Fusion technology of fuzzy theory and neural networks : Survey and future directions

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出版情報：Proceedings of International Conference on Fuzzy Logic & Neural Networks, Iizuka '90. 1, pp.13-26, 1990-07. ファジィシステム研究所
バージョン：
権利関係：

FUSION TECHNOLOGY OF FUZZY THEORY AND NEURAL NETWORKS †
- SURVEY AND FUTURE DIRECTIONS -

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[ABSTRACT] This paper describes the trend and research directions for future development of technology to fuse the neural network theory and fuzzy logic. Following to background, section 2 describes two possible fusing methods. One of which is a method by which individual merits are combined, and another is a method by which analogies between these are superposed. Section 3 introduces a report on the current status of fusion study. Author analyze them and divide into (1) initial state, (2) determination of membership function, (3) knowledge acquisition or knowledge expression, (4) fuzzy cognitive map etc., (5) clustering and pattern recognition, (6) serial connection of NN and fuzzy processing, and (7) other states. On the bases of these studies, section 4 describes the future prospects and proposals of the author.

1. INTRODUCTION

Studies on the Neural Network (NN) and fuzzy logic particularly in Japan accomplished substantial advancements in recent years, and by this, considerable overlap of application fields between these two studies are presently found in the fields of control and inference problem studies. For instance, in the field of Japanese security investment, approximate reasoning, NN, conventional AI, and mathematical approach are actually employed now, and the levels of these arrived at such a stage that actual fund flotation is made.

The simultaneous enlargements of these research field have brought not only the enlargement of individual field of study but the interrelationship between these fields. That is, compensation of inherent demerits of one field by the merits of another is now became possible, that is, a fusion of fields of study is now taking place. The fuzzy theory is generally advantageous in logical field, and can handle higher-order processing easier. The higher flexibility is a characteristic feature of NN produced by learning, and therefore, this fits to data-driven pattern processing better. Therefore, it should be possible that a powerful flexible knowledge processing tool adorned with a NN robe on a body structure of fuzzy logic could be produced by fusing these two fields.

Thus, the following is on the trend of researches and futuristic view prepared by the author who focused his attention on the fusion of fuzzy logic and NN. Most of these fusion studies are conducted for cases where NN is introduced into fuzzy logic, and both of these are being actively studied especially in Japan. Although this review is conducted on a worldwide scale, it is an author's intention to include the local activities of Japanese academic associations, and to introduce those to the world through this conference paper.

2. CONTACT POINTS OF FUSION PROCESS

Both NN and fuzzy theories object the humaneness, and the concerns to each had been aroused spontaneously and rapidly at a same time. So the similarities and mutual compensations between these are much discussed. The study of fusion can be started with the combination of either the individual merits or

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† This paper appeared in the proceedings of the First International Conference on Fuzzy Logic & Neural Networks (IIZUKA'90), pp.13-26 (July, 1990)

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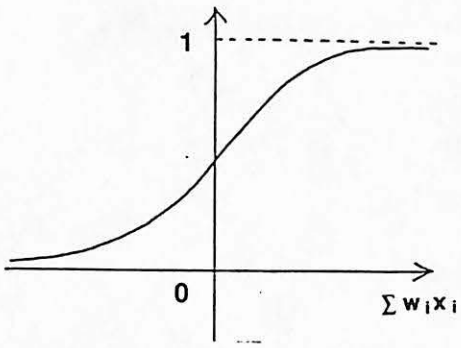

