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Yasuhiro KOMORI (CMU/ATR)
Shigeki SAGAYAMA (ATR)
Alexander H. WAIBEL (CMU)

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ATR 自動翻訳電話研究所
ATR Interpreting Telephony Research Laboratories

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Yasuhiro KOMORI (CMU/ATR)
Shigeki SAGAYAMA (ATR)
Alexander H. WAIBEL (CMU)

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ATR Interpreting Telephony Laboratories
Seika-cho Soraku-gun, Kyoto 619-02 JAPAN
Telephone: +81-7749-5-1311
Email: komori@atr-la.atr.co.jp;

Carnegie Mellon University
EDSH 109 Pittsburgh, PA 15213
Fax: +81-7749-5-1308

Abstract

In this report, we propose a new fuzzy training approach for a phoneme classification type neural networks. This fuzzy training approach is realized through back-propagation algorithm, but differs from the conventional training approach in the point of how to give the training target values for the neural networks. In the conventional training approach, the phoneme class of the input data are given to the target values for training; 1 for the output unit which corresponds to the input phoneme, and 0 for the other output units. However, in this fuzzy training approach, the target values are defined as how likely the input phoneme is to the phoneme classes. This likelihood is computed according to the distance between the input phoneme itself and other data in training data set. The phoneme classification experiments are performed on Japanese /bdgmnN/, 14 category English vowels and 40 category English all phonemes. This report also discussed these experiments.

Contents

1. INTRODUCTION

The recent incredible progress of computers made it possible to deal with a great amount of data. This progress also gave a great effect to the study of speech recognition and brought us a break-through from template matching type DTW speech recognition to new speech recognition approaches as Hidden Markov Model (HMM) [Rabiner86] and nueral networks [Lippmann87].

HMM and neural networks, of which the strong training algorithm were developed, appeared to be good phoneme classifiers. HMM is easily able to expand to continuous speech recognition by concatenating HMMs of phonemes. Thus, several speech recognition systems based on HMM are developted as; TANGORA [Jelinek85], SPHINX [Lee90], BIBLOS [Chow87], ATR [Hanazawa90]. On the other hand, in comparison to HMM, neural networks still retain many problems when applyed to continuous speech, even if the phoneme classification performance of neural networks is greater than that of HMM [Waibel87].

The main advantages of HMM for neural networks are; (a) the capability to deal with the time warping features of phonemes and (b) the probabilistic representation for each phoneme which indicates not only the belonging phoneme class but also the probabilities of belonging to every phoneme class. The first advantage easily leads to continuous speech recognition by concatenating phoneme HMMs and the second one leads to a good integration of phoneme HMMs with the upper level of speech recognition as language model.

Also, there are some neural networks approaches which attempts to deal with these advantages; Time-Delay Neural Networks (TDNN)[Waibel87], Dynamic Neural Networks (DNN) [Sakoe89] and Neural Prediction Model (NPM) [Iso90]. NMP is able to deal with both time warping of speech features and is able to concider the likelihood for each class and it is classified as prediction type neural networks. TDNN and DNN are classified as classification type nueral networks. Although TDNN has a capability of time shift invariance and DNN is able to capture the time warping features of the utterance, the neural networks trained through both approaches are considered to result only the belonging class of the input because the neural networks are trained as to result the belonging class for the input phoneme, not to result the probability or likelihood of the belonging to the classes. And it makes a big problem when integrating to language model for the lack of information from the acoustic level.

In this report, we focus on phoneme classification type neural networks and propose a new fuzzy training approach which trains the nueral networks to result the likelihood for each phoneme class in the output units. The proposed fuzzy training approach is realized through back-propagation algorithm, but differs from the conventional approach in the point of how to give the training target values for the neural networks. In the conventional training approach, phoneme class of the input data are given as the target values for the neural networks; 1 for the output unit which corresponds to the input phoneme, and 0 for the other output units. However, in this fuzzy training approach, the target values are defined as how likely the input phonemes are to the each phoneme class according to the distance between the input phoneme itself and other data in other phoneme classes. More details about this fuzzy training are described in the next section. In addition, the phoneme classification experiments, which are performed on Japanese /bdgmnN/, 14 category English vowels and 40 category English phonemes, are discuessed.

2. NEW FUZZY TRAINING

The idea of the proposed fuzzy training approach is to train the neural networks to result likelihood of the input phoneme for each phoneme class. This approach differs form the conventional training approach which trains the neural networks to result the phoneme class itself. Figure 1 shows the brief idea of the difference between the conventional training approach and the proposed fuzzy training approach.

Figure 1-a shows the target values for training data of the conventaional training approach. The target values are simply obtained as 1 for the group of the training data and 0 for the others, i.e. the target values are given as (1,0,0) for every datum which belongs to group A, (0,1,0) for group B and (0,0,1) for group C.

Figure 1-b shows two examples (Xa1 and Xa2) of the target values for the fuzzy training approach. For instance, the target values to train datum Xa1 in the figure are obtained as follows;

1. Find the nearest data of training datum Xa1 from each group A,B and C in the training data set. The result is Xa1 for group A, Xb1 for B and Xc1 for C.

2. Calculate the distance between the training datum X1a and the obtained data Xa1, Xb1 and Xc1; d10=d(Xa1,Xa1), d11=d(Xa1,Xb1), d12=d(Xa1,Xc1), where d() is a distance function as Euclidian distance between two data.

3. Compute the effect from each group to the training datum through the group effect function f(). Here, we assumed that the nearest data which belong to each group are the most simiral data to the training datum in each group. Moreover, we assumed that the effect of the group is able to compute through a function of a similarity between the training data and the neareset data of each group. The effect from the group will be smaller when the closest data of its group is further and is larger when the closest data of its group is closer. Thus, the effect function can be model as a monotonous decreasing function. For instance, f(d)=exp(-alpha*d*d) where (alpha>0) is a constant value. In this case, the effect from group A to datum Xa1 can be obtained as f(d10)=f(d(Xa1,Xa1)), from B as f(d11)=f(d(Xa1,Xb1)) and from C as f(d12)=f(d(Xa1,Xc1)), where f() is the effect function from group.

4. Finally, the target value for each group for training datum Xa1 is given as (f(d10),f(d11),f(d12)) when the neural networks are trained.

3. EXPERIMENTS

The phoneme classification experiments are performed on Japanese /bdgmnN/, 14 category English vowels and 40 category English phonemes. The neural networks are trained through the proposed fuzzy training approach and conventional training approach by back-propagation algorithm using the fast back-propagation training tool Dynet [Haffner89].

3.1. Japanese /bdgmnN/ classification

3.1.1. Data

The classification experiment on the Japanese phoneme /bdgmnN/ is performed on the phonemes cut out from the ATR database uttered by one male announser [Takeda88]. There are three utterance styles in the ATR database; a) high frequency Japanese isolated word (5240 words), b) short and long Japanese phrase (bunsetsu) utterance, c) continuous utterance. b) and c) consist of Japanese dialogues of "conference registration" which is the task of the ATR project. The neural network is trained by phonemes cut out from half (odd number) of the 5240 isolated words and tested by phonemes cut out from the other half (even number) of the 5240 words, from short and long phrase and from continoues speech. Table 1 shows the number of each phoneme for each utterance style.

Table 1. Number of phonemes for Japanese /bdgmnN/ task.

phoneme	train(word)	word	long phrase	short phrase	continuous
/b/	218	227	47	48	48
/d/	202	179	235	234	234
/g/	260	252	120	118	118
/m/	471	481	190	190	190
/n/	260	265	276	274	277
/N/	500	488	115	117	119

Every phoneme is cut out into a size of 70ms datum (7 frames) which the end label of the phoneme comes in the center of the datum. Every datum is sampled at 12kHz and is analyzed by FFT through a 21.3ms Hamming window at every 5ms shift. 16 melscaled coefficients are computed from the power spectrum to collaps adjacent coefficients in time resulting in an overall 10ms frame rate. The coefficients of each input token are then normalized to lie between -1.0 and +1.0 with the average at 0.0 (normalised in each cut out phoneme).

