Lithology Determination from Well Logs with Fuzzy Associative Memory Neural Network

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***Abstract*— An artificial intelligence technique of fuzzy associative memory is used to determine rock types from well-log signatures. Fuzzy associative memory (FAM) is a hybrid of neural network and fuzzy expert system. This new approach combines the learning ability of neural network and the strengths of fuzzy linguistic modeling to adaptively infer lithologies from well-log signatures based on 1) the relationships between the lithology and log signature that the neural network have learned during the training and/or 2) geologist's knowledge about the rocks. The method is applied to a sequence of the Ordovician rock units in northern Kansas. This paper also compares the performances of two different methods, using the same data set for meaningful comparison. The advantages of FAM are 1) expert knowledge acquired by geologists is fully utilized; 2) this knowledge is augmented by the neural network learning from the data, when available; and 3) FAM is "transparent" in that the knowledge is explicitly stated in the fuzzy rules.**

I. Introduction

LITHOLOGY determination from well-log responses is a labor-intensive, ambiguous, and subjective undertaking. Thus, considerable research has been directed toward automation of lithology identification in order to achieve efficiency, consistency, and objectivity. The traditional approach in this endeavor is the use of statistical methods such as principal component, discriminant function, and/or cluster analysis. Recently, the techniques of artificial intelligence, especially that of neural networks have steadily gained prominence over the statistical methods. Recent papers that employ neural networks in the determination of lithologies from well logs include: [3] and [4] using a self-organizing network; [15], [17], [20], and [21] employing an architecture known as the backpropagation neural network (BPNN). Despite the successful applications of BPNN to lithology determination as shown by these publications, the BPNN algorithm suffers from 1) training time is often too long; 2) there are chances that the network never converges; 3) the output can only yield pre-determined groups or clusters; that is, the network cannot handle cases or examples which lie outside the pre-defined training set; 4) determination of the numbers of intermediate or hidden layers and nodes (in each layer) still depends on "trial and error;" and 5) most importantly, it is difficult for the user to interpret or understand the "knowledge" that the neural network has, by simply examining the connection weights and thresholds obtained by backpropagation.

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The purpose of this paper is to introduce a new and better neural-network architecture called fuzzy associative memory (FAM) to determine rock types from well logs. The prime reason for this paper is that FAM possesses several advantages which overcome the shortcomings of the BPNN approach. They are: 1) FAM is transparent in that the knowledge is explicitly revealed in the rules; 2) FAM also learns the rules from the well-log signatures versus lithology relations during training, or directly from geologists or domain experts; and 3) FAM essentially coordinates available knowledge and makes fuzzy inferences based on associative memories in performing recursive learning to mimic human cognition and reasoning processes.

In the following sections, we give some brief description on FAM, then outline the FAM architecture, followed by an implementation of FAM employing the same data set in our previous paper [17], so that a direct and meaningful comparison may be made between the two neural-network architectures.

II. Background

A. What Is Fuzzy Logic?

Fuzzy logic is an extension of the classical logic (viz. two-valued logic) where every proposition is either true or false. This true-false dichotomy is problematic in some propositions which are neither completely true nor completely false, but somewhere in between. In order to deal with such propositions, different degrees of truth are used. This multivalued logic is called fuzzy logic [24]. Fuzzy logic is primarily concerned with quantifying and reasoning about fuzzy terms appearing in our natural language. These fuzzy terms can be represented by fuzzy sets. The most significant aspect of fuzzy set is the concept of unsharp boundaries between classes; that is, the concept of partial membership. An object does not have to completely belong to one set, but can partially belong to the set; this kind of set is called fuzzy set.

Fuzzy logic allows us to emulate the approximation of the human reasoning processes and draw conclusions based on fuzzy premises. This method of reasoning couched in fuzzy logic is known as fuzzy inference, or fuzzy reasoning [23]. The concept that plays a central role in the application of fuzzy sets is that of linguistic variables which provide knowledge representation in an imprecise or uncertain environment.

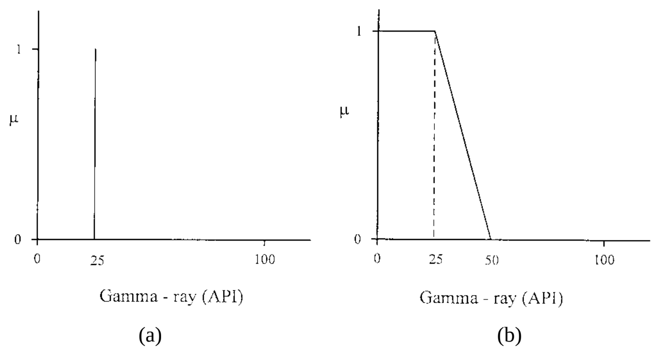

Fig. 1. Numerical value versus linguistic value. (a) Crisp numerical value for gamma-ray is 25. This translates to $\mu = 1$ at API = 25 and $\mu = 0$ elsewhere; (b) Linguistic value for gamma-ray is *low*. This means that $\mu = 1$ for API = 0–25, and $\mu = 0$ at API = 50, and μ is between 0 and 1 for API = 25–50.

