Chapter 18
OFN-Based Brain Function Modeling

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Abstract A modeling approach may significantly help to explore the problem of weak understanding of the physiological and pathological central nervous system function in the most noninvasive and comprehensive way. The aim of this chapter is to assess and discuss the extent to which possible opportunities concerning computational brain models based on fuzzy logic techniques may be exploited.

18.1 Introduction

Structured networks and functional connections of interacting neural populations underlying both physiological and pathological central nervous system (CNS) function are still poorly understood. Interdisciplinarity and independence of research provide a variety of scientific approaches, used tools, and wide coverage and even overlapping of the research fields, especially as regards human research, including neuroscience [1]. The modeling approach may significantly help to explore the aforementioned problem in the most noninvasive way. The aim of this chapter is to assess and discuss the extent to which possible opportunities concerning computational brain models based on fuzzy logic techniques may be exploited.

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18.2 State of the Art

18.2.1 Theory

Researchers within the basic sciences follow their intuition, knowledge, and creative thinking, finally formulating principles of nature [1]. It is easier to derive general mechanisms because they are often repetitively used in many versions. Thus gathered information may be more complete. An additional problem within knowledge gathering is ensuring the highest possible quality of research. An important way to assess relevance of research seems to be critical peer reviews, including novel approaches including the role of preprint servers (such as ArXiv) and open reviews. Due to emerging interdisciplinary approaches, a variety of used methods and tools, and overlapping methodologies, it is hard to ensure the quality control of scientific papers. Weaknesses of traditional preprint reviews (such as inability to detect errors/fraud, lack of transparency and reliability, potential for bias and unethical practices, inconsistencies among reviewers) may be eliminated by quicker postprint reviews, supporting the relevance of evidence and building knowledge. This may constitute a novel gold standard in the assessment of scientific papers [12, 22, 24, 30, 60]. The functional organization of the central nervous system (CNS) in humans is not fixed. No doubt functional representations are dynamic and continuously modified by the human's experience due to experience-dependent plasticity as far as neurological diseases or injuries and natural age-dependent neurode-generative changes are concerned.

18.2.2 Modeling Complex Ideas with Fuzzy Systems

Fuzzy set theory [66, 67] offers powerful potential in modeling imprecision understood differently from possibility. There are many publications that gather basic ideas [38, 39, 56]. As mentioned in previous sections, researchers who work on the problem of brain modeling often try to connect practical observation results with intuitive knowledge. Some parts of this knowledge are precisely formulated but other parts are vague. This gives us an opportunity to use an experience of the brain modeling scientists and merge it with the concrete results of available research. The theory of fuzzy sets offers help for defining formal models in situations where only linguistic description is possible [67]. The idea of hierarchical fuzzy systems [19, 20, 48] offers special modeling potential which is a good tool for representing complex dependencies. It preserves the intuitive linguistic description of a model and also allows description of highly complicated relationships. When the modeled object needs quantitative parameter representation, use of the classical theory of fuzzy sets can pose some calculation problems. The specific model of Ordered Fuzzy Numbers (OFNs) overcomes typical computation problems with classic fuzzy numbers (see [27, 28, 42] and also Sect. 4.2 of Chap. 4). An additional advantage of OFNs is the potential for modeling a trend, which provides a process with more information than only value. As it is intuitive information provided by the experienced brain modeling scientists it makes it easier to represent the dependences as growing and decreasing. In the following parts of this text the idea of a fuzzy inference block is presented (see also [45]). It is a basic conception for modeling complex dependencies using the general fuzzy concept. The OFN have special application potential there.

As another interesting application of OFNs, in Sect. 18.6.3 of this chapter the proposition for modeling the learning rate coefficient (an important element of the neural network adaptation procedure) is presented and discussed.

18.2.3 Clinical Practice

Knowledge exploitation is not easy, the evidence-based medicine (EBM) paradigm. The so-called EBM triad combines three main factors influencing the clinical decision-making process:

- Individual clinical knowledge and experience
- Actual, reliable, valid, and statistically significant in the particular case of external evidence
- Values and expectations of an individual patient (and sometimes his or her family) [33]

Incorporation of EBM provides conscientious, explicit, judicious, and reasonable use of novel reliable evidence in clinical decision making about the care of individual patients [33]. An ideal research method for clinical purposes should be direct, noninvasive, and sufficient spatial and temporal resolution of the purposeful representation imaging in an awake patient. The common strategy aims at a more complete brain atlas incorporating and integrating anatomy in macroscale, microscale, and nanoscale, and data from medical imaging, including functional ones (fMRI, MRI, DTI, MEG, etc.).