3.1.2. Neural Networks

The structure of neural network used for this classification experiment is a sub-network of TDNN [Waibel87]. The sub-network is shown in Figure 2. The dot-line in the figure shows the original structure of TDNN. And the bold-line inside TDNN shows the sub-networks which is a three layer neural network. The neural network consists of one input layer with 7 frames * 16 spectral coefficient units, one hidden layer with 5 frames * 20 units and one output layer with 6 units corresponding to each phoneme, /bdgnmN/. The connection between the input layer and hidden layer is tied-connected with a window of three frames to one. The reason why we adopt the sub-networks of TDNN for the original structure of TDNN is because we found that the classification result was better in case of both continuous speech and shifted data, when the sub-network is trained on shifted data. The comparison classification result of these is shown in Table 2.

Table 2. Classification rate of TDNN and its subnetwork.

utterance style	TDNN	sub-network
isolated word	95.6	95.2
long phrase	75.8	80.5
short phrase	76.9	79.5
continuous	61.7	71.6
-20 ms	91.2	* 92.8
-10 ms	94.7	* 95.5
0 ms	* 95.6	* 95.2
10 ms	94.1	* 95.5
20 ms	85.9	* 92.9

* inidicates the position of training data

3.1.3. Results

The next tables show the experiment results on Japanese phoneme /bdgmnN/ classification using conventional 0, 1 training approach with mean square error function (HDsig) and McClelland error function (HDmcl) and the proposed fuzzy training approach with mean square funtion (TGsig), in Table 3-a, 3-b and 3-c, respectively. For the group effect function f(), exp(-alpha *d *d) is adopt, where d is a mean square error distance and alpha is 0.005. Additionally for the fuzzy training, the target values are normalized from 0.05 to 0.95 to use the linier part of the sigmoid function in the output layer. The itteration of training epoch was performed up to 100 epochs. The top2620 in the tables indicates the best classification rate in the epochs of training iteration for word utterance phoneme of testing after the training is almost converged (when the rate of training comes over 98.0%). The number of the epoch is shown in the bracket []. The ave. indicates the avarage classification rate after the training was converged. In the bracket, the begining and end number of the avaraged epochs are shown. The maximum and minimum shows the maximum and the minimum classification rate with in the epochs in the above bracket. Figure 3 shows the convergence for thr training data of each approach. HDsig, HDmcl and TGsig standing for a) conventional training approach with mean square error function, b) with McCleland error function and c) fuzzy training approach. Table 4 shows the top-Nth classification rate for each approach.

Table 3-a. Conventional training approach with mean square error function.

utterance	train	word	long phrase	short phrase	continuous
top2620 [91]	99.20	97.00	82.50	85.40	74.30
ave. [11-99]	98.90	96.41	82.37	84.49	74.59
maximum [–]	99.20	97.00	86.10	87.10	77.20
minimum [–]	97.90	95.20	76.10	78.40	70.90

Table 3-b. Conventional training approach with McCleland error function.

utterance	train	word	long phrase	short phrase	continuous
top2620 [60]	99.90	97.20	85.20	84.90	75.70
ave. [6-99]	99.75	96.48	84.24	85.27	75.88
maximum [–]	100.00	97.20	87.40	87.50	80.40
minimum [–]	97.80	94.70	79.50	81.20	69.80

Table 3-c. Fuzzy training approach with mean square error function.

utterance	train	word	long phrase	short phrase	continuous
top2620 [87]	99.20	97.10	85.70	86.20	78.00
ave. [10-99]	98.73	96.55	85.25	86.09	77.88
maximum [–]	99.40	97.10	88.50	88.60	80.50
minimum [–]	98.00	95.60	77.80	79.00	73.00

Table 4. Top-Nth classification rate

uttrance	approach	top	2nd	3rd
train	HDsig	99.2	99.7	99.8
	HDmcl	99.9	100.0	100.0
	TGsig	99.1	99.9	100.0
word	HDsig	97.0	99.4	99.7
	HDmcl	97.2	99.4	99.9
	TGsig	97.1	99.5	99.0
long phrase	HDsig	82.1	93.7	98.0
	HDmcl	85.4	94.8	98.1
	TGsig	85.7	95.9	98.0
short phrase	HDsig	85.2	93.9	97.0
	HDmcl	84.8	93.8	98.2
	TGsig	86.0	94.2	97.7
continuous	HDsig	74.0	88.7	94.7
	HDmcl	75.7	89.4	95.0
	TGsig	77.8	91.1	96.7

HDsig: conventional with mean square error function
HDmcl: conventional with McClelland error function
TGsig: conventional with proposed fuzzy

The scatter plots of each data for each training approach are shown in Figure 4. The number after the - (dash) 1,2 and 3 indicates the training approach; 1) Conventional training approach with mean square error function (HDsig), with 2) McCleland error function (HDmcl) and 3) Fuzzy training approach (TGsig), moreover, the alphabet (a,b,c,d and e) indicates the data; a) train, b) word, c) long phrase, d) short phrase and e) continuous data. Each number in the figures show the number of data located on the scatter plot space and each plot are located at the level of the activation for the most active non-true output node (i.e. the most active node that does not represent the correct classification) versus the level of the activation for the true output node (representing the correct classification). The horizontal axis shows the scale for the ture output value and the verticle axis shows the scale for the maximum non-ture output value, from 0.0 to 1.0 each.

3.1.4. Discussions

From Table3-a, 3-b, 3-c and Table 4, we can say that the proposed fuzzy training approach (TGsig) works slightly better than both conventional training approaches; mean square error (HDsig) and McClelland error (HDmcl), not only the top choice recognition rate but also in the 2nd and 3rd choices. This tendency of improvement can be seen better when the utterance style differs greater from the training data utterance style. In other words, there is no improvement when the utterance style is isolated word, which the utterance style of the data between the training and the testing is very close. Slight improvement can be seen when the test data is phrase utterance and more can be seen when the utterance is continuous style. From this result, we can say that the neural network trained through the proposed fuzzy training, obtained better generalization than through the conventional training approach.

From Figure 3, the convergence speed of each approach is not so different. The HDmcl seems to be faster than the others. But in other hand comparing to the testing data of isolated word utterance, it can be said that the HDmcl is over tuned to the training data.

The distribution of the scatter plot for each training approach is very different form Figure 4-1 (HDsig) and 4-2 (HDmcl) to 4-3 (TGsig). The distribution of HDsig and HDmcl, from the macro-spect, scatters along the edge of the square, and gathers especially into two locations which are top-left and bottom-right. This result means that the neural network makes a binary dicision either absolutely correct or absolutely incorrect. When the classification is correct, the neural network indicates the correct class with no other competitive class. But once the classification is incorrect, the neural network indicates the absolote incorrect class with no information for the correct class. This mis-classification brings a big problem when the phoneme classification neural network is integrated with the language model because of the lack of the correct class information. From this point of view, the scatter plot for the TGsig shows a better result. The distribution of this scatter plot spreds out in the square but only several classification results are located in the top-left part of the square. And almost all the results have some information for the correct class, even if the classification result indicated the incorrect class for the first candidate.

From the experiment on the Japanese /bdgmnN/ experiment, the proposed fuzzy training approach is able to train the neural network better than conventional training approaches not only in the point of classification performance but also in the information of the output units for the upper level integration as language model. The improvment can be seem better when the utterance style of the testing data differs greater form that of the training data, which indicates that the proposed fuzzy training approach obtained better generalization to the neural networks.

3.2. English 14 vowels and all phonemes

3.2.1. Data

The classification experiments on the English 14 vowels and all phonemes (40 categories) performed on the phonemes cut out from the CMU/ATR datebase uttered by one male (mlbw). This database consists of English dialogues for "conference registration", which is the task of ATR project. The database has 12 dialogues, and from 1 to 3 dialogues are uttered twice and others once. The neural network is trained by phonemes cut out from the first uttrance and tested by phonemes cut out from the second utterance, from 1 to 3 dialogue. Table 5 shows the number of each training and testing phoneme.