Fig.1 (a) Sigmoid Function

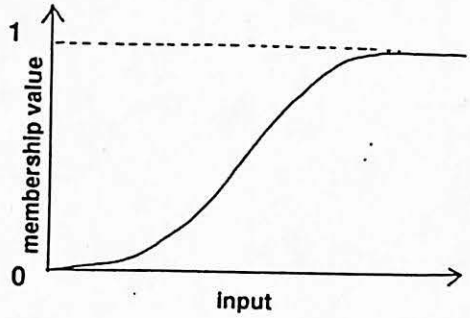

Fig.1 (b) Membership Function

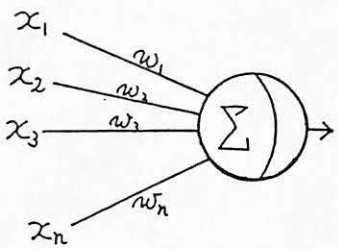

Fig.2 (a) Sum of Products of Neuron

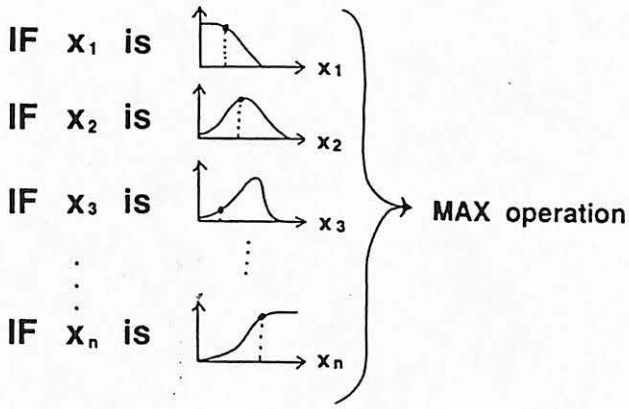

Fig.2 (b) MAX-MIN Operation of Approximate Reasoning

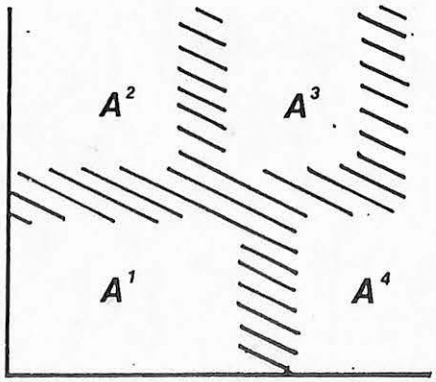

Fig.3 (a) Ordinary Fuzzy Rule Partition
membership function is hypercube surface

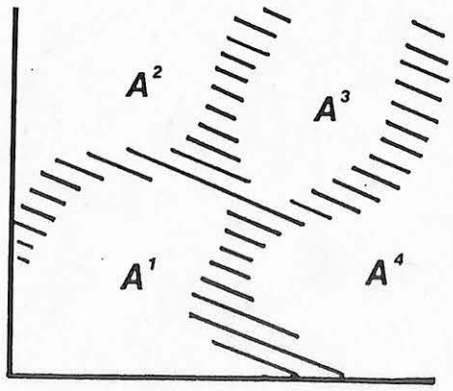

Fig.3 (b) Fuzzy Rule Partition by NN
membership function is hypercurve suface

the similarities between these two.

Table 1 Contact point of Fusion

Difference	Fuzzy logic:	Logicality
	NN:	Learning function
Similarity	(1)	Output characteristics of NN and membership function
	(2)	Multiply-add operation of neuron and MAX-MIN operation of approximate reasoning.

The first fusion pattern is a method combining individual advantages. Fuzzy logic can express logic explicitly taking a form of rule. NN is helpful when it is employed for pattern identification because of its learning function. From these advantages of view, (a) a method to endow learning function to fuzzy logic or to conduct pattern processing before fuzzy logic is applied, and (b) a method to incorporate logics in NN structure etc. could be possible for combining these two techniques. The employment of former is, however, now prevailing so far as the reviewed studies are concerned. As for the difficulty of the latter, it could be attributed for the far less number of NN researchers who engage in the study of fuzzy logics.

The second fusion method is to superpose similarities. The first similarity (1) shown in Table 1 is to give a membership function to NN without causing a crisp boundary between classes formed by a pattern classification type NN. The reason is that threshold function of its neuron have sigmoid characteristics to attain continuous values of [0, 1] as shown in Fig. 1.

The second similarity is that (a) the MIN operation of input and fuzzy variables conducted at each proposition of IF parts of fuzzy inference rule corresponds to a product of input to the neuron and synaptic weights, and (b) the MAX operation to obtain a final inference value from the THEN part of these plural inference rules corresponds to the input sum within neuron as shown in Fig. 2.