The aforementioned solution would be useful for better understanding of brain structure and function, both from a physiological and pathological point of view [58]. The ultimate aim is the identification of disease-related alterations affecting neural structures and their functional connectivity [23]. Moreover, interdisciplinary studies may fill the gaps between all of the involved disciplines that are still unexplored. It requires bigger teams consisting of neuroscience theorists, physicians, neuroanatomists, and specialists in image analysis, data analysis, computational neuroscience, molecular biology, physiology, cognitive science, and even philosophy. Invalid or incomplete integration of neural information within the human brain is perceived as the main cause of mild and severe neurological disorders, affecting not only cognitive processing, but also emotional processing and motor control. Invalid synchronized or simply unsynchronized structures may be deployed far from each other, and their weaker than usual co-occurrence of excitation/inhibition may be hard to detect. Thus structural connectivity (SC) is only one part of functional connectivity

(FC). Their exact and complete description is far beyond our current possibilities, but despite that, such results for particular diseases have been reported [23]. Analysis of the interaction between social and biological determinants of behavior emphasizes better understanding of the complexity of the human brain in action thanks to:

- Coequal contributions of emotions and affects towards normal brain functioning regarding the "higher" and "lower" cognitive functions built into human neurophysiology
- Brain relation to body in biological psychiatry thanks to embodiment, embeddedness, enactivism, extended cognition, and situatedness
- Importance of "being in relation" for reasonable neural functioning, especially in terms of social relationships for the human brain from birth until death
- Computational neurosciences taking into account information integration theory [37]

Large prospective datasets of patients with Alzheimer's disease (AD) allow us to construct advanced brain models of (physiologically) healthy subjects and patients with AD (with pathophysiological changes occurring over time). Despite the huge amount of information taken into account and efforts of scientists, the aforementioned models are still regarded as inadequate. Their limitations are: lack of scaling (i.e., they are single-scale) and lack of reflecting the complexity and interdependence of brain changes at different levels (molecular, cellular, tissue) [49]. We should take into consideration that changes in a patient's brain may take place much earlier than visible symptoms and diagnostic outcomes. Thus early diagnosis providing datasets for early changes within the central nervous system may be difficult to obtain. MR elastography (MRE) varies for a healthy brain, but is regarded as a reliable marker of neurodegenerative disease (e.g., dementia) [35]. Rapid development of artificial stimulation techniques (e.g., transcranial direct current stimulation, tDCS) both in clinical practice and cognitive neuroscience research requires development of a completely novel family of computational models of such phenomena [47].

18.2.4 Models for Linking Hypotheses and Experimental Studies

The simplest relationships among theory, computational models, and experimental research are:

- Predictive understanding of brain processes needs for experimental data placed into a quantitative framework.
- Aforementioned framework is provided by biologically plausible computational models.
- Computational models provide a tool for exploring cognitive and brain processes too complex for direct exploration (e.g., due to diverse timescale or simultaneous multilevel processing).

- Aforementioned environment allows us to interpret results from empirical studies and generate novel hypotheses, testable using further models and experimental studies.
- Computational models may inspire novel theories that are difficult to formulate based only on analysis of the experimental results [47].

Detailed strengths and limitations of computational brain models have been analyzed in [45]. The most advanced projects within neuroscience such as the EC Human Brain Project are hard to plan and develop; there is a lack of simple principles within understanding the brain (neural codes, transformation laws) and no particular scientific method has proven to be the right one. Even selecting any single direction regarded as the most probable is not always possible; despite the best current knowledge, previous achievements, and further efforts there is very limited chance to hit the target. Thus application of traditional scientific paradigms that proved to be successful during the last several centuries may be insufficient [1]. There is a need for a novel approach, derived from accumulated knowledge and experience of many scientists, creatively engaging interdisciplinary approaches and tools. Henry Markram has defined seven challenges for neuroscience [32]:

- Big research teams with the resources sufficient to deal with the big scientific problems
- Data ladders, interlinked sets of data providing a complete image of single areas of the brain at their different levels of organization
- Efficient predictive tools
- Novel hardware and software sufficiently powerful to simulate the brain
- New ways of classifying and simulating brain diseases, leading to better diagnosis and more effective drug discovery
- New brain-inspired technologies, with benefits for industry and for society
- Social understanding of neuroscience and its benefits for society [32]

Although the assumption that realistic computational models are easier and quicker solutions than reconstruction of the whole brain region or even the whole central nervous system [14] may be true. To build a model of the whole brain we have to take into consideration 1,000 different gray matter regions, 5,000 neuron classes, and up to 100,000 macroconnections between the aforementioned neuron classes, which are not always fully identified [4]. The volume of the human cerebral cortex similar to a pinhead (1 cubic millimeter) can even contain up to 27,000 neurons and 1,000,000,000 synapses. Moreover, the data derived from research on nonhuman brains cannot fully substitute information on humans. Although some brain organization aspects are common to all mammalian species, certain fundamental structural and behavioral aspects are unique to humans, including evolutionary adaptations and neurotransmitter modulatory effects involved in many neuropathologies (Parkinson's disease, Alzheimer's disease, depression, etc.) [13]. Computational models may be regarded as simplified abstractions but they link more complete data concerning anatomical structure with incomplete information concerning somata and the processes within cellular components gathered thanks to light microscopy and electron microscopy [10].

18.3 Concepts

Requirements for relevant computational models of CNS are:

- Reproducibility: Available built-in, run and assess outcomes of simulation features (structures, signals, features) within processes reported earlier in a scientific paper
- Transparency: Highly visible internal properties
- Accessibility: Available to other scientists in an understandable format

Some researchers also require portability (i.e., cross-simulator validation and exchange of models thanks to formats open to interconnection), but it may be hard to achieve.

18.3.1 Data Ladder

Reconstruction of the connectivity map of the brain (connectomics, i.e., tracing the aforementioned map accompanied by better understanding of related interactions) need diverse approaches and scales [54]. A data ladder shows coincidence and correlation among processes and mechanisms taking place at subsequent levels of the human body (from the bottom): genes →, proteins →, neurons →, neuronal dynamics →, and whole brain process → behavior [32]. Genetic factors may influence prognosis in many diseases and injuries, including pathophysiology of traumatic brain injuries. The aforementioned assumption may potentially lead to new treatments and improved outcomes of therapy and rehabilitation [16]. A more detailed view of CNS covers nine levels (from the bottom):

- Ion channels
- Signaling pathways
- Synapses
- Dendritic subunits
- Neurons
- Microcircuits
- Neural networks
- Subsystems
- Nervous system

18.3.2 Models of a Single Neuron

There are many shapes and sizes of neurons. Thus modeling of a single neuron constitutes a true challenge and requires an individual approach. The key question is: how does a particular neuron transform synaptic inputs into potential action output.

Although a single neuron can be divided into distinct morphological and functional regions:

- Receptor apparatus: Formed by the dendrites and cell body or soma
- Emission apparatus: Axon
- Distribution apparatus: Terminal axonal arborization

there are many exceptions: bidirectional connections, electrical synapses, various axosomatic and axodendritic synapses, and the role of neuron-glial interaction within information processing [14]. Realistic modeling of brain functions is based on a more detailed biophysical description of neurons and synapses (at the molecular and cellular levels) integrated into microcircuits, and then further integrated in large-scale brain networks and even brain systems [11]. Seven models of a single neuron may be multilayer: from the electric field distribution, through modeling of the single compartment effects, to the multicompartment neuron model [47]. Accurate 3D reconstructions of neurons are typically created using:

- Neurolucida after biocytin histology
- Neuromantic to reconstruct from fluorescence imaging (FI) stacks acquired using 2-photon laser-scanning microscopy during physiological recording [3]

18.3.3 Models of Biologically Relevant Neural Networks

According to the concept by DeFelipe [14] there is a need to identify the general connection matrix of the brain based on three main levels of operation and modeling:

- Macroscopic: Providing a map of major tract connectivity (connectome), acquired using medical imaging (e.g., fMRI)
- Intermediate: Providing a map of connections, acquired using light microscopy
- Ultrastructural: Providing a map of the synaptic connections (synaptome), acquired using electon microscopy [14].

