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A FUZZY NEURAL MODEL FOR TARGET RECOGNITION

BY KIRAN R. BHUTANI ALI FARSAIE BRENDA DAY

WEAPONS SYSTEMS DEPARTMENT

4 FEBRUARY 1991

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FOREWORD

The last decade has witnessed tremendous interest and development in artificial neural networks. They are beginning to be accepted as powerful adaptive tools for solving a variety of recognition problems. Despite their dynamic success, there is a perpetual challenge presented by the human brain, which can handle tasks dealing with fuzzy or uncertain data. In this report, we demonstrate that merging of neural networks and fuzzy sets, where the former is a powerful tool for performing massive computation and the later for coping with uncertainty, provides better tools for modeling the human classification process.

This study was partially funded by the Office of Naval Technology (ONT). Kiran R. Bhutani, currently with The Catholic University of America, was an ONT Postdoctoral Fellow at the Naval Surface Warfare Center while this study was carried out.

This technical report was reviewed by Dr. Kenneth F. Caudle, Head of the Advanced Weapons Division.

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INTRODUCTION

Defense capabilities, which are being sought by the Navy, require effective weapon systems. Major improvements in autonomous real-time target recognition are critically needed to achieve success with the next generation of smart weapons. Neural networks have attracted tremendous interest in the last decade. They are beginning to be accepted as powerful adaptive tools for manipulating and solving a variety of problems related to target recognition, speech recognition, stock market prediction, etc.

Artificial neural networks are modelled based on the biological nervous system and inspired essentially by the neurosciences and computer sciences fields. These networks provide a greater degree of robustness and fault tolerance than sequential computers. Thus the decision making process of the network is not globally affected due to a local damage of few nodes. The human brain on the other hand is capable of handling and performing tasks dealing with fuzzy or uncertain data. Indeed the majority of us think fuzzy in most situations, and much of human reasoning is imprecise in nature. Thus human reasoning is not suitable for formalization within the language of classical logic and probability theory.

Fuzzy set theory as pioneered by L. A. Zadeh[1] and investigated further by many researchers[2,3] provides tools for modeling uncertainty and ambiguity which is so prevalent in human interpretation and thought process. This promising field, which is a generalization of abstract set theory, allows us to assign a degree of membership to an object for a class. This degree is a number between "0" and "1", where "0" means no membership and "1" means full membership. For the classification task, the human mind evaluates the perceived information by assigning memberships to the various attributes in the input space and the stored classes.

Thus in order to build intelligent systems for target recognition, we must understand and represent mathematically the issue of uncertainty in human knowledge. We believe that the merging of neural nets and fuzzy sets, where the former is a powerful tool for performing massive computations and the later for coping with uncertainty, will provide better tools for emulating human classification process.

This paper reports development of a preliminary neural net model which can be viewed as a dynamical network. It is aimed to incorporate fuzziness into the network, thus resulting in improved performance of the recognition process.

DESCRIPTION OF THE MODEL

ARCHITECTURE

The proposed model is a dynamical neural net model with the number of levels, as well as the number of neurons in the input layer of each level, to be determined by the user. Each level of the network has an input layer, two hidden layers, and an output layer (see Figure 1). The number of neurons in the first hidden layer at each level is equal to the number of neurons in the input layer. This number is equal to the number of features input at that level. The number of neurons in the second hidden layer at each level is equal to the number of targets, and the number of neurons in the output layer is equal to the number of target classes plus 1, an extra node for no match.

Assume there are n levels in the network and k targets with m features of each target input to the system. Let m1,m2,....,mn be the number of features input to the various levels 1,2,..,n then m1+m2+...+mn = m. We denote the i-th feature of the j-th target by f_{ij}, and the tolerance associated with the i-th feature of the j-th target by Q_{ij}. We associate a vector (f_{i1}, f_{i2},..., f_{ik}) representing the i-th features of the various targets with the i-th neuron in the first hidden layer. We also associate a vector (Q_{1j}, Q_{2j},..., Q_{tj}) representing the tolerance vector associated with the target j, with the j-th neuron in the second hidden layer at any level, where t is the number of features input at that level.