Consider a linguistic variable, such as gamma-ray reading whose linguistic values are *low*, *medium*, and *high*. These linguistic values are defined by membership functions. The advantages of using linguistic values are 1) it is more general; 2) it mimics the way in which humans describe attributes; and 3) the transition from one linguistic value to a contiguous linguistic value is gradual rather than abrupt, resulting in continuity and robustness. Fig. 1 compares the corresponding linguistic value with a numerical value. In natural language, humans may add additional information to a given expression by using adverbs such as *very*, *very very*, or *more-or-less*. For example, the gamma-ray reading which has linguistic value *low* may be modified to *very low* or *very very low*. To account for this modification, some mathematical operations may be employed to transform the existing fuzzy set—*low* into a new fuzzy set—*very low* or *very very low*.

Fuzzy logic has been widely applied to engineering control processes, including cement kilns, wood pulp grinders, sewer treatment plants, elevators, subway trains, air conditioners, and refrigerators [13]. The theory also has been applied to environmental problems—such as, groundwater management [14], and hydrology [1], [2]. During the past several years, we have applied fuzzy logic to petroleum prospect appraisal [5], [6], [8], qualitative X-ray analysis [22], and thin-section mineral identification [9]. In this paper, we propose a technique which combines fuzzy logic with a neural network and use it to determine rock types from well logs.

B. What Is Associative Memory Network?

Human memory operates in an associative manner, one thing reminds us of another, and that, of still another. Like human memory, the associative memory neural network not only returns a full and correct memory when an incomplete or imprecise memory is supplied to it, but also sends back a different memory associated with the one provided to the network. These characteristics are reminiscent of human cognitive processes and bring artificial neural networks one step closer to an emulation of the human brain.

Each association is an input-output vector pair. The architecture of an associative memory neural network may be feedforward, bidirectional, or recurrent [10]. In this paper we use a feedforward net; well-log data flow from the input layer through the net and invokes the output layer resulting in the associated lithology for the given well-logs signatures.

C. What Is Fuzzy Associative Memory?

Kosko [12] coined the name, FAM, denoting a neural network architecture of associative memory modified with fuzzy logic and rules. By combining the two approaches, the advantages of each method are enhanced. The neural network and fuzzy rules behave as associative memories, which link input data with corresponding outputs. FAM learns from example and/or geologist's knowledge without requiring mathematical formulae describing how the output functionally depends on the input data. The knowledge learned by the neural network is encoded in the connection weights, and the knowledge in fuzzy rules is described by "if-then" rules. Neural networks acquire knowledge through learning (or training), and the geologist provides the knowledge as fuzzy rules.

III. Fuzzy Associative Memory Neural Network

A. FAM Mappings

By combining associative memory and fuzzy logic, Kosko [12] devised fuzzy associative memory (FAM), which encodes the fuzzy output set Y with the fuzzy input set X (see Fig. 2). Thus, FAM resembles neural network processing, and yet, retains fuzzy approach that is characterized by linguistic rules. In other words, explanations and justifications are done in the fuzzy part, but not in the neural network, thus removing the major deficiency of the "opaqueness" of ordinary neural networks. The numerical framework of FAM allows us to adaptively add and modify fuzzy rules, directly from experts or from statistical techniques. As shown in Fig. 2, associative neural networks are simple nets, in which the weights, denoted by W, are determined by the fuzzy Hebb rule (described under "FAM learning" in a following subsection) matrix or the "correlation-minimum encoding" scheme (see Appendix B). Each association is a pair of vectors connecting X and Y. The weight or correlation matrix W maps the input X to the associated output Y by a max–min composition operation "$\circ$" (see Appendix B):

$$Y = X \circ W.$$

If an input X' is fuzzy (a degree of membership is provided to indicate the closeness of X' to X), the output Y' will also be a fuzzy set. If X' is exactly identical to X, then Y' will be identical to Y. The more X' resembles X the more Y' resembles Y.

B. Proposed FAM System

Consider a fuzzy association: "If gamma-ray reading is *low*, then lithology is *limestone* or *dolomite*." The fuzzy association is (*low*, *limestone*) or (*low*, *dolomite*). The input linguistic variable gamma-ray assumes the fuzzy-set value *low*. The output linguistic variable lithology assumes the linguistic value *limestone* or *dolomite*. In general, a FAM system encodes and processes a set of rules in parallel. Each input to the system