Imprecise connectomes and incomplete synaptomes require an integrative approach to fill the gaps. Statistical models allow us to determine the range of variability of the particular parameters by sampling relatively small regions of the brain, especially within the cortex. There is a need for careful limitation of such an approach to avoid imprecision of estimation (e.g., ranges and types of synapses). The main initiatives concerning modeling of biologically relevant neural networks are:

- Human Brain Project (HBP) based in the European Union
- Brain Activity Map based in the United States [25, 32, 68]
- Allen Institute for Brain Research [Allen Institute]
- NeuroMorpho.Org [2]
- BAMS2 Workspace [5]
- The Canadian Brain Imaging Research Platform (CBRAIN) [52]

Analysis and interpretation of the functional brain networks during different cognitive activities require advanced approaches to the spatiotemporal and spectrotemporal brain data such as Functional Pattern Graph, NeuCube, and Intrinsic Signal Optical Imaging [26, 36, 57]. Simplified computational models of convective drug distribution in the primate brainstem were consistent with the outcomes of in vivo experiments [55].

18.3.4 Models of Human Behavior

The key issue constitutes models of learning within CNS. The learning process is often identified with modification of interneuron connection strength. Different learning rules may be applied. Moreover, synapses may change the strength of their response to neural activity in two basic ways:

- Short-term changes, lasting from milliseconds to seconds, which are important, but regarding them as learning is still discussed.
- Long-term potentiation (LTP) and long-term depression (LTD), lasting from hours to years. We also should take into consideration a noise effect, overlapping of neural fields, and choice of information relevant in the current task (e.g., decision making). Another problem constitutes neural plasticity, for example, spike-time-dependent plasticity (STDP).

18.4 Traditional versus Fuzzy Approach

There are three basic areas of OFN application within computational brain modeling:

- Reflecting physiological brain procedures normally performed by fuzzy-like neural networks, such as natural language processing, but one should take into consideration that the assumption of the right hemisphere being better at processing fuzzy signals than precise information may be true
- Simplification of complex computational procedures, hard to familiarize in another way, for example, kWTA-like mechanisms
- Reflection of various pathological processes, for example, fuzziness (absence of precision) of information in some diseases

18.5 OFN as an Alternative Approach to Fuzziness

The OFN model is introduced in detail in Chaps. 3 and 4. Generally, it is a tool for processing imprecise quantitative values represented by fuzzy numbers. OFNs have an additional feature used in processing: direction/orientation. It allows us to define arithmetical operations in a new way. The proposed methods maintain the basic computational properties of the operations known for real numbers. Apart from a good calculation capacity, OFNs also offer new possibilities for processing imprecise information. The new property, an order, has a major impact on the calculations, but also provides a new potential for processing data in fuzzy systems. We can include into the fuzzy value additional interpretations apart from the membership value. The new feature of processing is called ‘sensitivity for the direction’ (see [43, 44, 46] and Chap. 5) and makes it possible to involve in a model such expressions as, ‘The temperature is about 20 °C and it is increasing’.

In the case of the OFN model and processing methods that can be called ‘arithmetic’ (see [40, 41, 43, 44]), at each stage of the fuzzy system process we deal with the quantitative aspect of the data. Thus we consistently obtain fuzzy numbers at each step: the aggregation of premises, the inference and the accumulation-aggregation of the rules answers. Such property of a fuzzy system is even more important when modeling the complex relationships of the brain functions. It can be used as a parameter for other calculations without the direct output of individual rules. It can be hard to achieve this in a traditional fuzzy approach when during processing in the fuzzy system the quantitative character of processed data is generally lost.

18.6 Patterns and Examples

18.6.1 Intuitive Modeling of the Complex Functions

This concept was already presented in [45], and its key elements are provided here. A significant part of our knowledge about the functions of the brain is vague and imprecise. Thus, fuzzy logic seems to be a good solution when we look for tools used in modeling such an object. Although fuzzy techniques are used in object recognition and linguistic property modeling [29], there is only poor evidence concerning their use in brain simulations. There is a need for a novel, more effective approach, providing a better, clear, and easy understanding of the processes underlying brain function.