Every level k (except level 1) in the network receives input from level (k-1) as well as a new set of features of the target. The justification of having various levels in the network rests essentially on the fact that the human mental processing scheme goes through various levels of classification for identifying an object. We first look at the strongest features of an object and try to classify based on that information. However if the decision can't be made at the strongest level (that is, at level 1 in the proposed network), we then go to the next set of features and try to classify with the help of additional information. This process continues until all the features at our disposal have been consumed. If the first level of the network can classify the target, there is no need to proceed to the other levels. However if no classification is made at the first level, computation is carried out sequentially at the next level and so on until the classification decision is made.

From the i-th neuron in the first hidden layer (representing the i-th features) to the j-th neuron in the second hidden layer (representing the j-th target), we have a vector denoted by Wij = (wi1j, wi2j, ..., wimj), where winj represents some relation between the i-th and the n-th feature of the j-th target with the i-th and the n-th feature of the input vector.

Let a = (a_1, a_2, ..., a_n) be the input vector consisting of

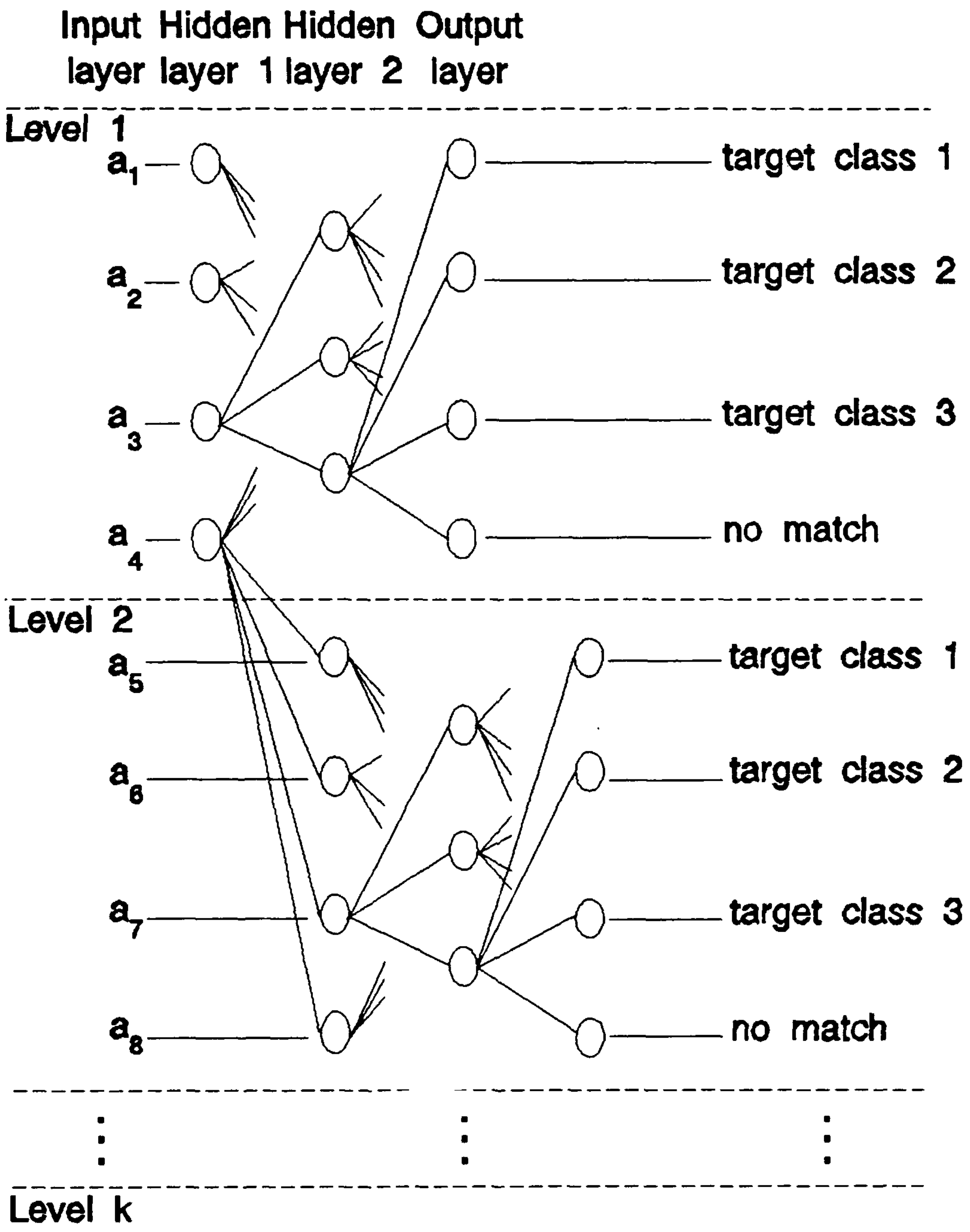
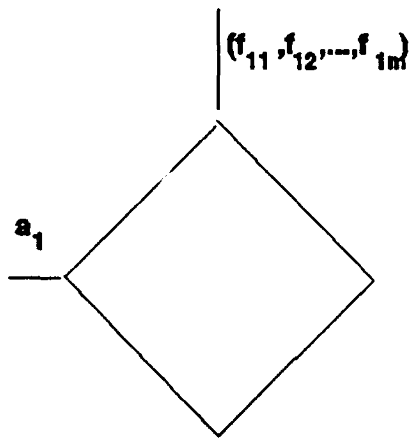