Table 5. Number of phonemes for English task.

no	lbl	ph	train	test	collaps	no	lbl	ph	train	test	collaps
1	AA*	a	107	14	(AA)	22	L	l	231	27	(L,EL)
2	AE*	1	131	21	(AE)	23	M	m	184	30	(MM)
3	AH*	2	402	52	(AH,AX)	24	N	n	450	74	(NN,EN)
4	AO*	3	74	16	(AO)	25	NG	@	40	3	(NG)
5	AW*	4	38	3	(AW)	26	OW*	o	77	8	(OW)
6	AY*	5	160	35	(AY,OY)	27	P	p	229	22	(P,PCL)
7	B	b	117	12	(B,BCL)	28	Q	-	15	2	(Q)
8	CH	c	31	4	(CH)	29	R	r	260	64	(R)
9	D	d	298	42	(D,DCL)	30	S	s	351	64	(S)
10	DH	#	152	23	(DH,DHCL)	31	SH	S	50	9	(SH)
11	DX	D	62	9	(DX,NX)	32	SIL	+	139	52	(SIL)
12	EH*	e	246	50	(EH)	33	T	t	550	51	(T,TCL)
13	ER*	E	174	14	(ER)	34	TH	=	54	9	(TH,THCL)
14	EY*	8	139	22	(EY)	35	UH	u	62	17	(UH)
15	F	f	190	32	(F)	36	UW	U	159	27	(UW,UX)
16	G	g	58	10	(G,GCL)	37	V	v	102	22	(V,VCL)
17	HH	h	75	10	(HH)	38	W*	w	124	20	(W)
18	IH*	i	282	46	(IH,IX)	39	Y*	y	108	24	(Y)
19	IY*	I	244	45	(IY)	40	Z	z	139	21	(Z)
20	JH	j	52	17	(JH)						

* indicates the 14 vowels

English vowels [train:1251, test: 368]

English phonemes [train:3449, test:1075]

Every phoneme is cut out as a size of 50ms datum (5 frames) which the center label of the phoneme comes in the center of the datum. Every datum is sampled at 16kHz and is analyzed by FFT through a 21.3ms Hamming window at every 5ms shift. 16 melscaled coefficients are computed from the power spectrum to collaps adjacent coefficients in time resulting in an overall

10ms frame rate. The coefficients of each input utterance (normalized in one sentence utterance, different from Japanese data) are then normalized to lie between -1.0 and +1.0 with the average at 0.0.

3.2.2. Neural Networks

The structure of neural network used for English vowel classification experiments is a simple feed-forward three layer neural network, which consists of one input layer with 16 coefficient units * 5 frames, one hidden layer with 20 units and one output layer with 14 units corresponding to each vowel category. The connection between the layers are fully connected. The structure of neural network used for English all phoneme classification experiment is a simple feed-forward four layer neural network, which consists of one input layer with 16 coefficient units * 5 frames, two hidden layers with 40 units in each layer and one output layer with 40 units corresponding to each phoneme category. The connection between the layers are fully connected, either.

3.2.3. Results

The table 6 and 7 show the experiment results on English vowel and English all phoneme classification using conventional 0, 1 training approach with mean square error function (HDsig) and McClelland error function (HDmcl) and the proposed fuzzy training approach with mean square funtion (TGsig), with the top-Nth classification rate. For the group effect function f(), exp(-alpha *d *d) is adopt, where d is a mean square error distance and alpha is 0.1. Additionally for the fuzzy training, the target values are normalized from 0.05 to 0.95 to use the linier part of the sigmoid function in the output layer. The iteration of training epoch was performed up to 500 epochs. The weights were chosen from the epoch which gave the best results to the testing data.

Table 6. English 14 vowel classification result.

approach	epoch	train			test		
		top	2nd	3rd	top	2nd	3rd
HDsig	474	61.4	79.0	86.2	50.3	70.1	82.3
HDmcl	406	69.3	86.0	93.0	59.0	77.4	86.7
TGsig	139	70.2	85.9	91.8	62.0	77.4	85.3

Table 7. English 40 phoneme classification result.

approach	epoch	train			test		
		top	2nd	3rd	top	2nd	3rd
HDsig	270	53.7	66.0	71.5	46.0	60.8	68.9
HDmcl	195	76.7	90.0	94.8	57.1	72.7	80.2
TGsig	165	71.7	86.3	91.2	58.1	72.2	79.1

Figure 5 (English vowels) and Figure 6 (English phoneme) show the convergence for the training data of each approach. HDsig, HDmcl and TGsig correspond to a) conventional training approach with mean square error function, b) with McCleland error function and c) the proposed fuzzy training approach.

The scatter plot of each data for each training approach are shown in Figure 7 (English vowels) and in Fugure 8 (English all phonemes). The number after the - (dash) 1,2 and 3 indicates the training approach; 1) Conventional training approach with mean square error function, 2) with McCleland error function and 3) fuzzy training approach. And the alphabet "a" is for training data and "b" is for testing data. Each number in the figures show the number of data located on the scatter plot space and each plot are located at the level of the activation for the most active non-true output node (i.e. the most active node that does not represent the correct classification) versus the level of the activation for the true output node (representing the correct classification). The horizontal axis shows the scale for the ture output value and the verticle axis showes the scale for the maximum non-ture output value, from 0.0 to 1.0 each.

3.2.4. Discussion

From Table 6 and Table 7, HDsig showed the worst result. This is because the training iterations for neural networks were not enough. The training speed of this HDsig approach is very slow compared with the others, HDmcl and TGsig approaches. This can be said from Figure 5 and Figure 6. When comparing HDmcl and TGsig, the recognition rate for the top choice was slight better in TGsig than HDmcl, but the third choice was contrary. Moreover, the scatter plots in Figure 7 and Figure 8 are almost identical and is difficult to tell the difference between the result of HDmcl and TGsig. The speed of convergence is a little bit faster in the case of TGsig than HDmcl on English vowel case, but on the all English phoneme case is almost the same. Thus, from all of these results, it can said that the both approaches, HDmcl and TGsig, are almost same, which means that the proposed fuzzy training approach does not improved any more in the case of English vowel calssification and English all phoneme classification.

The distribution of the scatter plots both HDmcl and TGsig are spreding over the square. The difference between the distribution for English case and for Japanese case derives from the difficulty of the separation of phoneme classes. The English vowels and phonemes are very similar each other so that it is impossible or very hard to distinguish them. Thus, the neural networks are training as the results.

In addition, there is another reason why the classification result did not improve in the English case. In the English case the training data and the testing data are both cut out from the continous speech, of which speech features are very similar. This is very similar in the experiment tested on Japanese phoneme cut out from isolated word utterance. Also, in this case there was not an improvement comparing the both approach of HDmcl and TGsig. From these results, we can say that when the training data and testing data are very similar, the proposed fuzzy training approach will not help. And it only helps when the training data and the testing data is a little bit different.

4. CONCLUSION

In this report, we focused on phoneme classification type neural networks and proposed a new fuzzy training approach which trains the neural networks to result the likelihoods for each phoneme class in the output unit. The proposed fuzzy training approach is realized through back-propagation algorithm. The target values for this approach are given in the way of how likely the input phonemes are to the each phoneme class according to the distance between the input phoneme itself and other data in other phoneme classes. The phoneme classification experiments are performed and discussed on Japanese /bdgmnN/, 14 category English vowels and 40 category English phonemes. The new fuzzy trained neural networks on Japanese data achieved better performance than the conventional trained neural networks, especially on the phonemes cut out from continuous utterance. The fuzzy trained results on the English data were as same performace as the conventional ones which means no improvement. From these experiment results, we found that when the training data and testing data are very similar, the proposed fuzzy training approach will not help. But it helps when the training data and the testing data is a little bit different, which means that the proposed fuzzy training approach give a better generalization to the neural networks.

For the further research, the proposed fuzzy training approach needs a great amount of computation to set the training values for each data. It needs all the distances between all two data in the training set. This computation amount can be greatly reduced using a VQ techneque representation, using the codewords representation for some training data.