It is difficult to describe a simplified brain function in the form of mathematical equations. As mentioned before, brain function arises from complex behavior of units on the lower level (neurons, synapses, etc.). It makes this situation similar rather to multiagent architecture. However, a cascade and hierarchical fuzzy logic systems [19, 20, 48] may provide another insight into the behavior of the particular subsystems or mechanisms, allowing easy configuration and use of complicated sets of semirealistic features. Processing of information using a fuzzy system usually begins with a fuzzification operation and ends with defuzzification. Fuzzification, in general, is the conversion of a crisp value into a fuzzy one and defuzzification is a reverse operation. This operation can be done in many different ways. A choice of a proper method (especially the defuzzification method) often has a significant impact

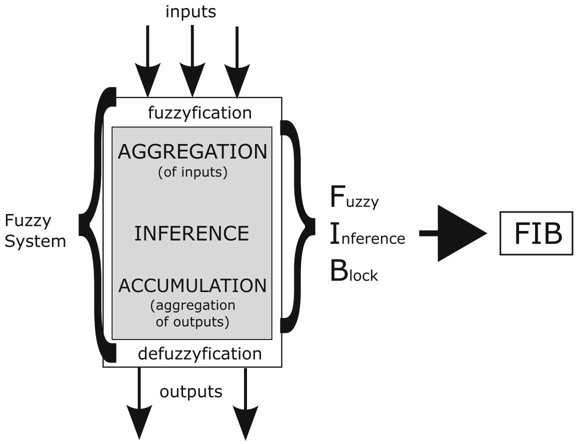


Fig. 18.1 A scheme of the fuzzy inference block (FIB)

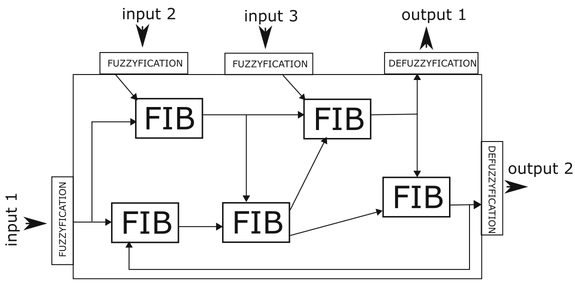


Fig. 18.2 The example of complicated dependencies modeled by FIBs

on the correctness and effectiveness of the whole model. Furthermore, the change of a fuzzy value into a crisp one is the replacement of a complex value with a simpler one. Such action usually involves some approximation or rounding, therefore it introduces an additional error into the results, as it is generally associated with losing some part of the information. The repetition of such operations is not recommended, due to the cumulation of the amount of lost information. It is especially inappropriate to use the output value of one stage as the input value for another.

If we want to use fuzzy values for modeling more complex structures such as the brain, the exclusion of the fuzzification and defuzzification operations outside the base system is recommended. Therefore as the basic tool for processing complex functionality expressed linguistically we propose to define a fuzzy system without fuzzification and defuzzification stages as the fuzzy inference block (FIB). The idea is presented in Fig. 18.1.

Such an element is a conceptual base for cascade modeling of complex relations described linguistically. The potential of such an idea in modeling complex relations is presented in Fig. 18.2.

It is worth noting that every FIB can represent one agent from the multiagent architecture. With this approach, we can describe even more complex structures. It is easy to imagine that, in place of individual FIBs, we can insert another complex system so it seems to be a kind of recursion, where only the lowest level relates directly to the FIBs. Still, despite the high complexity of the model, relations are described linguistically at various stages.

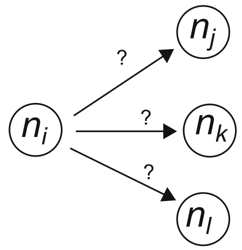
However, although the idea of FIBs seems to be quite suitable for the linguistic modeling of complex relations, some problems may arise. The classical methods for fuzzy models often produce fuzzy answer sets, which are quite fragmented, not normal, and not convex. Such results are formally still fuzzy sets, but their forward processing without defuzzification could be questionable.