There are a number of papers on the fusion of NN and fuzzy theories conducted at these contact points. For example, the study cited in Sec. 3.2 is an approximate reasoning logic combined with a learning function of NN on the bases of similarity (1), and the one mentioned in Sec. 3.3 is the one to establish a logic by learning function of NN. The one mentioned in Sec. 3.5 is to use the similarity points (1) and (2) themselves.

The endowment of learning function to the fuzzy logic is one of the major purpose of fusion with NN. However, we have to be conscious that the learning function is not a particular characteristics of NN only. One of such reports is made on a system to reduce the difference between frequency of appearances and sensation of user who conducted a fuzzy document retrieval by learning [59]. The degree of association between keywords is expressed in a form of matrix, and the learning is conducted by using the steepest decent method. Although the matrix in this case could be interpreted as a two-layered NN in a way, it could apart from the general accepted image of NN.

3. STATUS QUO OF FUSION TECHNOLOGY

3.1. Early Stage

In its early stage, introduction of fuzzy logics into NN constituted a core of those studies. The first paper is concerned "multi-input/multi-output neuron model" presented by S.C.Lee et al.,[51]. They generalized it so that intermediate values can be dealt, while the output of neuron model proposed by McCulloch & Pitts was a binary step function, and they also showed possibilities of fuzzy automata and λ-fuzzy language recognizer.

The study of correlation to the neural physiology had been further continued after them. D.Butnariu proposed a model of the eighth sensory nerve (hearing-vestibuler nerve) by using L-fuzzy automata [8], and A.F.da Rocha et al., employed tools such as fuzzy language, fuzzy entropy, and fuzzy automata in their try to analyze the nerve systems [61-64]. Meanwhile, O.G.Chorayan presented its application to analyze the neuron of the frog visual central analyzer and the crayfish sixth abdominal ganglion [9]. However, very little report has been made on the application of fuzzy logic to the neural physiology recently. Instead, L.C.Shiue et al., presented an application of automata to a fuzzy learning machine constituted of units of fuzzy neuron [66]. If the MAX-MIN operation is substituted by sum of products operation, stochastic neural automata can be obtained.

3.2. Auto-design of Membership Function

One of the most significant characteristic feature of fuzzy logic attained in view of the knowledge processing is the separation of its logic and fuzziness into a rule and a membership function respectively, and another is that the quantitative expression and processing of fuzziness became possible by this. Thus, those objects that had been considered highly difficult to deal with because of their fuzziness can now be dealt easily by using a framework of conventional knowledge processing. While a considerable time has to be spent for tuning the rules for dealing those objects having inherent fuzzinesses, such as talent or skillfulness of expert, by two valued logic based system wherein the fuzziness affects the logic, there exists no needs to tune the rules of logical expression when an approximate reason is employed.

However, the method itself for designing this membership function relies much on the experience now, and this inevitably becomes a bottleneck of system design. An employment of NN learning function to this is a typical pattern of fusion study described in this section.

The designing methods of membership function are roughly divided into three categories shown below.

(a) Manual cut-and-try
(b) Fuzzy clustering [28]
(c) Neural Network.

(a) is a method by which membership function is designed for each of fuzzy variables, and a fuzzy rule subspace in input variables space obtained by fuzzy partition is limited within a hypercube shown in Fig. 3(a). The method (b) is free of such a constraint, but it has to take a form such as hyper-ellipsoid and is constrained by a distance function for clustering. The method (c) is a first pattern introduced in this section, and by this, the fuzzy rule partition in an arbitrary hyper curved-surface becomes possible as shown in Fig. 3(b). However, if learning is continued without paying much attentions, the class boundary become constrained by the sigmoid characteristics of neuron, producing less ambiguous class boundary region as shown by a hatched region shown in Fig. 3(b). This problem could be fundamentally solved by changing the sigmoid characteristics according to the inference object, or by providing learning data considering the inclination of class boundary plane (the degree of fuzziness), but only a little had been discussed on this point except a paper telling the effects of learning iteration [13].