FIGURE 1. STRUCTURE OF THE MODEL

features of unknown target which has to be classified. The computation at each neuron in hidden layer 1 is carried out as follows. Consider the neuron representing the first feature of each target.

Compute $|f_{11} - a_1|, |f_{12} - a_1|, \ldots, |f_{1m} - a_1|$; then

$$k = \min_{1<=j<=m}\{|f_{1j} - a_1|\}$$



At each neuron in hidden layer 1, the network selects the class or classes (k) which minimize the distance between the stored feature and the input feature. We consider these classes winners at that neuron. Among these winners we select those targets which have a maximum number of wins. These are our winners at hidden layer 1, and they are the possible candidates for classification of the unknown feature vector. The neurons corresponding to these target winners become active in hidden layer 2. Assume target 1 and target 2 are winners at hidden layer 1, that is, they have the maximum number of matches with the input feature vector. Computations from hidden layer 1 to hidden layer 2 are carried for neurons representing these targets. Let $C_1 = (c_{11}, c_{21}, \ldots, c_{n1})$ be the feature coefficients of target 1 which are fixed. The output at neuron 1 (corresponding to target 1) in hidden layer 2 is represented by

$$(P_{11}, P_{21}, \ldots, P_{n1}) = \sum_{i=1}^{n} \Phi_i(a_i, w_{i1})$$

where Φ is some nonlinear function of the input vector and the weights. This vector $\vec{P}_1 = (P_{11}, P_{21}, \ldots, P_{n1})$ is then compared with the tolerance at that vector denoted by $\vec{Q}_1 = (Q_{11}, Q_{21}, \ldots, Q_{n1})$, and the degree of match between the unknown input vector $\vec{a}$ and the target class 1 is obtained by the method described in classification.