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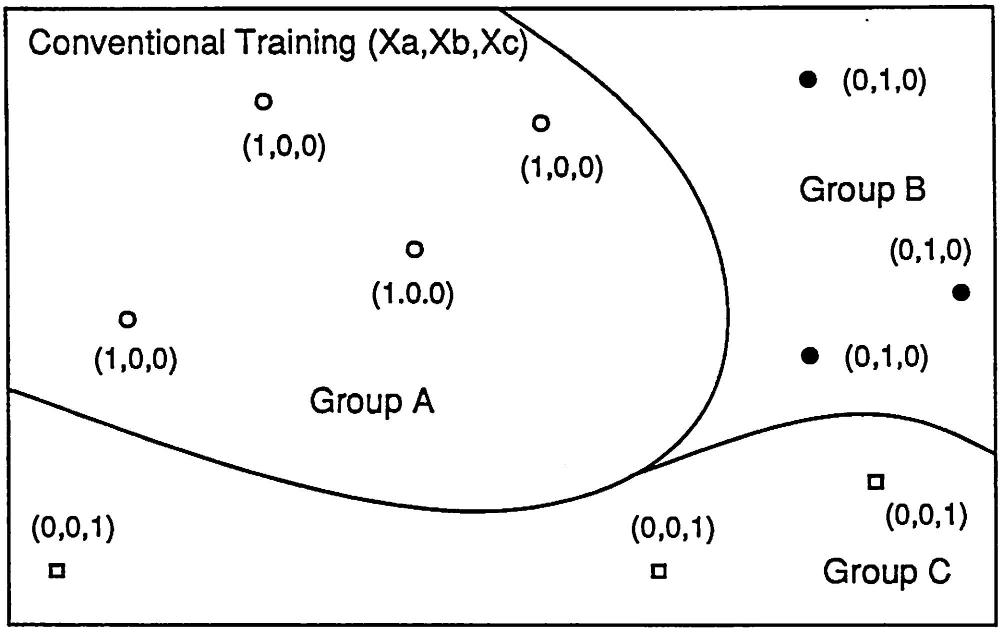
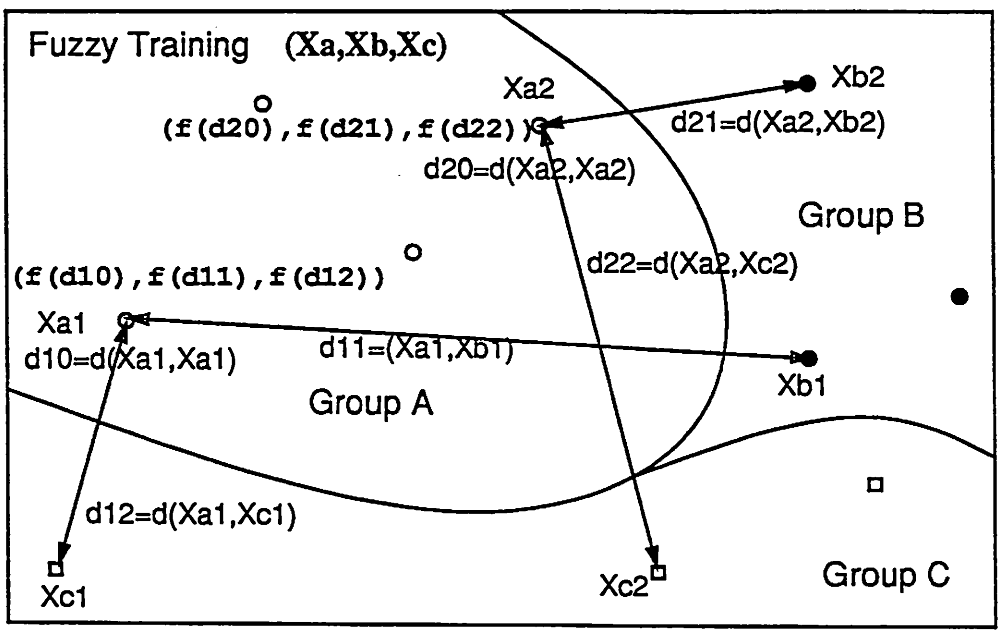