Such problems do not occur if we use the OFN model. Its important advantage here is that we get a kind of fuzzy number at each stage of data processing. Thus the further use of such a result is easy and smooth without the need for defuzzification and then fuzzification again.

18.6.2 Improving Policy Gradient Method

Apart from modeling complex functionality described linguistically, the OFN can be used in other areas connected with brain modeling. A neural networks idea comes from knowledge about basic brain structure: see articles of the neurophysiologist Warren McCulloch and a mathematician Walter Pitts (1943) [34], "The Organization of Behavior" of Donald Hebb (1949) [21], and articles of Bernard Widrow and Marcian Hoff on ADALINE and MADALINE in the early 1960s [61]. The aforementioned ideas periodically failed or became more popular, but in the twenty-first century, called the century of neuroscience, a reasonable use of the old ideas may cause another breakthrough with deeper understanding of the central nervous system function. Issues of the average reward optimization, especially in the domain with partial observability (e.g. noised), are not easy to replicate within models of predictive state representations. Computation of the average reward depends on many parameters, and varies significantly, especially in a nonstationary environment. Permanent states and actions make this task particularly difficult. Obviously, the complexity of a well-known task and the associated reduced number of dimensions may increase efficiency of the computational system, but we should be aware that the brain calculates such tasks almost in real-time, taking into consideration many hidden states (e.g., environment, past behavior, own preferences, or even emotions). Such computational processes may reflect natural error-driven learning and adaptation, thanks to built-in short-term neuroplasticity, and their influence on long-term brain plasticity (e.g., memories, motivations, feelings, etc.). Thus enhanced discrimination of the single neuron, use of synapses as estimators of presynaptic membrane potentials, and temporal and spatial processing may be reflected in neuronal computation of the brain area function/response. Even connectomics cannot avoid current technical limitations. Although fuzziness of this process and nonrandom features of cortical connectivity allow some attempts with OFNs, these attempts, although simple, may play a significant role within the richness of its high-level cognitive processes as well as provide quicker and more predictable calculations. Earlier studies on policy

Fig. 18.3 A problem of choosing the best connection



gradient methods within reinforcement learning [18, 59, 62, 65] showed the positive role of the optimizing parameterized policies with respect to the expected return by a gradient descent, without their many disadvantages. As a result, we can more deeply understand reward-related learning problems in animals, humans, or machines. Thus we propose our own solution of the element of the long-term cumulative reward, taking into consideration its fuzziness.

One important issue on this subject is also the problem of objective function optimization. Finding the maximum value of the reward function R is often a guarantee to find the best change in a given step. However, the cost of calculating such an optimum can be too high to ensure its practical usefulness. This applies especially to situations where this reward function changes dynamically during time steps. A better choice may be to improve other parameters such as the learning rate coefficient, for example.

The change of weight between n_i and n_j is calculated as follows.

$$\frac{dw_{ij}}{dt} = aR(t)e_{ij}(t) \tag{18.1}$$

where a is the learning rate, the number from the [0; 1] interval, R is the reward function, and e_{ij} is the eligibility trace between n_i and n_j neurons from two adjacent layers (see Fig. 18.3).

Both the reward function and eligibility trace are complex problems. Expanding them with further calculations requires a lot of caution, because it is easy to overload the process with time-consuming computations. Therefore to improve a solution of the problem with determining weights of neurons the learning rate coefficient seems the right choice, for a start. It is worth noting that the learning rate at the 0 level is in fact no change of weight, thus no adaptation will proceed in such a step. Therefore the interval (0; 1] could be used instead. However, the zero level can represent the perfect optimum where the adaptation of this weight definitely ends, thus formally we keep zero as the low-bound in the interval of values for the learning rate.