TRAINING PROCESS

Let $(a_1, a_2, \ldots, a_n)$ be the features of the first target. We then require that the output at the first neuron $\vec{P}_1 = (P_{11}, P_{21}, \ldots, P_{n1})$ in hidden layer 2, at level 1 be less than or equal to the tolerance vector $\dot{Q}_1 = (Q_{11}, Q_{21}, \ldots, Q_{n1})$ associated with that neuron. Assume for some k that $P_{k1} >= Q_{k1}$. Then the point P_1 lies outside the hyper-rectangle* $h(Q_1)$ in the n-dimensional space with the longest diagonal from the origin to the point Q_1. We say the

*If one considers two features of target 1, then $\overline{Q}_1 = (Q_{11}, Q_{21})$ and so the hyper-rectangle $h(Q_1)$ in this case is obtained by drawing a rectangle in the plane with one vertex at the origin and the opposite vertex at the point (Q_{11}, Q_{21}).

closest point to P_1 in the hyper-rectangle is a point $T_1 = (T_{11}, T_{21}, \ldots, T_{n1})$, where

$$T_{k1} = \begin{cases} P_{k1} & if \;\; P_{k1} \le Q_{k1} \\ Q_{k1} & if \;\; P_{k1} \ge Q_{k1} \end{cases}$$

Training requires that we change the weights and tolerances in such a way that $h(Q_1)$ expands and $T_1 = P_1$, that is, P_1 falls in the hyper-rectangle $h(Q_1)$. We interpret the training of the network as creating weak or co-weak isomorphism[4] of itself until it reaches a stable state, a state when $T_1 = P_1$.

CLASSIFICATION PROCESS

For the purpose of classification, we apply fuzzy reasoning to assign a degree of membership between unknown input features and the target classes.

Assume target class k is the winner at hidden layer 1 and let $(P_{1k}, P_{2k}, \ldots, P_{nk})$ be the output of neuron representing target class k in hidden layer 2. Recall that at this neuron a vector $(Q_{1k}, Q_{2k}, \ldots, Q_{nk})$ is associated. This vector represents tolerance the features of target k input at level 1. Let

$$m_{jk} = (Q_{jk} - P_{jk})\ c_{jk}$$

where c_{jk} is the j-th feature coefficient of the k-th target and is fixed. We define the degree of membership m_k of the input vector and target class k to be

$$m_k = 1 - \sum_{j=1}^{n} (Q_{jk} - P_{jk}) c_{jk}$$

$$= 1 - \sum_{j=1}^{n} m_{jk}$$

where n is the number of features input at level 1. The above formula of assigning class memberships considers to a greater degree those features whose weights are high. If the j-th feature coefficient c_{jk} is high, then larger difference $(Q_{jk} - P_{jk})$ would contribute to a large number for m_k and thus to a small degree of membership m_k in the target class k. If c_{jk} is low, then m_{jk} is low regardless of whether input features match the features of the k-th target strongly or not. The feature coefficients c_{jk} indicate the extent to which the j-th feature of the k-th target is important for classification purposes. The c_{jk} which are the degree of importance of the features will be computed using statistical methods. The winning target is the one for which the degree of membership is the highest, that is, target k is the winner if

$$m_k = \max_{1 \le i \le L} (m_i)$$

where L is the number of targets.

CONCLUSION

A mathematical model of a multi-level, multi-layer neural net was developed which uses fuzzy theory for classification. The developed architecture would allow imprecise or incomplete knowledge gained at one level of the network to be forwarded as additional input to the next level of the network. Fuzzy theory allows us to interpret the information in a more general form for developing methods in pattern clustering and recognition. For the model under development, a number of issues still need to be investigated. Some of these are:

1. Application of fuzzy theory in structuring neural networks for handling uncertain and imprecise concepts.
2. Mathematical representation of flow of information dealing with ambiguity from one level to the next level of the network.

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A mathematical model of a multi-level, multi-layer neural network was developed which uses fuzzy theory for classification. This model would allow imprecise or incomplete knowledge gained at one level of the network to be forwarded as additional input to the next level of the network. Fuzzy theory allows us to interpret the information in a more general form for developing methods in pattern clustering and recognition. We believe this approach will incorporate human thinking and decision making into neural networks.

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