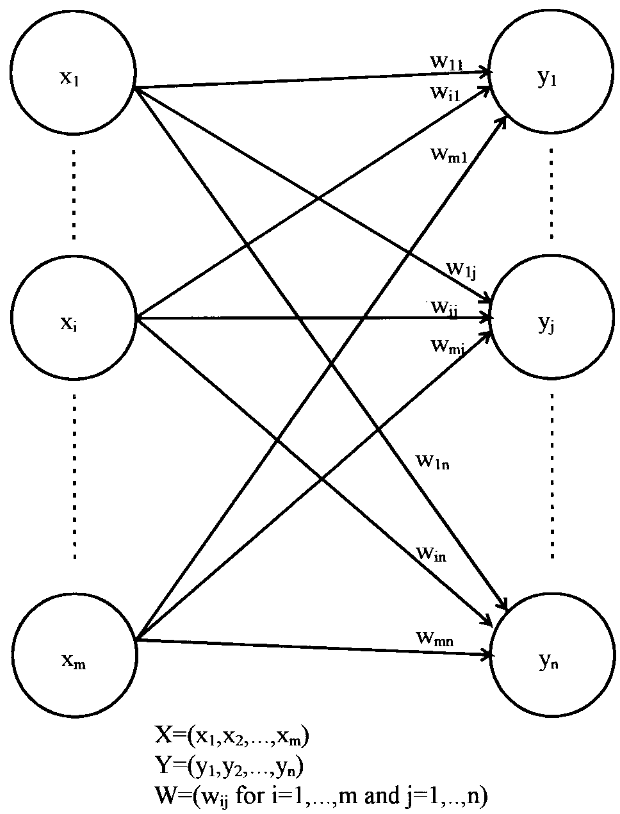

Fig. 2. Fuzzy mapping.

will activate each encoded rule to a different degree. The proposed FAM network is composed of three layers: X, R, and Y, as shown in Fig. 3, which was redrawn from [16]. A node in the X-layer represents a fuzzy set in the antecedent part of a fuzzy rule. A node in the Y-layer represents lithology. Input well-log values are first fuzzified to *high* (H), *medium* (M) or *low* (L), and various degrees of membership of $X_i (i = 1, \cdots, m)$ become the numerical inputs for the network. Fuzzy inference is then invoked between the X-layer and the R-layer by the $\max\text{–}\min$ composition operation. Finally, the inferred results obtained by each rule are aggregated to produce a final result for the Y-layer. The aggregation is given by adding the associative relationships between the R-layer and the Y-layer.

Therefore, the FAM encodes each linguistic association or "rule" in a numerical FAM mapping. The FAM then numerically processes numerical input data, and generates a degree of membership for each $Y_j (j = 1, \cdots, n)$. These degrees of membership are then translated into linguistic outputs where a popular method of maximum-membership defuzzification scheme is used. In this scheme, all Y_j with memberships greater than 0.6 are candidates, instead of only one Y_j that has the maximal membership in the Y-layer. After normalization ($\sum Y_j = 1$ for $j \in$ candidates), the Y_j with the highest value is considered as the rock type. For example, if the output is: "the degree of rock type being dolomite is 1 and the degrees of being all other rock types are 0," then the linguistic output will be: "the lithology is dolomite." If output

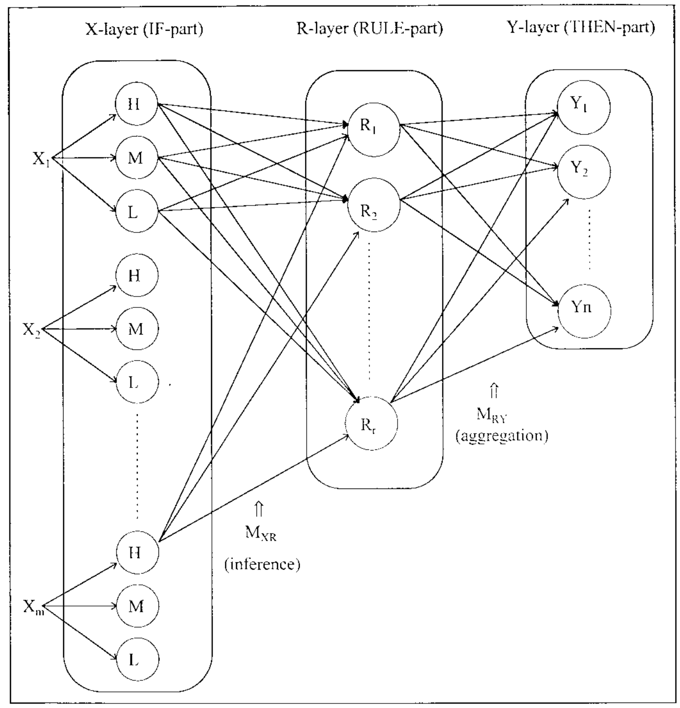

Fig. 3. A FAM neural network with r rules.