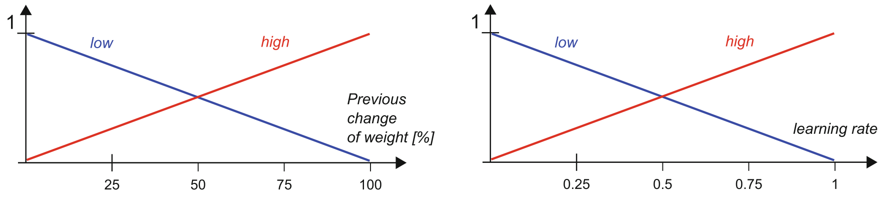


Fig. 18.4 Input and output values for the classic fuzzy system

18.6.3 Modeling Learning Rate with the OFNs

The learning rate is a real number from the [0; 1] interval. The less value there is, the smaller are the changes applied to the weight (see formula 18.1). Many scientists focus their work on the adaptation and other changes of this coefficient [15, 31, 53]. In general, when an idea of switching the learning rate is used in the neural network it is recommended that values of this parameter should be greater at the start of the process adaptation, when weight changes also are higher. In the course of the adaptation development the changes of weights are smaller, and the learning rate also should decrease. The above assumptions enable formulation of linguistic rules in a classic fuzzy system context as follows.

- IF 'previous change' is 'low' THEN 'learning rate' is 'low'
- IF 'previous change' is 'high' THEN 'learning rate' is 'high'

If we define 'low' and 'high' as fuzzy numbers (see Fig. 18.4), we can generate the learning rate value directly from such rules. The general conception of the proposed fuzzy system is to appoint the learning rate on the basis of previous change of the weight expressed as a percentage.

As an alternative, a simple fuzzy system based on the OFN model and its special methods and properties is proposed.

With the use of the OFN model context, we can formulate just one rule that expresses a trend of changes in the learning rate parameter.

- IF 'previous change' is 'about 50% and decreasing' THEN 'learning rate' is 'about 0.5 and decreasing'

Figure 18.5 presents the OFN for the rule above.

If we use 'the directed inference by multiplication with a shift' presented in Sect. 5.4.1 of Chap. 5 a single rule will be sufficient to express the expected dependency. Figure 18.6 shows the examples that present the general idea of the proposed processing. One can see that the activation in the *down-part* area of input, 'the previous change' will shift the result in the direction of the *down- part* of the OFN from the conclusion. An analogous situation will be with the *up-part*. Thus it is possible to reach the whole space of output values.

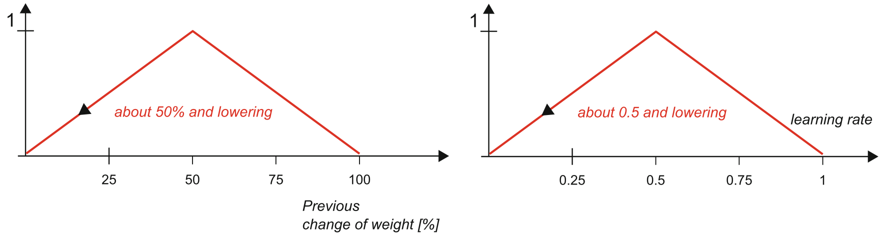


Fig. 18.5 OFN for fuzzy system

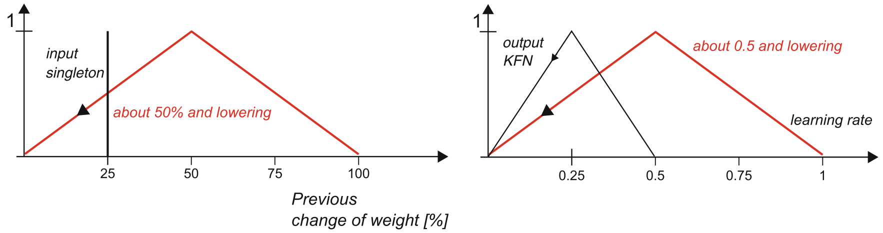


Fig. 18.6 OFN for fuzzy system

18.7 Discussion

The system proposed in the previous section is very simple, and generally gives exactly the same results as simple mapping from the [0; 100] interval into [0; 1]. But this proposition shows the potential of applying OFNs in linguistic modeling of the learning rate. We may intuitively change the algorithm by changing the linguistic expression. If we want to obtain a smaller learning rate in the case where the previous change of weight is below 30% we may formulate the rule linguistically:

- IF 'previous change' is 'about 30% and decreasing' THEN 'learning rate' is 'about 0.5 and decreasing'.