Figure 1-a. Conventional Training



f() is a function of effect for the group depended upon distance

Figure 1-b. New Fuzzy Training

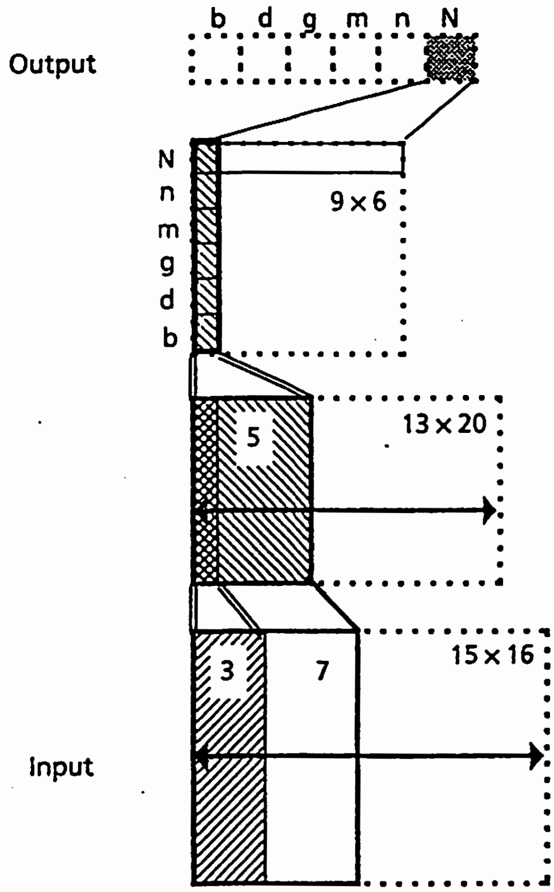


図2　TDNNとそのサブネットワーク

Fig.2 TDNN and sub-network of TDNN

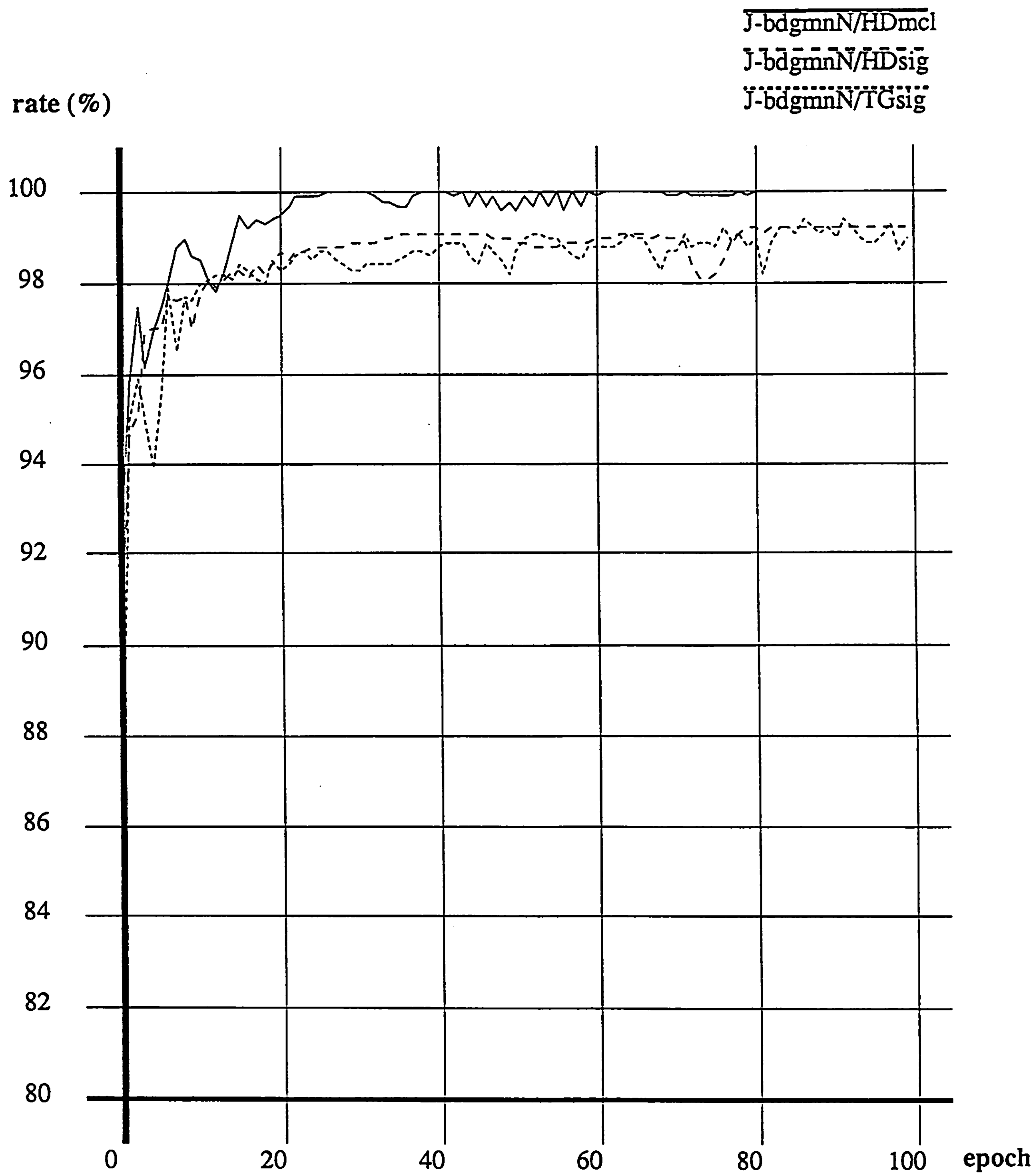


Figure 3. Convergence for Japanese Training Data

```
2 . . . . . . . . . . . . . . . . . 1 . . 2 . 1 3
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
1 . . . . . . . . . . . . . . . . . . . . . . 1 1
. . . . . . . . . . . . . . . . . . . . . . . 1 3
1 . . . . . . . . . . . . . . . . . 1 1 1 . . 1 8
2 . . . . . . . . . . . . . . . . 1 . . . . . 438
1 . 1 . . . . . . . . . . . . . . . . 1 . 1 718**
```

correct : 99.2 (1843) wrong : 0.8 (14)

Figure 4-1a. Scatter-plots for Training Data
Conventional Training Mean Square Error

```
10 1 1 . 1 . . . . . . . . . . . . 2 1 . . . 1 . 3
 1 . . . 1 . . . . . . 1 . . . . . . . . . . . . 2
 2 . . . . . 1 . 1 . . . . . . . . . . . . . . . 1
 1 . 2 . . . . . . . . . . . . . . 1 . . . . . . .
 1 . . . . . . . . . . . 1 . . . . . . . . . . . 1
 2 . . . . . . . . . . . . . . . . . . . . . . . .
 1 . . . . . . . . 1 . . . . . . . . . . . . . . .
 . . . . . . . . . . . . . . . . . . . . 1 1 . . .
 1 . . . . . . . . . . . . . . . . . . . 1 1 . 1 1
 1 2 1 . . . . . . . . . . . . . . . . . . . 1 1 1
 . 1 . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . . . . . . 1 . . . 1 . . 1 1 1 . . . 3
 1 . . . . . . . . 1 . . . . . . . . . 2 . . 1 2 1
 . . . . . . . . . . . . . . . . . . 1 . 1 . 1 . 3
 . . . . . 1 . . . . 1 . . . . . . . . . . . 1 . 2
 1 . . . . . . . . . . . . . 1 . . . . . . . . . 3
 2 . . . . . . . . . . . . . 1 . . . . . . . . . 2
 . 1 . . . . . . . . . . 1 . 1 . 1 . . . . 1 1 1 4
 2 . . . . . . 1 1 . 1 . . . 1 . . . . . . 1 1 1 5
 3 . . . . . . . . . . 1 . . . . . . . . . . 2 2 7
 2 . . . . . . 1 . 1 . . . . . . . . . . . 1 1 615
 . 1 . . . . . . . . 1 . . 2 1 . . . . 1 . 2 1 634
 3 . 2 . . 2 2 . 2 1 . 4 1 3 1 2 2 2 2 4 6 11122**
```

correct : 97.0 (1835) wrong : 3.0 (57)

Figure 4-1b. Scatter-plots for Continuous Data
Conventional Training Mean Square Error

```
37 3 3 1 . 1 . . . . . 2 2 1 . . . . . . . . . 1 1 1 7
 8 . . . . 1 . . . . . . . . 1 1 1 . 1 1 . . . . . . 5
 5 1 . . 1 . . . . . . . . . . . . . . 1 . 1 . . . 6
 4 . . . . . . . . . . . . . . . . . . . . 1 . . . 5
 1 . 1 1 . . . . . . . . . . . . . . . 1 . 1 . . 1 2
 . 1 1 . . . . . . . . . . . 1 . . . . . 1 . . . . 3
 1 . 2 . . . . . . . . . . 1 1 . . . . . . . 1 . 1 .
 2 . . . . . . . . . . . . . . . . . . 1 . . . . . .
 . . . . . . . . . . . . . . . 1 . . . . . . 2 . . . 1
 3 . . . . 1 . . . . . . . . . . . 1 . . . . . . . 1 1
 1 . . . . . . . . . . . . . . 1 1 . . . . . . . 1 . 3
 1 . . . . . . . . . . . . . 1 . . . . . . . . . . . 1
 4 . . . . 1 . . . . . . 1 1 . . . . . . . . . . . . 3
 4 . . . . . . . . . . . . . . . . . . . . 1 . . . . 3
 4 . . . . . . . . . . . . . . . 1 . . . . 1 . . 1 1
 1 . . . . . . . . . . . . . . . . . . . . . . 1 1 3
 1 . . . . 1 . . . . . . . . . . 1 . . . . . . . . . 2
 1 . . . 1 . . . . . . . . . . . . . 1 . 1 . . 1 . 2
 3 2 1 1 . . 1 . . . . . . . . 1 . . . . . . . 1 . . 3
 4 . . . . . . . . . . . . . . . . 1 . . . . . . . . 6
 2 2 1 . . . . . 1 1 . . . 1 . . . . . . . . 1 . . . . 4
 4 1 . . . . . . . 2 . . . . . 1 1 . 1 . . 1 . . 1 1 9
 4 . . . 1 . 1 . 1 1 . . . . 1 . . . . 1 . . 1 1 1 214
 9 . . . 1 . 1 . . . . . 2 1 1 . 1 . 2 . 1 2 1 3 122
24 5 5 5 5 3 3 1 2 2 1 4 3 2 2 6 4 2 4 6 6 91726**
```

correct : 82.1 (807) wrong : 17.9 (176)

Figure 4-1c. Scatter-plots for Long Phrase Data
Conventional Training Mean Square Error

```
30 3 2 2 3 1 . . 1 1 . . . 1 1 . 1 . 2 1 . 1 . 2 8
 6 1 . . . . . . . . . . . . . . . . . . . . . . 5
 3 1 1 . . . . . . . . . . . . . . . . . . . . . 3
 2 2 . . . . . . . . . . . . . . . . . . . . . . 1
 2 . 1 . 1 . 1 . . . . . . . . . . . . . . . 1 1 .
 . . 1 . . . . . . . . . . . . . . . . . . . . . 1
 . 1 . . . . . . . 1 . . . . . . 1 . . . . . . . 1
 2 . . . . . . . . 2 . . 1 . . 1 . . 1 . . . . . 1
 . . . . . . . . . . . . . . . . . . . . . . . . 1
 . . 1 . . . . . . . . . . . . . . . . . . . . 2 2
 3 . . . . . . . . . . . . . . . . . . 1 . . . . .
 4 1 1 . . . . . . . 1 . . . . 1 . . . . . . . . 1
 . . . . . . . . 1 . . . . . . . . . . 1 . . 1 . 1
 2 2 . . . . . . . . 1 . . . . . . . . 1 . . 1 . 1
 . . . . . . 1 . . . . . . 1 . . . . . . . . . 1 2
 . . . . . . . . 1 . . . . . . . . . . . . . . . 6
 1 . . . . . . . 1 . . . . . . . . . . . . . . . 4
 2 . . . . . . . . . . . . . . . . . . . . . . . 2
 6 1 . . . . . . . . . . 1 . . . . . . . . . . . 5
 1 . . . . 1 . . . . . . . . . . . . . 1 2 1 1 . 4
 6 . . . . . . . . . . . . . . . 1 . . . 2 1 . 1 4
 1 . . . . . . . . 2 . . . . . 1 . . 1 . . . 1 1 7
 4 . . 1 . . . . 1 1 . . . 1 . . 2 . . 1 . 1 1 111
 4 2 1 1 . 1 . 2 . 1 1 1 . 2 . . . 1 . 1 . . 2 522
2511 5 5 2 3 2 2 3 2 2 8 2 3 3 3 6 3 1 410132014**
```

correct : 85.2 (836) wrong : 14.8 (145)