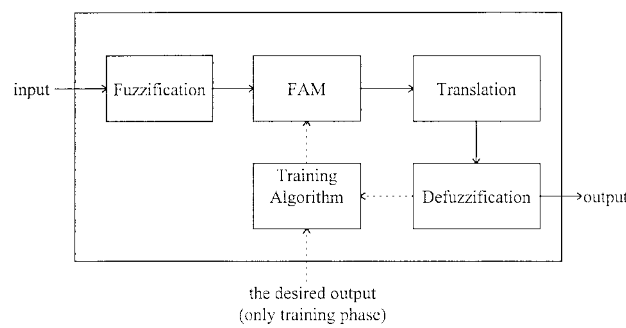

Fig. 4. The proposed FAM system.

is "the degree of dolomite is 0.6, and the degree of limestone is 0.4 and the degrees of all other lithologies are 0," then the output will be "the lithology is limy dolomite."

In our system, there are four separate modules—fuzzification, FAM, translation, and defuzzification. In addition, a training module that modifies FAM weights (or associative matrices) to improve system performance is also included. The outline of the proposed system is shown in Fig. 4. If the rules provided by the geologist are complete, then the training module may be bypassed. If additional data sets containing different relationships are available, the training module can also learn these different pairs from the data sets.

C. FAM Learning

The if-then rules encoded in the FAM can either be learned and/or refined by the given network from a training set [19]. A generalized delta rule, for instance, can be employed to determine the weights for an FAM network (see Appendix C for detail). There are two sets of weights M_{XR} and M_{RY} (see

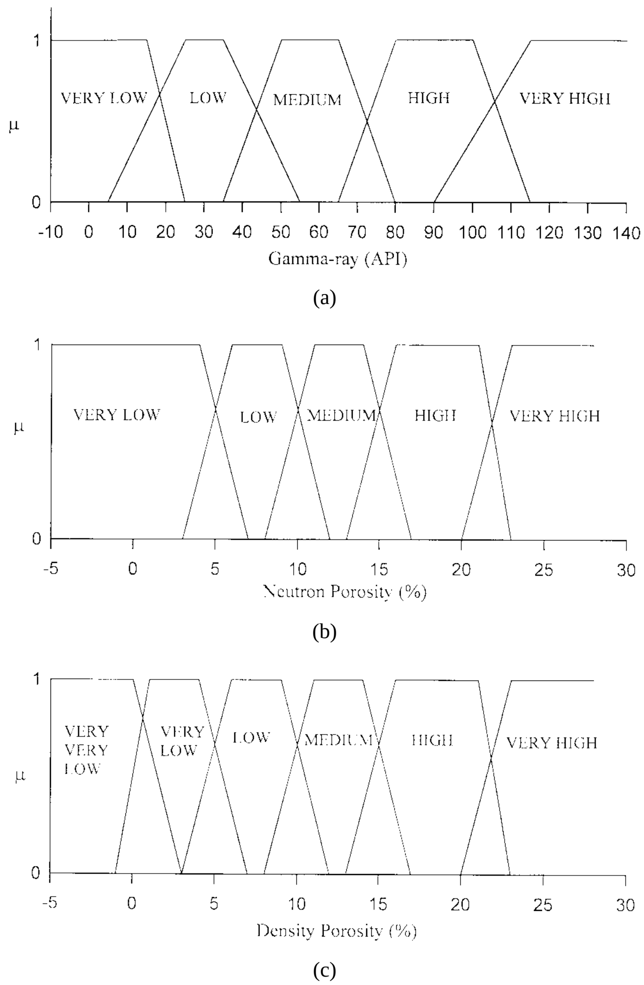

Fig. 5. Fuzzy subsets for well-log responses.

Fig. 3) that can be changed. If the errors between the results computed by the FAM system and the desired output are used to modify the rules, then M_{RY} weights will be updated. If the errors will cause the modification of membership functions, then M_{XR} weights will be updated. Thus, if we are not completely confident that membership functions are defined correctly, we can learn membership functions from the data set. Similarly, we can train the existing rules, and ask for comments from the log analysts or geologists. It is perhaps easier for the experts to comment upon these rules than it is for them to create consistent and all-inclusive, or all-exclusive rules.

IV. Implementation and Results

Three types of well logs (gamma-ray, neutron, and density) of the lower Paleozoic sequence in Nemaha County, northern Kansas were used. Doveton [7] used this suite of logs as an example to illustrate graphical methods of lithology determination in his book. The 500-ft section penetrates the Hunton Groups (Silurian), Maquoketa Shale, Viola Limestone, and Simpson Group (Ordovician).

Ten fuzzy rules are encoded in the network:

Rule 1 If gamma-ray reading is *low* or *very low*, neutron porosity is *low*, and density porosity is *very very low*, then the lithology is dolomite.

Rule 2 If gamma-ray reading is *low* or *very low*, neutron porosity is *medium*, and density porosity is *very low*, then the lithology is dolomite.

Rule 3 If gamma-ray reading is *low* or *very low*, neutron porosity is *high*, and density porosity is *low*, then the lithology is dolomite.

Rule 4 If gamma-ray reading is *low* or *very low*, neutron porosity is *very low*, and density porosity is *low* or *very low*, then lithology is limestone.