H.Takagi and I.Hayashi proposed a NN-driven Fuzzy Reasoning by which a membership function of approximate reasoning can be formed by employing a feed-forward NN [72,17,70,71]. This is to cluster the learning data first to determine the number of fuzzy inference rules, and to form the forms of each rule boundary in NN. This NN becomes an NN producing all of the membership functions, and all of the membership functions of each rule are produced by this. The point is that, by substituting the membership functions given conventionally in a form of table-look-up or formula by NN, a nonlinearity and learning function can be endowed the fuzzy system. Furthermore, a reasoning system can be constituted by using this core NN. This was applied to an inference problem to confirm the effectiveness of this system [18,19,72]. Regular studies of fusion in Japan began in Spring of 1988 after the above shown paper was presented, and those have been focused mainly on the design of inference rule and learning.

T. Furuya et al., also proposed a Neuro Fuzzy System (NFS) employing a feed-forward NN [10,11,13]. The degree of conformity between a pattern that NN learned in advance and the input vector pattern is used as the membership values, too. Furthermore, T. Furuya et al., proposed μBRAIN as an unit of knowledge processing to be employed in future [12,14,15]. In an architecture form, this is an knowledge processing unit of which minimum unit is three NNs consisted of an associative memory NN as memory, a feed-forward NN as operating director and is mutually linked to the former, and NN as a sequence controller of these. NFS which conducts approximate reasoning can be used as NN of operating director. This is a study of knowledge processing unit that would constitute next generation computer like the modern computer constituted of logical elements.

T. Yamaguchi et al., derived a membership function using Learning Vector Quantization (LVQ) [85]. LVQ has a similarity to the fuzzy clustering, and J. C. Bezdek identified this relationship to have a high freedom of obtained boundary form in 2nd NASA Workshop. In contrast to a conventional approximate reason-

ing that fuzzy partitions the input space, LVQ maps the input vector on a new space and, then this new space is fuzzy partitioned. By going through this mapping step, a non-linear fuzzy partition of the input vector space can be accomplished.

T. Yamaguchi et al., proposed a learning fuzzy neural network [87,86,83,34,35,84]. This is purposed to control the fuzziness at the composition of membership function by introducing Bidirectional Associative Memories (BAM, proposed by B.Kosko), into the approximate reasoning.

While the object of above studies is to control the form of membership functions using NN at the designing stage, A. Morita et al., proposed a simplified method by which the gain of membership function of fixed form can be adjusted by NN [56]. Since a system described the knowhow of expert machinist by approximate reasoning rules is conventionally inferior to the actual skill of machinist particularly at its initial stage, the membership function is considered a must to be tuned at the later stage. The method proposed by A.Morita et al., was to introduce learning to minimize the difference between the machining instruction given by the system and the actual machining instructions given by an expert.

H. Ishibuchi et al., carried out an experiment to construct various membership functions using NN [31], and derived a fuzzy language by which the form of membership function is transformed into that of instructor [32], and they further derived an interval-valued membership function of which values are broadened [75].

N. Watanabe et al., expressed a fuzzy rule by NN that is finely tuned through learning by allocation of one fuzzy variable to one neuron, and the weighting factor is so initialized that its sigmoid characteristics comes closer to the predetermined membership function [79]. this is an approach similar to that of the later which gives a fuzzy expert shell "MORITA", although no paper concerning this is presently available except technical manual.

C-c. Lee proposed a inference method by which the activity of each fuzzy inference rule (corresponding to the MIN operation at IF) is determined by the self-organization by introducing two neurons therein [50].

Although this is unrelated to the determination of membership function, H.Nomura et al., [58] applied a Hopfield model to determine the controlled variables of THEN part of a simplified fuzzy inference [30].

Those shown above are the papers that NN is used for determining the membership function. The following four advantages shown below are noticeable in these approaches.

(1) Shorter designing time since it is algorithmically determined without requiring manual works.

(2) Design of nonlinear membership function is possible because of inherent nonlinearity of NN.

(3) Automatical acquisition of rule from experts using the learning function of NN.

(4) Dynamical adaptation to inference environment by the learning function of NN.

As an example of (1), reported is a case where an adjustment conventionally required 30 to 40 hour manual works was substituted by an NN learning of 30 minutes to one hour conducted on a personal computer. (2) is a point emphasized in [17,72] and [85], and a cross-section of hyper-curved surface of nonlinear membership function obtained by this is shown also [17,72].

