) = \sum_n f(h|n) e(n,h,p)^2 / N_h; \quad (16)$$

$$\phi(p|h) = p(h|p) / \sum_{p' \in h} p(h|p'); \quad p(h|p) = (2\pi\sigma_h^2)^{-1/2} \exp\{-0.5 \sum_p \varepsilon(h,p) / \sigma_h^2\}, \quad (17)$$

The dynamics of the word contents of the phrase-models is given by modifying P (the number of words in phrases) in the iteration process, say, by defining $P_h \sim P\sigma_h$, or by requiring $\phi(p|h)$ to be above a threshold value, and keeping in each phrase-model words satisfying this criteria. The dynamics defined in this way results in learning phrase-models (concepts) and accomplishes the

goal of the language acquisition project without combinatorial complexity, the computational complexity is moderate, $\sim H*K*P^2$.

The “bag-of-word” phrase models considered above are simpler than tree-like dependencies or known structures of natural languages [9,10,12,13,48,52]. These more complicated “real” linguistic models can be used in place of a simple distance measure $e(n,h,p)$ in (15). In this way the models of noun and verb phrases and tree structures can be incorporated into the above formalism of MFT.

5.3 JOINT LANGUAGE AND SENSOR MODELS

Integration of language and sensor cognition in MFT is attained by joint language and cognitive models, so that a complete concept-model \mathbf{M}_h is given by [53,33,51]

$$\mathbf{M}_h = \{ \mathbf{M}_h^C, \mathbf{M}_h^L \}; \quad (18)$$

Here \mathbf{M}_h^C denotes cognitive (sensory) part of models of objects and situations in the world, like those considered in section 4 and \mathbf{M}_h^L is a language part of the model. Consider now this integrated model as the mind’s mechanism of integrating language and cognition. A data stream constantly comes into the mind from all sensory perceptions; every part of this data stream is constantly evaluated and associated with cognitive models using fuzzy dynamic logic mechanism described in previous sections. In this fuzzy dynamic association, at the beginning the models are fuzzy, the difference between language models and other models for sound signals are uncertain, and every piece of data is associated with many models, linguistic and cognitive. Gradually, models are adapted, their correspondence to specific data improve, selectivity to language signals and non-language sounds is enhanced. Language models are associated with some degree of specificity with words (sentences, etc.), and cognitive models are associated with objects and situations of perception and cognition. Some degree of association between language and cognitive models occurs before any of the model attain a high degree of specificity characteristic of our conscious concepts. Certain language models evolve faster than their corresponding cognitive models and vice versa. Correspondingly uncertainty and fuzziness of the two aspects of integrated models may significantly differ. Still, existence of a low-fuzzy linguistic model speeds up learning and adaptation of the corresponding cognitive model and v.v. I suggest that this is a mechanism of interaction between language and cognition.

The described mechanism of interaction between language and cognition may apply to ontological development and learning, biological specie evolution, and evolution of cultures. The differences between these learning and evolution processes is in the degree of specificity of a priori models (inborn, or accumulated in culture) and in the type of data available for learning and evolution. For example, child learning occurs in parallel in three realms: (1) language models are learned to some extent independently from cognition, when language data are encountered for the first time with limited or no association with perception and cognition (like in a newborn baby); (2) similarly, cognitive models can be learned to some extent independently from language, when perception signal data are encountered for the first time in limited or no association with language data; and (3) language and cognitive models are learned jointly, when language data are present in some association with perception signals; like during mother talking to a baby: “this is a car” (visual-perception-models and the corresponding language-word-

models are engaged together); another example is more complicated conversations: “Look at Peter and Ann, they are in love” (leads to learning related cognitive-models and phrase-models). A significant part of child learning (at the age between 2 and 5) consists in learning language models first; it would take a significant part of life to learn cognitive models corresponding to these language models. Language models learned first stimulate learning of cognitive models.

Development of high-level fusion systems should follow similar path. Integration of language and cognition in MFT is attained by characterizing objects and situations in the world with two types of models, language models considered above and cognitive models considered in section 4 and in [7,11,46]. A relatively simple system can use bag-models for each layer, like ‘bag of phrase’ model for the next level of concepts (say, sentence, paragraph), and so on. Alternatively, more realistic language models of sentences, paragraphs and large bodies of texts can be used [54,55]. Such integrated MFT system learns similarly to human, in parallel in three realms as described above. If this high-level fusion system will interact with human and computer agents, it would learn language and cognition, similarly to human babies. We can hope that such systems will improve with experience and not become obsolete.