Rule 5 If gamma-ray reading is *low* or *very low* and neutron porosity and density porosity are about the same, then the lithology is limestone.

Rule 6 If gamma-ray reading is *high* or *very high*, neutron porosity is *high* or *very high*, and density porosity is *low* or *medium*, then the lithology is shale.

Rule 7 If gamma-ray reading is *low* or *very low*, neutron porosity is *high*, and density porosity is *very high*, then the lithology is sandstone.

Rule 8 If gamma-ray reading is *low* or *very low*, neutron porosity is *medium*, and density porosity is *high*, then the lithology is sandstone.

Rule 9 If gamma-ray reading is *low* or *very low*, neutron porosity is *low*, and density porosity is *medium*, then the lithology is sandstone.

Rule 10 If gamma-ray reading is *low* or *very low*, neutron porosity is *very low*, and density porosity is *low*, then the lithology is sandstone.

The membership functions used are shown in Fig. 5. There are five fuzzy sets both for gamma-ray and neutron porosity, and six sets for density porosity. These numbers were chosen based on the available geological information. Although we expressed the fuzzy sets as trapezoid fuzzy numbers, triangular fuzzy numbers could be used.

The FAM output for the test example from Doveton [7] is shown in Fig. 6. Rock types given in [7] are denoted near the curves. Fig. 7 compares the result with our previous paper—the FAM output is shown in the middle; BPNN 1) and BPNN 2) are shown on the left and right, respectively. The different outputs from BPNN are due to different training sets. A cursory examination of these figures reveal that 1) there is almost perfect agreement between the results from the graphical method [7] and the FAM output, except that the FAM output yielded finer details—in FAM, the degree of detail is determined by the numbers and complexity of the rules, and 2) FAM does not give more than one determination depending on the different training sets used, as is the case with the BPNN results. This removes some uncertainty associated with the choice of different training sets.

V. Conclusions

We have introduced a new and better neural-network architecture FAM—a hybrid of neural network characterized by inductive reasoning and fuzzy expert system characterized by deductive reasoning. FAM has the following advantages over BPNN. First, FAM emulates human knowledge better than BPNN. In the latter architecture, the knowledge is modeled