As for the feature of (3), reports by I. Hayashi et al., [20,21] and the before-described one by A. Morita et al.,[56] can be cited. I. Hayashi et al., designed an NN-driven fuzzy reasoning from the data acquired from an experiment conducted on an 1-D pole balancing (inverted pendulum system) wherein a experimenter tries to swing up a pendulum. In this experiment, the fuzzy inference rule is automatically determined without providing preliminary knowledges, since NN acquires the knowhows of experimenter who tried pendulum inversion automatically. Moreover, as this is related to the term of (2), the rod supporting a pendulum can be swung up by only two rules because a nonlinear membership function is employed in this system.

As for (4), no report proving it is so far available, and this is a task left to be done in future, but this could be executed without bringing up complexity since its fundamental is similar to that of (3). However, since the learn-

ing method that a well learnt NN is reinitialized and the learning is restarted by the data acquired in an independent inference environment, this can not be employed in the currently operating fuzzy system, and an additional learning has to be introduced therein, but the problem of additional learning that uses only additional data is not completely solved yet in the field of NN.

3.3. Knowledge Acquisition, Knowledge Expression

There are many cases where the approximate reasoning is combined with an expert system (ES) because the approximate reasoning is rule-based. When NN has to be incorporated therein, it takes a form of knowledge acquisition or knowledge expression. In a case of knowledge expression, the knowledge NN acquires is incorporated in the system as it is. In a case where knowledge acquisition is mainly employed, the inference rules are derived from the analysis made on the learnt NN. This derivation of knowledge is conducted mostly from a statistical analysis of the hidden layer, but the acquisition of new knowledge from the distributed expressions is considered fairly difficult. However, it could be done slightly easier if a linguistic meaning is assigned to neurons of I/O layers, and by determining causal relationship.

K. Saitoh et al., constructed a muscular contractive headache diagnostic ES by a simple NN, and tried to derive rules out of the causal relationship of I/O [65]. They extracted 443 rules from this experiment. Those were inference rules based on the binary logic, and thus, the certainty of rule and importance of proposition were unknown. Though a extracted rules were evaluated, it is certain that a lot of points to be improved were left.

As a method to improve this point, Y. Hayashi et al., conducted an experiment to acquire fuzzy inference rules from the causal relationship of I/O of NN [26,22]. To acquire knowledge easier, a layered network of which each unit outputs only three values (True (1), Unknown (0), False (-1)) were supervised trained by a pocket algorithm developed by S. I. Gallant. This is to extract not only a casual relationship of I/O, but to determine the linguistic truth values included in each fuzzy proposition in a relation to its membership function, and to determine the certainty of each rule itself from the value of output unit at the last. This method is meaningful in considering the importance of individual rule as a criterion for selecting only essential rules. As an application of this method, diagnosis of four hepatobiliary disorder on the bases of a blood analysis on the nine biochemical items and sex distinction is conducted [23,90]. From the results of this, an accuracy of inference that is 10% higher than a ordinal discriminant function was obtained. Furthermore, an inference method suited for inference rule containing a fuzzy proposition having linguistic truth values was proposed [24]. They proved that the inference using the acquired rule was superior than the original NN [25].

The knowledge expression is incorporated in the self-organized fuzzy controller developed by T. Takagi et al.[69,57]. As the two types of NN are included in this system, the first NN is used as an identifier of control pattern, and the second NN is used as a knowledge expression of dynamic characteristics of control system for controlling the fuzzy controller.

D. L. Hundson et al., reported an experiment where the rule-based knowledge of fuzzy ES for lung cancer diagnosis is combined with NN for eliminating interviews with specialists [29]. Beside these shown above, although this may not be proper to mention in this section, C. G. Looney proposed an expansion of approximate reasoning to petri nets [52], and as an application of this, an algorithm to be applied to the inference of new NN was also proposed.

For those who interested in this field, it would be profitable to see Reference [73] wherein the description of review and analysis of NN+ ES is included.