Figure 4-1d. Scatter-plots for Short Phrase Data
Conventional Training Mean Square Error

```
52 3 1 4 2 . . . 2 3 1 . . . 1 . 4 1 . 1 1 1 1 116
10 2 1 . . 1 . . . . . . 1 . . . . 1 . . . . . . 3
10 1 3 1 . . . . . . . . . 1 1 . 1 . . . . 1 . . 1
 2 . . . 1 . . . . . . . . . . 1 . . . . . . . . 3
 5 . . . . . . . . . . . . . . . . . . . . 1 . . 3
 3 . . . . . . 1 . . . . . . . . . 1 . 2 . . . . 1
 2 1 . . 1 . . . . 1 . . 1 . . . . . . . . . . . 2
 2 1 . . . . . . . 1 . . . . . . . . . . . . . . 5
 3 1 . . . . . . . . . . . . . . . . . . . . . . 3
 3 . . . . 1 . . . . . . . . . . . . . . 1 . . . 1
 3 . . . . 1 . 1 . . . . . . . . . . . . 1 . . . 1
 3 1 . . . . . . . . . . . . . . 1 . . . . . . . 4
 . . . . . . . . . . . . 1 . 1 . . . . . . . 1 . 2
 1 1 . . 1 . . . . . . . . . . . . . . . . . . . 3
 4 1 . . . . 1 . . . . . . . . . . . . . . . . . 4
 3 1 2 1 1 . . . . . . . . . . . . . . . . . . . 3
 4 . . . . . . . . . . . . . . . . . . . . . . . 6
 1 . 1 . . . 2 2 . 1 . . . . . . . . . . 1 1 1 . 2
 1 . . . . . . . . . . 1 . . . . . . . . . . . . 3
 3 . . . . . . . . . 1 . 1 . . . . . . 1 . . . . 7
 4 2 . . . . . . . . . . . . . 1 . . . 1 . . . . 8
 8 . 1 1 . 1 . . . . . . 1 . . . 1 . . . . . 1 .10
 7 1 1 1 1 . . 1 . . . . 2 1 . . . 1 1 . . 1 . .18
 6 1 . 2 . . 2 . . 1 . . . 1 1 . 1 . . . . . 1 129
41 5 2 2 2 5 1 4 5 4 3 3 1 4 1 6 5 6 3 5 3111316**
```

correct : 74.0 (730) wrong   : 26.0 (256)

Figure 4-1e. Scatter-plots for Continuous Data
Conventional Training Mean Square Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . 1 . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . 1
. . . . . . . . . . . . . . . . 1 . . . . . . . .
. . . . . . . . . . . . . . . . . . . . 1 . 1 . .
. . . . . . . . . . . . . . . . . . . . . . . . 1
. . . . . . . . . . . . . . . 1 . . . . . . 1 1 .
. . . . . . . . . . . . . . . . . . 1 1 . . 2 . .
. . . . . . . . . . . . . . . . . 1 1 . . . 2 1 3
. . . . . . . . . . . . . . . . 2 . . 1 1 3 1 . 9
. . . . . . . . . . . . . . 1 . 2 1 1 1 . 1 2 314
. . . . . . . . . . . . . 1 . . . . 1 1 1 3 6 663
. . . . . . . . . . . 2 1 . . 1 1 1 1 4 8121751**
```

correct :   99.9 (1856) wrong   :   0.0 (1)

Figure 4-2a. Scatter-plots for Training Data
Conventional Training McClelland Error

```
5 1 2 . 1 1 1 . . . 1 . . . . . . . . . . . 1 1 1
1 . . . . . . . . . . . . . . . . . . . . . . . .
1 . . . . . 1 . . . . . . . . . . . . . . . . . 1
. . . . . . . . . . . . . . . . . . . . . . . 1 1
. . . . . . . . . . . . . . . . . . . . . . 1 . 1
. . . . . . . . 1 1 . . 1 . . . . . . . . . . . .
. . . 1 . . . 1 . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . 1 . . .
. . . . . . . . . . . . . . . . . . 1 . . . . . 2
1 2 . . . 1 . 1 . . . . . . . 1 . . . . . . 1 . 3
. . . . . . . . . . . 1 . . . . . . . . 1 1 . . 3
1 . . . . . 1 . . . . . . . . . . 1 . . . 1 . . 2
. . . 1 . . . 1 . . . . . . . . . . . . 2 2 . 1 .
. . . 1 1 . . . . . . . . . . . . . . . . . 1 . 3
1 1 . . 1 . . . . . . . . . . . . . . . . . 1 . 1
. . 1 . . 1 . . . . . . . . . . . . . . . . . . 1
1 1 . . . . . . . . . . 1 . . . . 1 . . 2 . 1 2 1
1 . . . . . . . . . . 1 . . . . . . . 1 . . . 1 3
2 . 1 . . . . . . . . . . 1 . . . . . . . . 1 . 3
. . 1 . . . 1 . . . . 1 . . . 1 . . . . . 1 . 2 5
. . . . . 1 1 . . 1 1 . . . . . . . 1 1 1 . 1 .10
2 . . . . 1 . 1 1 . . . . 1 2 . . . 1 . . 3 2 310
3 . . . 1 . . . . 1 . . . . . . . 2 . 1 1 2 3 422
. . 1 1 2 . . . 2 . . . . 2 1 . . 1 1 . 1 3 . 561
2 2 2 . 4 1 1 . 2 4 . 2 2 2 3 1 5 3 5 5 3122039**
```

correct :   97.2 (1839) wrong   :   2.8 (53)

Figure 4-2b. Scatter-plots for Isolated Word Data
Conventional Training McClelland Error

```
29 3 1 2 . . . 2 . . 1 . 1 . 1 . . . 1 1 . . . . 4
 4 . . . . . 1 1 . . . . . . . . . . . . . . . 1 4
 5 . 1 1 . . . . . . . . . . . . . . . . 1 . . . .
 3 . 1 . . . . . . . . 1 . . . . . . . . . . 1 . 3
 3 . . . . 1 . . 1 . . . . 2 . . . . . . . 1 1 1 3
 2 1 . . . . . 1 . . . . . . . . . . . . . . . . 3
 . 2 . . . . 1 . . . . . . . . 1 . . . . . . . . 1
 . . . . . . 1 . . . . . . . . . 1 . . 1 . . . . 1
 1 . . . . . . . . 1 . . . . . . . . . . 1 . . 2 1
 2 2 . . . . . . . . . . . 1 . . . . 1 . . . 1 . .
 1 1 1 1 . . . . . . . . . . . . . . . . 1 . . . 2
 1 1 . . . . . . . . . . 1 . . . . . 1 . . . . . 3
 2 1 . . . . . . . . 1 . . . . . . . . . . . . . 3
 1 . . . 1 . . . . . . . . . . . 1 1 . . . . . . 1
 1 . . . . . . . . . . . . . . . . . . . . . 1 . 3
 1 1 . 1 . . . . . . . . . . . 1 . . . . 1 . . 1 1
 1 . . . . . . 1 . . 1 . . . . . 1 . . . 2 . . . 6
 . 1 . . . 2 . . . . 1 . . . . . . . . . . . . 1 5
 2 1 . . . . . . . . . . . 1 . 1 . 1 . . 1 . . .10
 5 . . 1 1 1 . 1 . 1 . . . . 2 . . 1 . . . . 1 . 6
 1 1 . 1 1 1 . . . . . . . 1 . 1 1 . . . 2 1 . 1 9
 1 . 1 . . . . 1 2 1 1 . . 1 . 2 . . . 1 . 2 1 412
 2 . 2 1 . . 1 . 1 . 1 . 1 1 . 2 . 1 2 1 3 3 1 122
 7 1 1 . 2 1 1 . 2 . . . . 1 1 2 . 2 2 . . 1 5 732
16 7 4 1 6 2 4 2 4 4 1 5 4 2 4 2 5 2 3 7 9111420**

correct :  85.4 ( 839)  wrong   :  14.6 ( 144)
```

Figure 4-2c. Scatter-plots for Long Phrase Data
Conventional Training McClelland Error