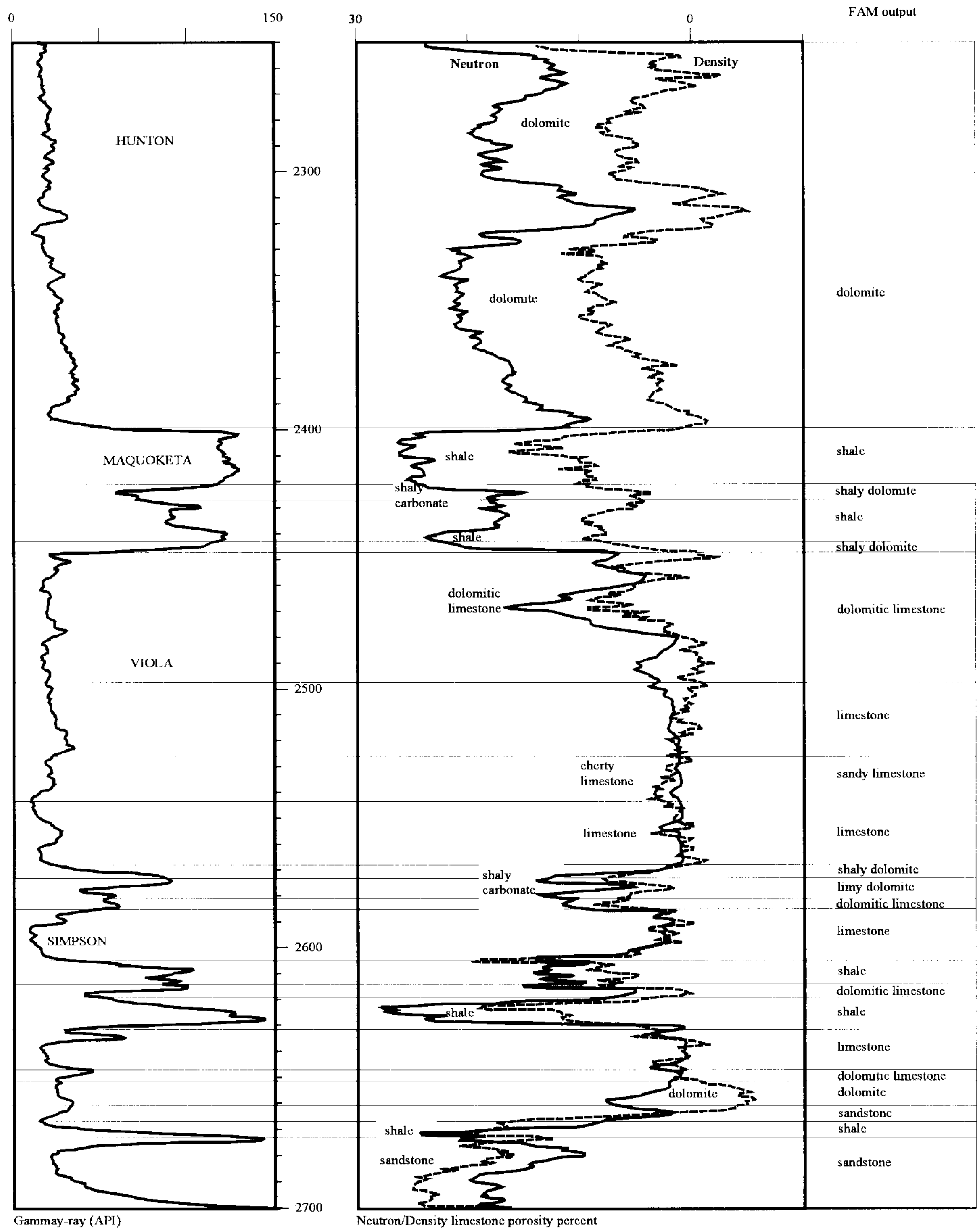

Fig. 6. The example logs—redrawn from Doveton (1986; pp. 125–157) and the FAM output.

in the connection weights, which are opaque to the user, but in FAM, in addition to the weights, "transparent" fuzzy rules are also employed. Second, BPNN acquires knowledge through training. Thus, the training set must be adequate and exhaustive. Otherwise, the network may make inaccurate (and may even erroneous) decisions. Whereas in FAM, the training is augmented by expert knowledge manifested in fuzzy rules. Finally, FAM can be tuned to yield different degrees of details.

Further studies using different lithologic sequences with diverse degrees of complexity will be needed to validate our conclusions.

APPENDIX A
REPRESENTATION BY FUZZY SETS

A crisp (conventional) set is expressed as $N = (1, 2, 3, 4, 5)$ indicating that the set is made up of five members or elements, with the membership of each element