3.4. Fuzzy Cognitive Maps etc.

B. Kosko proposed a Fuzzy Cognitive Maps (FCM) [41] which is derived by expanding the cognitive maps proposed by R. Axelrod [4]. The cognitive map is an oriented graph showing a causal relationship between different factors, wherein the causal relationship is expressed by either the positive or negative sign for knowledge expressions. FCM expresses the degree of this relationship. Comparing with the tree-structured inference knowledge expression employed in conventional ES, this is advantageous in respect of higher process speed attain-

able by its parallel processing capability, easy adaptability to the inferences containing feedback, and easy system unification by employing matrix expression. As for the problem of how to determine the degree of causal relationship, a differential Hebbian learning developed by improving self-organized learning of NN is proposed [42].

Beside a digital version of FCM proposed by W. Zhang [91], W. R. Taber et al., proposed a method of such employed to infer the expert weights. As an application of such, K. Gotoh et al., employed this for supporting a plant control system [16]. K. Gotoh et al., constructed four kinds of FCMs from the causal relationship acquired from four specialists who conducted pumping operations judging the conditions of rain precipitation per unit time, water level, and change of water level, and unified these to construct a final system. An easy unification of knowledges is accomplished by superposing plural small systems.

Moreover, B. Kosko, centering around ABAM (Adaptive BAM) which takes intermediate values from the binary output BAM by Hebbian law, developed CABAM (Competitive ABAM; BAM which conducts competitive learning) [45], FAM (Fuzzy Associate Memories; ABAM to express a fuzzy proposition) [46], and RABAM (Random ABAM: ABAM to conduct annealing by giving a noise) [48] and its model of NN, and discussed these with a new aspect of geometric interpretation of fuzzy entropy in n-cube space.

3.5. Clustering and Pattern Recognition

The similarities (1) shown in Table 1 is to separate a class, and those could be related with the clustering. One of such examples is a fuzzy clustering M. Izumida et al., [36,37] conducted by employing a Hopfield model. The relationship with the fuzzy clustering is described for a multi-input and multi-output NN model developed by Y. Tan [76,77], and as an application of this, Y. Katoh et al applied this model to an alphanumeric character recognition [38].

The model of Y. Tan et al., should be regarded as a multi-NNs with inhibition learning. They weren't conscious about the relation with the fuzzy theory in their development process, and their model also has no relationship with the multi-input/multi-output neuron model of S. C. Lee et. al., shown in Sec. 3.1.

A direct expression of similarities (2) shown in Table 1 is a fuzzy neuron developed by T. Yamakawa, and this is applied to a numeric character recognition [88,89]. The region wherein the line segment of hand-written character should cross, region wherein the line-segment should not cross, and the region which can be ignored because of large deviations, are expressed in terms of membership functions in this model. These membership functions can be regarded as synapses of neuron.

As for the studies other than those of above, W. Pedrycz commented on a pattern recognition method that introduces two NNs and uses a fuzzy level [60]. G. Bortolan et al. who developed an identification of ECG Fuzzy pattern are studying the relationship of it also [5]. M. Katoh et al., studied on the handwritten numeric character recognition [39]. It unifies plural outputs of NN by using a combination rule developed by A. P. Dempster. J. M. Keller et al., reported on an experiment to accomplish a fast convergence of linear discrimination problem by perceptron . They gave a higher learning priority according to the distance from the center of class [40].

3.6. Cascade Connection of NN and Fuzzy Processing

One of the generally practiced sharing of roles between so-called NN and fuzzy logic is that NN performs the pattern processing at first, and the later part is processed by fuzzy logic on the logic base. Viewing from this meaning, the cases of such a system would become more popular as the more complicated system has to be dealt in near future.

Although this can not be said as the rule-based fuzzy control, the air-conditioner control developed by F. Matsuoka et al., is the first case having keywords of NN and fuzzy control in Japan [53,54,55]. Therein, the three variables of actuators that interact each other is controlled by system command for each actuators and correlation command for cooperation of actuators, and a time-weighting (this was said to correspond to a membership function) is given to these two types of commands to composite a final control.

A. Amano et al., applied NN to consonant recognition, and attained a final judgment by inputting the output of NN into approximate reasoning. The errors of NN are restored by

this [3,2,1].