```
31 4 3 1 1 . 1 . . 1 . . . . . . 1 . . . 1 2 . . 7
 5 . 1 . . . 1 . . . . . . . 1 . 1 . . . . . . . 2
 4 1 . . 1 . . . . . . . . 1 . . . . . . . . . . 1
 2 . . 1 . . . . . . . . . . . . . . . 1 . . . . 2
 4 . . . . . . . . . . . . . . 1 . . . . . . . . .
 3 2 . 1 . . . . . . . 1 2 . . . . . . . . . . . 1
 1 . . . . . . . . . . . . . . . . . . . . . . . 3
 5 . . . . . 1 . . . . . . . . . . . 1 . . . . . 2
 3 . . . . . . . . . . . . . . . . . . . . . . . 1
 . . . . . . . . . 2 . . . . . . . 1 . . . . . 1 4
 2 . 1 . . . . . . . . 1 . . . . . . 1 . . . . . 1
 3 2 . . . . . 1 . . . . . . . . . . . . . 1 1 . 1
 . . . . . . . . . . . . . . . . . . . . . . . . 2
 4 . 1 . . . . . . . . . . . . . . . . . . . . . 4
 1 1 . . . . . . . . . . . . . . . . . 1 . . . 1 5
 . . . . . . . 1 . . . . . . . . . . . 1 . . . 1 4
 5 . 1 . . . . . . . . . . . . . . . . 1 . . . . 3
 3 1 . . . . . . 1 . . 1 . . . . . 1 . . . . . 1 4
 2 . . . . . . . . . . . . . . . . . . . . . . 1 7
 2 . . . . . . . . . . . . . . . 1 . 1 . . . . 1 6
 4 . . 1 . . . . . 1 . 1 . . . . 1 . . . 1 2 . 2 3
 2 . 1 . . . . . . 1 . . . . . . . . 1 . . . . 3 8
 7 1 1 1 . . . 1 2 1 1 1 . . . . . . 1 . 2 2 2 119
 3 2 . . . 2 . . 2 1 . 1 2 . 1 1 1 2 1 . 2 . 3 236
 9 3 5 . 6 5 2 1 2 4 3 2 . 2 . 3 4 3 6 31013 936**

correct :  84.8 ( 832)  wrong   :  15.2 ( 149)
```

Figure 4-2d. Scatter-plots for Short Phrase Data
Conventional Training McClelland Error

```
55 4 4 . 2 . . 1 1 . . . 1 1 . 2 . 1 3 . . . . 412
 7 . 1 . . . . . . . 1 . . . 1 . . . . . . . . . 5
 7 1 . . . . 1 1 . . . . . 2 . . . . . . 1 . . . 3
 3 2 2 . . . 2 1 1 . . . . . . . . . 1 . . . . . 2
 6 . . 1 . . 1 . . . 1 . . . . . . . . . . . . 2 1
 2 1 . . . . . . . . . . . . . . 1 . . . . . . . .
 3 . 1 . 1 . . . . . . . . . 1 . . . . . . . . 1 2
 7 1 . . . . 1 . . . 1 . . . . 1 . . 1 . . . . . 1
 2 2 . . . . 1 . . . . . . . . . . . 1 . . . . . 1
 3 . . 1 . . . . . . . . . . . . . . . . . . . . 2
 5 1 . 1 . . . . . . 1 . . . . . . . . 2 . . . . 3
 2 . . . . . . . . . . . . . . 1 . . 1 . . . . 1 2
 3 . . . . . . . . . 1 . . . . . . . 1 . . . 1 1 1
 2 . . . . 1 . . . . . . . . . . . 1 . . . . 1 . 6
 3 . . . . 1 . . . . 1 1 . . . . . . . . . . 1 1 3
 1 . 2 . . . . . . . . 1 . . 1 . . . 1 . . 1 . 1 3
 1 . . . . . 1 . . 1 1 . . . . 1 . . . 1 . . . 1 3
 3 1 . . . . . . 1 . . . . . . . . . . . . . 1 1 6
 3 1 . . . . . . . . . . . . . . . . 1 . . . . . 3
 3 . 2 . 1 . . . . . . . 1 . . . . . . 1 . 2 . 1 8
 3 . . . . 2 . 1 1 . 2 . . . . 1 . 1 . . 3 . . . 7
 7 1 2 1 . 1 1 . . 1 . . . . 2 . . 1 1 . . 1 . 3 8
 7 2 1 1 1 . . 1 . . 1 . . . . . 2 2 . . 3 3 . 220
 4 1 2 2 . 2 . . . 2 2 1 . . 1 . 1 . 4 1 1 . 4 221
25 7 4 5 . 2 1 1 1 . 2 1 3 1 1 7 7 3 4 6 910 918**

correct :  75.7 ( 746)  wrong   :  24.3 ( 240)
```

Figure 4-2e. Scatter-plots for Continuous Data
Conventional Training McClelland Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . 1 1 . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . 1 . . . . . . .
. . . . . . . . . . . . . . 1 1 . . . . . . . . .
. . . . . . . . . . . . . . . . 1 1 . . 1 1 . . .
. . . . . . . . . . . . . . . . . . 1 1 . . . . .
. . . . . . . . . . . . . . . . . . . . 1 2 1 1 .
. . . . . . . . . . . . . 1 1 . 1 2 . 1 5 8 8 3 1
. . . . . . . . . . . . . 1 1 . . 1 1 2 9 813 5 1
. . . . . . . . . . . . . . . . 1 1 2 5 2152014 5
. . . . . . . . . . . . 1 . . 1 . 2 2 610202939 5
. . . . . . . . . . . . . . . . . 1 . 41112375313
. . . . . . . . . . . . . 1 . . 1 1 2 5 315386218
. . . . . . . . . . . . . . . . . 1 3 61120296735
. . . . . . . . . . . . . . . . . . 2 41013286234
. . . . . . . . . . 1 . . . . . 1 1 3 1 5 9205236
. . . . . . . . . . . . . . 1 . 1 1 1 5 4 7184244
. . . . . . . . . . . . . . . . . . . 2 5 3203441
. . . . . . . . . . . . . . . . . . . 1 2 7152931
. . . . . . . . . . . . . . . . . 1 . . 4 5111519
. . . . . . . . . . . . . . . . . . 1 . . 2 41331
. . . . . . . . . . . . . . . . . . . . . 1 11440
. . . . . . . . . . . . . . . . . . . . . . 12274
. . . . . . . . . . . . . . . . . . . . . . 230**
. . . . . . . . . . . . . . . . . . . . . . . .35
```

correct : 99.1 (1841) wrong : 0.9 (16)