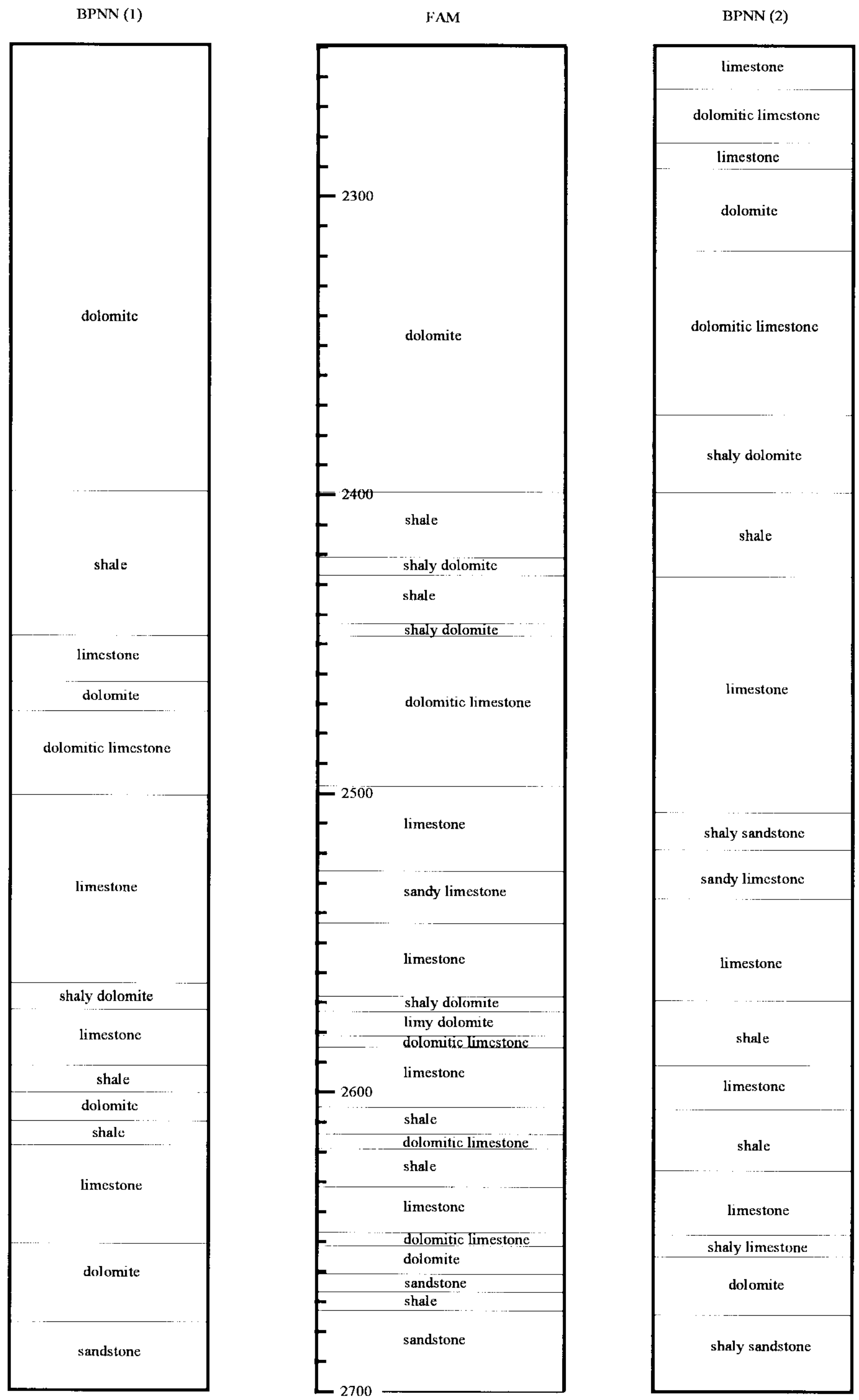

Fig. 7. Comparison between the FAM and BPNN outputs.

equals to one. In other words, a crisp set is defined in such a way to dichotomize the individuals as members or nonmembers; that is, the grade or the degree of membership is either one or zero. A fuzzy set, on the other hand, is written as

$$A = \left(\frac{0.1}{1}, \frac{0.5}{2}, \frac{1.0}{3}, \frac{0.5}{4}, \frac{0.1}{5}\right)$$

where the "denominators" are integers (1 through 5 of the crisp set) and the "numerators" are the grades of membership associated with the corresponding integers given in the "denominators." Note that the fuzzy sets allow grades of membership to assume fractional values between zero and one.

Thus, we can represent a linguistic value *low* for, say, the gamma-ray readings:

$$low = \left(\frac{1.0}{5}, \frac{1.0}{10}, \frac{1.0}{15}, \frac{1.0}{20}, \frac{1.0}{25}, \frac{0.8}{30}, \frac{0.6}{35}, \frac{0.4}{40}, \frac{0.2}{45}, \frac{0.0}{50}\right).$$

Another type of fuzzy representation is as follows:

$$\text{gamma-ray reading} = \left(\frac{0.9}{low}, \frac{0.3}{medium}, \frac{0.0}{high}\right)$$

meaning that the gamma-ray is *low* with membership $\mu = 0.9$, is *medium* with $\mu = 0.3$, and is *high* with $\mu = 0.0$. The fuzzy rules given in the text are of this type. For example, if gamma-ray (G) is *very-low* or *low*, the neutron porosity (ϕ_N) is *almost low*, and the density porosity (ϕ_D) is *low* or *near very-low*, then the lithology (L) is limestone. This fuzzy rule is translated into the fuzzy representations as

If

$$G = \left(\frac{1.0}{very\,low}, \frac{1.0}{low}, \frac{0.0}{medium}, \frac{0.0}{high}, \frac{0.0}{very\,high}\right)$$

$$\phi_N = \left(\frac{0.2}{very\,low}, \frac{1.0}{low}, \frac{0.2}{medium}, \frac{0.0}{high}, \frac{0.0}{very\,high}\right)$$

$$\phi_D = \left(\frac{0.5}{very\,low}, \frac{1.0}{low}, \frac{0.0}{medium}, \frac{0.0}{high}, \frac{0.0}{very\,high}\right).$$

Then

$$L = \left(\frac{1.0}{limestone}, \frac{0.0}{dolomite}, \frac{0.0}{shale}, \frac{0.0}{sandstone}\right).$$

Note that the fuzzy representation of ϕ_N has a degree of 1.0 for *low*, a degree of 0.2 for *very low* and a degree of 0.2 for *medium* to reflect the fuzzy concept "*almost low*." The term *almost*, is a hedge used for fine-tuning the primary fuzzy set *low* [18].

APPENDIX B
FUZZY VECTOR–MATRIX COMPOSITION RELATION

Given a system of r rules, we consider the kth rule: If A_k then B_k, where $A_k = (u_1/a_1, u_2/a_2, \cdots, u_m/a_m)$ and $B_k = (v_1/b_1, v_2/b_2, \cdots, v_n/b_n)$ are two fuzzy sets. A_k is the antecedent and B_k is the consequence of a given rule. We form an associated pair (A_k, B_k), and the fuzzy associative memory W_k, which is defined by the minimums of u_i and v_j:

$$W_k = (w_{ij} \text{ for } i = 1, m \text{ and } j = 1, n)$$

where $w_{ij} = \min(u_i, v_j)$ for $i = 1, m$ and $j = 1, n$, and W_k is called the "correlation-minimum encoding" matrix. For example,

$$A_k = \left(\frac{0.1}{very\,low}, \frac{0.5}{low}, \frac{0.9}{medium}, \frac{1.0}{high}, \frac{0.3}{very\,high}\right)$$

$$B_k = \left(\frac{0.5}{\text{limestone}}, \frac{1.0}{\text{dolomite}}, \frac{0.2}{\text{shale}}, \frac{0.8}{\text{sandstone}}\right)$$

we can obtain

$$W_k = \begin{bmatrix} 0.1 & 0.1 & 0.1 & 0.1 \\ 0.5 & 0.5 & 0.2 & 0.5 \\ 0.5 & 0.9 & 0.2 & 0.8 \\ 0.5 & 1.0 & 0.2 & 0.8 \\ 0.3 & 0.3 & 0.2 & 0.3 \end{bmatrix}.$$