In the 1960s and 70s artificial intelligence relied on “symbolic” methods. In the 1980s intelligence research switched to exploring a variety of neural paradigms. Since mid-1990s mixed techniques were explored, the proper tradeoffs between neural and symbolic techniques received a great deal of attention. In this new research, however, the fundamental limitation of the old “symbolic” methods was not identified. Namely, it was not analyzed why the same word “symbol” is used for trivial objects, like traffic signs, and for culturally significant artifacts provoking wars and piece, like Magen David, Cross, or Crescent. We suggest the reason is that the word “symbol” is used for two different meanings. One is the logically defined definite objects; another is dynamic processes unifying language and cognition. A mathematical description of these dynamic processes is proposed in this section. The conclusion is that combining axiomatic-logical notation-signs with standard neural architectures will not lead to symbolic ability. The promising approach to describe symbols mathematically is outlined above: symbols are adaptive processes combining language and cognition. These symbols are initially domain-independent; they learn specific domain-dependent information “on their own.” In the following section we consider psychological interpretation of these symbol-processes and relate the above mathematics to the working of mind.

6. DISCUSSION

6.1 WHY MIND, INSTINCTS AND EMOTIONS?

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 the history of science and engineering. Newtonian laws can be written in a few lines, but an engineering manager cannot hand these few lines to a young engineer and ask her to design an airplane, or rocket. Similarly, Maxwell 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 the conclusion of this paper we summarize the main aspects of working of the mind as described by equations given in this paper.

6.2 MFT DYNAMICS

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 processes ensuring a smooth convergence is a correspondence between uncertainty in models (that is, in the knowledge of model parameters) and uncertainty 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 $\mathbf{X}(n)$, when parameter values match object properties, and $f(h'|n)$ values become close to 1 for $n \in \{n'\}$ and 0 for $n \notin \{n'\}$. 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. Cognition is different from perception in that models are more general, more abstracts, and input signals are the activation signals from concepts identified (perceived, cognized) at a lower hierarchical level; 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) [^{56,57,58}]. An initial “mapping” between Kantian theory of the mind and MFT was outlined in [¹¹]. We now briefly discuss

relationships between the MFT and concepts of mind originated in psychology, philosophy, linguistics, aesthetics, neuro-physiology, neural networks, artificial intelligence, pattern recognition, and intelligent systems.

6.3 ELEMENTARY THOUGHT-PROCESS, CONSCIOUS, AND UNCONSCIOUS

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 [11,14,62]. Here and in the following subsections 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 [14], in other words, bottom-up and top-down signals coming from outside (external sensor signals) and from inside (internal representation signals). According to Carpenter and Grossberg [59] 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 \mathbf{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. The elementary thought-process also involves elements of conscious and unconscious processes, imagination, memory, concepts, instincts, emotions, understanding and behavior as described later.

A description of working of the mind as given by the MFT dynamics was first provided by Aristotle [60], describing cognition as a learning process in which an a priori form-as-potentiality (fuzzy model) meets matter (sensor signals) and becomes a form-as-actuality (a logical concept). Jung suggested that conscious concepts are developed based on genetically inherited structures of the mind, archetypes, which are inaccessible to consciousness [61], and Grossberg [14] 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.

6.4 IMAGINATION AND COGNITION

Visual imagination involves excitation of a neural pattern in a visual cortex in absence of an actual sensor stimulation (say, with closed eyes). The same visual cortex neurons that serve for perception are also used by the brain for imagination. Carpenter and Grossberg resonance model [59] and the MFT dynamics both describe imagination as an inseparable part of perception and cognition: imagined patterns are top-down signals that *prime* the perception cortex areas (*priming* is a neural terminology for making neural cells to be more readily excited). In MFT, models \mathbf{M}_h give the imagined neural patterns. Perception and cognition occur as a match between top-down imaginations and bottom-up signals from sensory organs or from model-concepts recognized at lower levels. Kant [57] came amazingly close to explaining the mechanisms of perception and cognition, when he called them “a play of cognitive functions of imagination and sensing” [25].

6.5 MIND VS. BRAIN

Historically, the mind is described in psychological and philosophical terms, whereas the brain is described in terms of neurobiology and medicine. Within scientific exploration the mind and brain are different description levels of the same system. Establishing relationships between these description is of great scientific interest. Today we approach solutions to this challenge [62], which eluded Newton in his attempt to establish physics of “spiritual substance” [63]. General neural mechanisms of the elementary perception and cognition (which are similar in MFT and ART [59]) have been confirmed by neural and psychological experiments, this includes neural mechanisms for bottom-up (sensor) signals, top-down “imagination” model-signals, and the resonant matching between the two [62,64]. Adaptive modeling abilities are well studied and adaptive parameters identified with synaptic connections [65]; instinctual learning mechanisms have been studied in psychology and linguistics [8,20,66]; identifying neural structures responsible for knowledge and language instincts is a next challenge for the neural sciences.

