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Commentary on: "A Nonlinear, GA-optimized, Fuzzy Logic System for the Evaluation of Multisource Biofunctional Intelligence"

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Biofunctional artificial intelligence is an interesting and effective approach that lies between the two extremes of symbolic (top-down) and subsymbolic (bottom-up) artificial intelligence. It offers the best of these hitherto separate worlds and integrates them through a comprehensive perspective on brain functioning. Homaifar, Copalan, Dismuke, and Iran-Nejad (2000) use the biofunctional approach to simulate two multisource intelligence evaluation systems. Their preliminary work inspires a number of new research extensions and directions.

In the biofunctional model of learning, three interacting functional subsystems, to be distinguished from the model's nervous system subsystems, may be identified: the ongoing brain activity (OBA) subsystem, the momentary constellation firing (MCF) subsystem, and the biofunctional self-regulation (BSR) subsystem. Homaifar, Copalan, Dismuke, and Iran-Nejad (2000, this issue) use these functional subsystems of the biofunctional model to develop two non-linear intelligence evaluation systems (IES). The two IESs are similar only in their manifestations of the OBA, MCF, and BSR functional subsystems. The OBA functional subsystem is modeled by nonlinear equations of intelligence with a definite structure in the form of the summation of fuzzy values multiplied by their associated coefficient (or weight raised to the associated exponent). The MCF is represented by a sequence of behavioral decisions in the form of graded responses to multiple choice items on a behavioral test that was administered to a number of human subjects. The

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BSR is represented by a genetic algorithm which evolved the variables, domains, coefficients and exponents for the OBA functional subsystem. The results reported showed that both IES variations were able to evolve (self-regulate) near-optimal parameters for the OBA even though the nonlinear structure of the OBA was unknown to the BSR.

It is important to understand where the biofunctional paradigm fits within the larger area of artificial intelligence (AI). Artificial intelligence techniques can be separated into two basic groups: symbolic and subsymbolic (Nilsson, 1998). Symbolic AI methods are based primarily on the physical symbol system hypothesis. This hypothesis states that any physical symbol system possesses the potential substance for intelligent behavior. Symbolic AI methods are typically implemented in a top-down fashion. Subsymbolic AI methods, on the other hand, are primarily based on the physical grounding hypothesis which states that intelligent behavior can be achieved by allowing a number of different functional subsystems to interact with an environment. In subsymbolic AI paradigms, intelligent behavior is emergent (bottom-up).

Biofunctional AI can be viewed as occupying a position between the two extremes. The biofunctional paradigm is flexible in that there is no constraint on the implementation of any of the three basic functional subsystems. These decisions are problem specific. For example, the biofunctional method used for the IESs would probably be seen more as subsymbolic than symbolic. However, if the OBA was implemented using first-order logic and/or if the BSR was implemented as a deterministic tree search procedure, then the resulting biofunctional method would seem more like a symbolic approach.

In fact, Homaifar, Baghdadchi, Hawari, and Iran-Nejad (2000) have developed a biofunctional method for robot motion planning and obstacle avoidance where the OBA is modeled by two sub-OBAs. The first sub-OBA was implemented as a Sugeno fuzzy logic controller (Jang, Sun, and Mizutani, 1997) while the second sub-OBA was implemented as a classifier system (Goldberg, 1989).

Another aspect related to its flexible nature is that the biofunctional model is not a hybrid system. In other words, many AI models begin with a self-standing modular structure and must be supplemented later with other self-standing modular structures through coupling (as the need arises for additional functions), much in the same way that a computer might be later supplemented with a printer. For instance, neural network models initially lacked any self-regulation function. Later, this function was added in the form of separate modules resulting in what is commonly known in AI as hybrid models. The biofunctional model represents a natural integration of its functional subsystems.

Currently, the field of biofunctional AI is wide open. The IES variations presented by Homaifar et al. perform multiobjective optimization using value preference (Yu, 1989). There exists a number of other alternatives including lexicographic and Pareto preference. It would be interesting to see biofunctional extensions along these lines. Similarly, as mentioned earlier, the evaluation equations of the IESs had a predefined nonlinear structure; it is important to allow even the underlying structure of an OBA to adapt. The OBA may best be represented as an ever-evolving program. With the advancements in the field of Genetic and Evolutionary Programming (GEP) [Fogel, 1995; Koza, 1992], this line of research is promising. It is envisaged by the commentator that fuzzy GEP will be to biofunctional learning what backpropagation was to neural computing.

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The Nature of Distributed Learning and Remembering

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Researchers have held different views on what role the nervous system should play in the study of psychological phenomena. By far, the most informative line of research in the area has been conducted by Lashley whose work has opened our eyes to the possibility that learning and remembering are unexplainable in terms of the storage and retrieval of specific traces. However, with this exception, the twentieth century is likely to be remembered as an era during which the brain has been considered irrelevant for the study of the mind. This has certainly been the case with the research following the computer-inspired cognitive revolution. Perhaps the most revealing indication of the degree of reluctance to embrace the brain in the study of the mind can be found in the so-called brain-inspired connectionism that purports to use the brain as a metaphor, and not as the literal foundation it really is, for the structure of cognition. Focusing on the topics of learning and remembering, this paper discusses the role of the brain in the research of Lashley, brain-inspired connectionism, and the emerging field of biofunctional cognition. The hope is to illustrate, through biofunctional cognition, the productive nature of basing psychological thinking on the foundation of a comprehensive theory of the functioning of the nervous system.

Lashley (1915, 1929, 1950) devoted more than three decades of research in pursuit of localized memory traces in the brain. His detailed investigations uncovered no such traces, but prepared the empirical groundwork for the development of the nonlocalizationist perspective on learning and remembering. After Lashley (1890–1958), the research on distributed memory con-

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