Fuzzy associative memory (FAM) can be treated as a kind of neural network consisting of two layers A_k and B_k. The combination intensity between the nodes of A_k and B_k is represented by the matrix W_k, where the components (w_{ij}) are degrees of interrelationship between node i of layer A_k and node j of layer B_k. If a vector A_k is input to the FAM, B_k is finally associated by taking the fuzzy inner product of vector A_k with the jth column of W_k:

$$v_j = \max_{1 \le i \le m} \{\min(u_i, w_{ij})\}.$$

Thus, we can say that the FAM system exhibits "perfect recall" in the forward direction. This $\max$–$\min$ operation is called "$\max$–$\min$ composition operation" [11]. Mathematically, we denote this operation by

$$B_k = A_k \circ W_k.$$

If the input vector A'_k is not exactly identical to A_k, even in fuzzy terms, the FAM maps input A'_k to B'_k, a partially activated version of B_k. The more A'_k matches A_k, the more B'_k resembles B_k. The above concept can be applied for all rules in the system.

APPENDIX C
GENERALIZED DELTA LEARNING FOR FAM

Given a collection of input–output pairs of data $\{(x_1, y_1), (x_2, y_2), \cdots, (x_t, y_t)\}$, we construct a simple procedure to modify the weights (w_{ij} for $i = 1, m$, and $j = 1, n$) of the FAM with a "supervised learning." The standard learning procedure usually encompasses a series of iterations to minimize an error function (denoted by E) which may be the mean-squared error, or the total error incurred in the network. Mathematically, this learning scheme can be described as

$$\Delta w_{ij} = -\lambda \frac{\partial E}{\partial w_{ij}}$$

where Δw_{ij} is the increment of w_{ij}, and λ is a learning rate. The weights of the network are then modified by

$$\text{new\_}w_{ij} = \text{old\_}w_{ij} + \Delta w_{ij}, \qquad \text{for all } i, j.$$

For the FAM proposed here, we adjust weight w_{ij}, which is the connection between node x_i and node y_j, (as shown in Fig. 2), after presentation of each training-data pair. Given a pair of training data, (X_1, Y_1) where $X_1 = (u_1/x_1, u_2/x_2, \cdots, u_m/x_m)$ is a fuzzy input, and $Y_1 = (v_1/y_1, v_2/y_2, \cdots, v_n/y_n)$ is a desired fuzzy output, we first compute outputs of FAM with a set of pre-determined w_{ij} (either provided by the expert or randomly generated) and input X_1. It is assumed that the error is defined as the squared differences between the desired output v_j and the actual output o_j:

$$E = (v_j - o_j)^2, \qquad \text{for } j = 1, n.$$

Note that o_j is the output produced by node y_j. Applying a generalized delta learning rule, we obtain the gradient of E as

$$\frac{\partial E}{\partial w_{ij}} = -2\left[(v_j - o_j)\frac{\partial o_j}{\partial w_{ij}}\right].$$

Recall (see "Fuzzy vector–matrix composition relation" in Appendix B) that

$$o_j = \max_{1 \le i \le m} \{\min(u_i, w_{ij})\}.$$

Let $s_i = \min(u_i, w_{ij})$, we can rewrite the above equation for o_j in a new form as

$$o_j = \max\{s_1, s_2, \cdots, s_i, \cdots, s_m\}$$

while the calculations involved are standard generalized delta rules, the computation of the derivative of the maximum operation needs special attention [25]. In this maximum operation, o_j can be either 1) $o_j \neq s_i$ or 2) $o_j = s_i$.

In case of 1), we have

$$\frac{\partial o_j}{\partial w_{ij}} = 0.$$

However, in case of 2), we obtain

$$\frac{\partial o_j}{\partial w_{ij}} = \begin{cases} 1, & \text{if } u_i \ge w_{ij} \\ 0, & \text{if } u_i < w_{ij}. \end{cases}$$

If $\partial o_j / \partial w_{ij} = 1$, the weight adjustment becomes

$$\text{new\_}w_{ij} = \text{old\_}w_{ij} + \lambda(v_j - o_j).$$

Recall that the initial weights can be provided by the experts in the "if-then-rule" forms or can be generated from any random value between zero to one, if no expert knowledge available. The above learning scheme has to be repeated until E is acceptably small for each of the training pairs.

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