6.6 INSTINCTS AND EMOTIONS

Functioning of the mind and brain cannot be understood in isolation from the system’s “bodily needs”. For example, a biological system (and any autonomous system) needs to replenish its energy resources (eat); this and other fundamental unconditional needs are indicated to the system by instincts, which could be described as internal sensors. Emotional signals, generated by this instinct are perceived by consciousness as “hunger”, and they activate behavioral models related to food searching and eating. In this paper we were concerned primarily with the behavior of perception, cognition, and language learning, which are governed by the instincts for knowledge and language. Other instinctual influences modify perception and cognition processes in such a way that desired objects “get” enhanced recognition. It can be accomplished by modifying priors, $r(h)$, according to the degree to which an object of type h can satisfy a particular instinct. Details of these mechanisms are not considered in this paper.

6.7 AESTHETIC EMOTIONS AND INSTINCT FOR KNOWLEDGE

Recognizing objects in the environment and understanding their meaning is so important for human evolutionary success that there has evolved an instinct for learning and improving concept-models [67,25]. 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). According to Kant [57] these are aesthetic emotions (emotions that are not related directly to satisfaction or dissatisfaction of bodily needs). Aesthetic emotions in MFT correspond to changes in the knowledge instinct (1). The aesthetic emotion is negative, when new input signals do not correspond to existing models. The mathematical basis for the theorem in section 4.2 can be interpreted psychologically: during dynamic logic iterations the aesthetic emotion is always positive. MFT system ‘enjoys’ learning.

In sections 4 we considered perception and cognition concept-models and similarity measures; using them in (1) yields an instinct driving the MFT system to improve the knowledge

about the world. Similarly, using in (1) language models and similarity measures considered in section 5, yields the MFT system improving the knowledge of language, or the language instinct. Combining cognitive and linguistic models results in a system with combined linguistic and thinking abilities: language and sensor information together help adapting both, language and cognitive models. This is the main mechanism of cultural accumulation and transmission of knowledge; and it can serve as a foundation for knowledge accumulation and transmission in collaborative multi-level fusion systems.

6.8 COGNITION, SIGNS AND SYMBOLS

Signs and symbols are essential for working of the human mind, for accumulation and transmission of knowledge in human culture, and are extensively used 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 [68] 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 as 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 conscious and unconscious [61], 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 [69]. Deacon [68] thought that the essence of the human symbolic ability is two interacting parallel hierarchies, like described in sections 4 and 5 hierarchy of cognitive models and a hierarchy of sign (language) models; he called it symbolic reference.

Combining mathematical developments in sections 4 and 5 with the above discussion, we reach the following conclusion for consistent meanings of signs and symbols [25,51]. 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. Symbol are psychological processes of sign interpretation, they are equivalent to elementary thought processes (section 6.3), 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 and involve multiple levels of MFT or the mind hierarchy. Future intelligent systems with multiple levels of fusion, future sensor-webs, will be designed using this biological knowledge. They will participate in human-computer collaborative networks. They will integrate learning of language with learning of complex cognitive concepts. They will integrate communication with information fusion, and instead of quick obsolescence, their performance will improve with time and experience by accumulating knowledge similar to human cultures.

7. SUMMARY

This paper proposes that flexible and adaptive high-level fusion, as well as high-level cognition is not possible without fusion of cognition and language. High-level cognition as understanding of contents of sensor signals cannot be developed separately from language-type communication. One reason for this statement is biological analogy, only the human mind is capable of high-level fusion, cognition, and language; and the human mind develops these capabilities jointly. Another reason for this statement is mathematical, high-level models or understandings cannot be learned (developed, adapted) directly from sensor signals, because they are not grounded directly in sensor signals; they are grounded in high-level language-communication messages. Language, in turn, is grounded in mutual understanding among multiple communication agents. Future adaptive high-level fusion systems, therefore, will be collaborative systems involving man and machine.

The paper proposes a mathematical approach to developing such integrated sensor-communication or cognition-language systems. It combines PBIS with MFT. The main elements include phenomenology of the human mind and sensing processes, a dual hierarchy of MFT, a cognitive hierarchy and language hierarchy. At each hierarchical level there are models, similarity measures, and the dynamic logic mechanism maximizing similarity between the models and input signals. Input signals to each level are concept-models recognized at a lower level, output signals are new concept-models. In addition to this upstream of more and more complicated concept-models, there is a downstream of adaptational, attentional, and behavioral signals. Cognitive interpretation of this structure includes models as mechanisms of conceptual understanding, similarity maximization as the instinct for knowledge, changes in similarity as aesthetic emotions. An important aspect of dynamic logic operation is that the initial states of cognitive and language models are vague and fuzzy uncertainty corresponding to absent or uncertain knowledge. In the result of learning and adaptation, uncertain models develop into certain crisp or probabilistic knowledge. In this process all available information is extracted from signals and fused jointly in sensory and communication domains.

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