W. R. Taber et al., reduced the influence of noise by conducting fuzzy post-processing after the recognition of orca call with the neuron ring [68].

Nihon Unisys Ltd., exhibited a stockbroking judging ES at "International Symposium Computer World '88" held in Kobe. This ES was constructed by inputting the results of technical analysis into NN, and utilizing the output of it that is a dealing command as a partial input to the approximate reasoning.

While fuzzy processing follows NN in these four examples, H. Takahashi employed these in a reversed order [74]. The input unit performs statistical processing of vehicle data, and this output is fed into the feature extraction unit to which fuzzy inference rules based on multi-variable analysis are incorporated for the analysis. The NN part delivers the output of human subjective judgment on the relative difficulties based on these features' values.

3.7. Other Studies

Studies other than the above-mentioned include the reports made on the employment of NN for identifying the system having fuzzy I/O (e.g. lecture of L. A. Zadeh at Kyoto and the 2nd NASA Workshop), wherein the learning of NN was so conducted to input a membership function and to output a membership function. R. R. Yager proposed an OWA (Ordered Weighted Averaging Aggregation) operator [81] to be used in the fields where decision making is performed based on plural criterions. From the similarities of this application field to the multi-input neuron, his paper discussed the relationship with NN [82]. D. C. Kuncisky et al., presented a discussion made from a view point defining that the inputs to neuron are the elements of a fuzzy set and the output of neuron is a fuzzy measure of truth [49], in addition to their comment on the prospects on the learning algorithm. F. J. Bremner et al., presented non-parametric methods of analyzing fuzzy-set data using transforming neuron polarization values [7].

As for the relationship between NN and fuzzy logic, it was reported first at the NASA workshop held in May 1988. Although the proceedings of meeting was not published, a report of the meeting prepared by K. Hirota is available [27]. According to this, four people presented papers with two key-words. It was told that B. Kosko reported on the analysis and design of fuzzy associative memory with fuzzy entropy, and M. Togai on the fuzzy-NN processor using an approximate reasoning chip, and W. R. Taber and R. R. Yager reported on the similarities between sum of products operation of neuron and MAX-MIN operation of approximate reasoning. At the 2nd NASA Workshop held in April of this year, the number of papers having two key-words is found doubled over those at the first workshop.

4. FUTURE DIRECTIONS

As seen from the trend of these commented papers, current fusion study is to bring NN into fuzzy logic. From the author's future view, importance of the itemized developments as future research directions shown below would be increasing.

(a) Automatic Acquisition of Fuzzy Inference Rules Using NN.

The learning function of NN is recently introduced in the field of fuzzy control succeeding to the fuzzy adaptive control, recurrent fuzzy control, and the leaning fuzzy control. Whereas cases like exercises had been considered so far, automatic tuning and acquisition of inference rule structure will be applied to practical applications more often to prove its effectiveness to upgrade the development efficiency and performances. Plural corporations that already put fuzzy ES in the market are trying to incorporate NN into their development tools aiming their applications probably in auto-tuning or knowledge acquisition.

ESs employing NN for knowledge expression that was described in Sec. 3.3 would be increasing. However, as for the method by which knowledges are acquired in a form of production rule from NN, an accomplishment of break-through in future seems essential.

(b) Adaptation of Fuzzy Inference Rule to Inference Environment.

The development of new learning method by which the inference rules can be modifyed according to the changes of inference environment is now necessary. Ultimately, this would lead to the day when we develop "equipments of which handling easiness is improved as it is used more". At the present age of "Individual-

ity", the control used to be adapted mainly for a large system has to be now shifted to a control adapted to individual character and need for the mass produced products. Therefore, the additional learning problem that requires partial rewriting of the function formed in NN, discarding the past learning data, has to be developed. Presently, this can be accomplished only either by complete re-learning or by adding new learning data to the whole past learning data which are held.

(c) Development Started From Similarities of Processing.

Considering an expanded operator capable of unified handing of two similarities (2) shown in Table 1, there could be a probability to develop a new processing form based on this. Were this realized, highly effective results could be expected to both fields.