Figure 18.7 presents the example for such a rule. The input value is the same as in the previous case (see Fig. 18.6), therefore we can compare the results. Now it is not a simple proportional mapping between intervals [0; 100] and [0; 1]. It considers the preferences expressed linguistically. One can observe in Fig. 18.7 that a trend is preserved, because the input is still on the *down-part* side of the OFN for the premise part of the rule, thus the result is on the *down-part* side of the OFN from the conclusion.

Using the same intuitive way, we can easily modify the conclusion of the rule. If we want, for example, to keep the value of the learning rate above 0.7 until the previous change of weight is not lower than 30%, we can express it by the rule as follows.

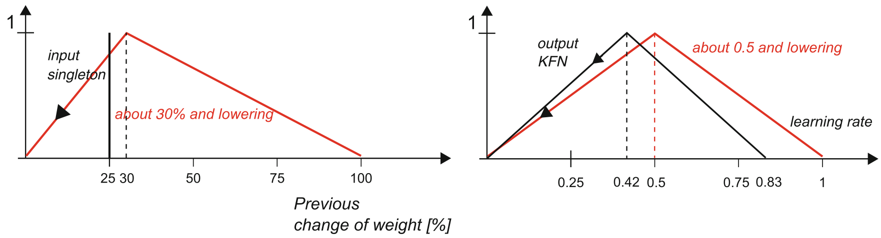


Fig. 18.7 OFNs for fuzzy system

- IF 'previous change' is 'about 30% and decreasing' THEN 'learning rate' is 'about 0.7 and decreasing'.

The above examples show the intuitive and flexible usefulness of modeling the learning rate using OFNs. Nevertheless it is also worth noting that we have OFNs at output. We can, of course, defuzzify the result, but the learning rate is only part of a complex algorithm of calculating the weight change of connections between neurons as presented in the formula 18.1. If we use the OFN for modeling other elements such as 'reward function' or 'eligibility trace' there will be another fuzzy number in the algorithms. Because defuzzification generally causes loss of part of the information, we should therefore do it at the end of all calculations instead of only after determining the learning rate coefficient. It enables us to process full imprecise information contained in the data until the moment when we really need a precise result.

18.7.1 Results of Other Scientists

Current approaches to central nervous system modeling aim at bringing experimental, computational, and theoretical results closer. Scientific questions should help to decide which approach can be regarded as minimal. Experimental outcomes and nonlinear interactions cannot be ignored even within the minimal computational models, because they may cause misleading conclusions or even confirm erroneous theories. Thus ad hoc simplification must be very careful. There are still many gaps in neuroscience (e.g., fragmented data sets), as regards both knowledge and experience; thus there are discussions concerning limitation of amounts of free parameters within models (which may cause so-called island models) without the possibility of comparison with the others and tuning using experimental datasets. The most important challenge is integration of the current data into a unified model of the brain as a single multilevel model. We need to explore, verify, and apply experiences from many various areas of science: from modeling of severe illnesses [17] and traditional neuronal networks [50, 51], through liquid state machines [63, 64] to liquid and gas distribution in porous materials [7–9].

18.7.2 Limitations of Our Approach and Directions for Further Research

The main limitation is a high amount of knowledge and experience as well as a need for an interdisciplinary research team to prepare valid and relevant models. Such teams, incorporating clinicians, are rare.

Consensus concerning model classification, performance, and interpretation is needed to provide consistent methodology to ensure diagnostic and prognostic consistency. A coherent theoretical framework for explaining SC and FC patterns and their alterations in brain diseases is required. The high computational power of the brain coupled with low consumption of energy may serve as a basis for the next generation of computational devices. Neuromorphic computing systems may allow us to reflect the stochastic behavior of simple, reliable, very fast, low-power computing devices embedded in intensely recursive architectures, based on brain-derived patterns [6].

18.8 Conclusions

Our results confirm that our new OFN fuzzy-based approach towards brain function modeling may be efficient and helpful in some time-consuming computational problems. Such a fuzzy-based approach may in selected cases also be more similar to natural neural signal processing than classical digital models. The idea of a fuzzy inference block opens a new direction towards the use of good processing properties of an OFN model in describing complex functions while preserving the intuitiveness of linguistic description. It seems to be of particular importance for the area where two scientific disciplines meet, that is, medical research dealing with diseases and injuries of the brain and computer science research.

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