(d) Fast Approximation by Introducing Network Structure

The form of inference rule that is capable of both parallel processing and multistage inference is a very structure of NN. While the parallel processings are popular at present in the field on NN such as the silicon system and optical neuro devices, the efforts to develop higher speed NN will surely affect the approximate reasoning.

While the studies of network reasoning and multistage inference are active in the field of fuzzy theory, These studies are made also in People's Republic of China [78], and it is being incorporated in a system [80]. This may give an affect to NN field. Since very little about the studies of fuzzy mathematics is known in Japan except its titles, the author would like to expect fruits of technical exchange at "Sino-Japan Joint Meeting on Fuzzy Sets and Systems" which will be held in October this year.

(e) Introduction of Fuzzy Logic into NN.

It is said that the improvement of functions of NN could not be obtained by starting with cut-and-try, but it depends on how to incorporate the preparatory knowledge into NN. Conventional knowledge incorporation had been done either by (1) conduct a preprocessing according to the statistical information of input data, (2) prewiring for units connection, (3) combination of functional NNs, or by others. It seems that a higher order processing could be attained by incorporating fuzzy inference rule thereto.

As the one of such efforts, the NN-type ES "MORITA" of Brains Co., is automatically manufactured by using production rules of fuzzy ES "NORIO"[6] wherein a fuzzy proposition in the inference rules is allocated to one of the NN units, and thus the relationship between IF and THEN parts is expressed by a connection between units. The final value of weighting factor of NN is determined by the learning made after the initial value setting made on the degree of confidence of inference rule. This approach is to incorporate an approximate reasoning structure into NN.

In the field of NN study, a number of structurized NNs have been proposed. In the field of fuzzy theory study also, excluding the paper presented this conference, the NN-driven fuzzy reasoning, NFS, and the learning fuzzy neural network described in Sec. 2.3 are the models related to structurized NN. Thus, the positive employments of fuzzy logic structure for NN designing is a definite trend in future.

(f) Introduction of Fuzzy Theory into Fast NN Learning.

There exists a high expectation on the effects of introducing the fuzzy theory into NN learning to make it higher speed. However, unlike the study fields of above, even the starting of this has not been made yet except the related one made by J.'M. Keller et. al., mentioned before.

The employment of NN by fuzzy theory researchers was made in an early date, and many of them have continued concerns to NN as a tool. However, since there are very little who are versed very well in the fuzzy theory, the development of this study may take some more time. The reason of this is that fuzzy theory gave an vague impression since it combined with many fields and is diversified too much although NN offered a tool that can be used as a black box. The advancement of fuzzy researchers into the fields of NN could be one of possible solutions. If an advancement in such fields were made, and the high-speed learning became a promising prospect, this is what the author wished to see.

5. CONCLUSION

An analytical pattern of the studies to fuse NN and fuzzy logic, and the survey of status quo of fusion studies divided into seven fields are carried out. And based on these, the author derives and describes the future prospects and the research directions to be taken.

As laboratories advocating the fuzzy and NN themes are being established in Japan and France, and the first and second workshop meeting in NASA and the conference in Iizuka have been held, the author would like to expect this trend would be largely expanded to create revolutional fusion technologies in near future.

Whereas the provision of conversational humane environments such as gentleness, warmness and friendliness are essential to conduct successful communication between human beings. The future age where such environment is provided even for the man-machine communication so that the nonspecialist can establish a friendly communication with machine, is at around the corner, the author would like to see the study of NN and fuzzy logic would become a key technology to realize such society.

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IEICE: The Institute of Electronics, Information and Communication Engineers (Japan)

IEE Japan: The Institute of Electrical Engineers of Japan

IPSJ: Information Processing Society of Japan

SICE: The Society of Instrument and Control Engineers

ISCIE: Institute of Systems, Control and Information Engineers (Japan)

SOFT: Japan Society for Fuzzy Theory and Systems

ICNN: IEEE International Conference on Neural Networks

IJCNN: IEEE & INNS International Joint Conference on Neural Networks

IIZUKA-88: International Workshop on Fuzzy System Applications

Fuzzy Syst. Symp.: sponsor was IFSA Japan Chapter