Figure 4-3a. Scatter-plots for Training Data
Fuzzy Training Mean Square Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . 1 . . . . . . 1 . . . . . 1 . . . .
. . . . . . . . 1 . . . . . 1 . . . 1 . 1 . . . .
. . . . 1 . . . . . . . . . . . 1 1 1 . 1 . . . .
. . . 1 . . . . . . . . . . 1 2 1 . 1 1 1 3 1 1 .
. . . . . . . . . 1 1 1 1 1 1 1 1 1 . 4 4 4 1 1 .
. . . . . . 1 . . . . . . 1 . . 1 3 1 1 . 9 6 2 .
. . . . . . . . . . 1 . . . 3 1 1 2 4 7 5 611 6 3
. . . . . . . . . . . . . 1 . . 3 2 2 410112010 1
. . . . . 1 . . . . 1 . . . 2 1 1 5 3 2 9112721 5
. . . . . . . . 1 . . 1 1 . 1 3 4 2 2 412184636 7
. . . . . . . . . . . . 1 . . 2 1 1 . 5 817535121
. . . . . . . . . . . . . 2 . 4 1 1 211 417276417
. . . . . . . . 1 . . 1 . . . 1 2 . 5 2 6 8256533
. . . . . . . . . . . . . . 1 1 1 1 . 1 513284834
. . . . . . . . . . . . . . . . 1 2 3 2 3 7144932
. . . . . . . . . . . . . 1 . . . . 1 2 2 4133243
. . . . . . . . . . . . . . 1 . 1 . 2 3 1 3 83242
. . . . . . . . . . 1 . 1 . . . . . . . 1 . 91728
. . . . . . . . . . . . . . . 1 . . . . 1 2 51833
. . . . . . . . . . . . . . . . . . 1 . 1 . 51331
. . . . . . . . . . . . . . . . . . . . . . 1 940
. . . . . . . . . . . . . . . . . . . . . . 21390
. . . . . . . . . . . . . . . . . . . . . . 226**
. . . . . . . . . . . . . . . . . . . . . . . .50
```

correct : 97.1 (1838) wrong : 2.9 (54)

Figure 4-3b. Scatter-plots for Isolated Word Data
Fuzzy Training Mean Square Error

```
. . 2 . 1 1 1 . . . . . . . . . . . . . . . . . .
. 1 2 . . . 1 . . . . . 1 . 1 . . . 1 . 1 . . . .
. . . . . 1 . . . . . 1 2 1 1 . . . 1 1 . 1 1 . .
. . . . . . . . . 1 1 . . . . . 1 . 1 1 1 2 2 . .
. . . . 1 1 1 . . . 1 1 . 1 . 2 1 . 2 2 4 1 . . .
. . 1 1 1 . . . . . . . . . 4 . 1 3 2 2 2 2 2 1 .
. . . . . 1 1 2 . . 1 2 . 2 1 4 2 3 2 2 3 4 3 3 1
. . . . . . 1 . . 2 2 1 1 2 4 3 1 4 5 3 4 5 7 4 1
. . . . . 1 . 1 1 3 1 1 . . 3 2 7 4 2 2 9 5 4 5 .
. 1 . . . . . . . . . 2 . 2 1 2 3 6 7 8 6 41311 4
. . . . 1 . 3 . . 1 1 2 2 1 1 3 2 312 6 61114 7 4
. . . . 1 . . . . 1 . . . . 2 4 7 110 510 61224 2
. . . . . . 1 . 1 . . 1 2 . 2 . 1 3 3 4 610141614
. . . . . . . 1 . . . 1 . 1 1 . . . 6 5 8151612 7
. . . . . . 1 . . . 1 1 1 . . 2 1 2 2 4 4101316 8
. . . . . 1 . . . . . 2 1 . 2 2 2 1 2 1 2 4132611
. . . . . . . . 1 1 . . 1 . 1 1 2 3 1 3 3111117 9
. . . . . . 1 . . . 1 . . 1 . . 1 1 1 . 3 8 7 7 9
. . . . . . . . . . . 1 . . . 1 . . 1 . 1 6 5 511
. . . . . . . . . . . . . . 1 1 1 . . 1 . 3 1 711
. . . . . . . . . . . 1 . . . . . . . . 2 1 2 214
. . . . . . . . . . . . . . . . . . . . . . 2 4 9
. . . . . . . . . . . . . . . . . . . . . . . 214
. . . . . . . . . . . . . . . . . . . . . . 1 .26
. . . . . . . . . . . . . . . . . . . . . . . . 8
```

correct : 85.7 (842) wrong   : 14.3 (141)

Figure 4-3c. Scatter-plots for Long Phrase Data
Fuzzy Training Mean Square Error

```
. 1 1 . . 1 1 1 . . 1 . . . . . . . . . . . . . .
. . 2 . . 1 . . . . 1 1 . . . . . 1 . . . 1 . . . .
. . . 1 . . 1 1 . . . . 1 1 . . 1 . . 2 1 . . . . .
. 1 . 1 . . . 1 1 . . . 1 1 . . 3 . . . 1 5 3 1 .
. . 1 . . . 1 . 1 . . . 1 . 1 . 2 1 4 1 1 5 1 1 .
. . . . . . 1 . . . . . 1 . 1 . 1 2 . 2 6 . 2 1 .
. . 1 . 3 . 2 1 . . 1 1 . 2 . . . . 4 2 311 1 6 .
. . . . 1 . 1 2 2 . . 1 1 4 2 1 3 1 1 5 7 6 4 4 1
. . . . . 1 1 1 1 1 2 2 2 1 . 1 1 4 1 5 8 3 8 8 3
. 1 . . . . . 1 . 1 1 1 2 1 2 3 8 5 2 3 5 8 9 9 1
. . . 1 . . . . . . 6 . . 2 2 . 2 3 5 3 8 91115 4
. 1 . . . . . . . 1 . . 1 1 4 1 4 2 4 3 9 81413 5
. . . . . 1 . 1 1 . 1 1 . . 2 3 1 5 6 31110141913
. . . . . . . 1 . . . . 1 1 2 2 5 2 3 5 4 3121313
. . . . . . . . . 1 . 1 . 1 1 2 . 3 3 6 5 9121213
. . 1 . . . . . . . . . . 1 1 1 1 1 2 9 611 51811
. . . 1 . . . . . 1 1 . 2 1 . 2 2 1 1 3 4 8 41422
. . . . . . . 1 1 . 1 . . . . 1 . . 1 2 1 8 6 918
. . . . . . . . . . . . . 1 . 1 1 2 . 1 5 2 4 9 5
. . . . . . . . . . . . . . . . . 1 2 . 2 2 2 113
. . . . . 1 . . . . . . . . . 1 . . 1 . . 3 1 9 6
. . . . . . . . . . . . . . . . . . 2 . . 1 1 1 5
. . . . . . . . . . . . . . . . . . . . . . 2 614
. . . . . . . . . . . . . . . . . . . . . . . 232
. . . . . . . . . . . . . . . . . . . . . . . . 4
```

correct : 86.0 (844) wrong   : 14.0 (137)

Figure 4-3d. Scatter-plots for Short Phrase Data
Fuzzy Training Mean Square Error

```
 . 1 . 1 . . . . . . . . . . . . . . . . . . 1 . .
 1 . . . . . . 1 1 . . . 1 . . 1 3 . . . . . . . .
 . 2 . 1 . 1 . . . . 2 . 1 1 . . 1 . 1 . . . . . .
 1 . . 1 . 1 1 . 1 1 . . . 1 1 1 1 . . . 1 2 1 . .
 . 1 . . . . . 1 . 3 1 1 . 1 . 2 2 . 2 . . 2 . . .
 . . . . . . 1 1 3 . 2 2 . . 1 1 2 1 1 1 3 1 1 1 .
 . 1 . . . 2 1 1 . . 1 3 1 . 1 . 1 4 5 3 4 1 2 3 1
 . . 1 . . 1 2 2 1 2 . 4 3 2 . 4 3 . 3 3 4 5 6 1 .
 . . . 1 1 . . . . 1 3 1 4 2 3 4 . 1 6 . 4 9 5 2 .
 . . 1 . 1 2 . 2 1 1 1 2 2 . 5 3 4 2 2 4 9 6 8 3 1
 . 2 . . 1 . 1 2 2 1 2 . 2 2 . 3 3 4 6 9 813 5 6 3
 . . . . 1 . . 1 . . 2 1 . 2 1 1 3 3 2 7 21312 8 6
 . . 1 1 . 1 . 3 2 2 1 4 . 2 2 3 2 5 1 3 5101314 5
 . . . 1 1 3 1 1 1 1 3 2 2 3 . 4 4 1 1 8 4 912 915
 . 1 . 1 . 1 5 1 3 1 . 2 2 1 3 2 5 5 3 3 3 6 91117
 . . 1 . . 3 1 1 1 1 1 . 1 1 2 2 2 2 4 1 5 6 91112
 . . . . . . . 1 . 1 1 1 . 1 3 1 1 . 2 4 2 3 71513
 . . . . . . 1 1 2 . . . 3 1 . 1 3 1 1 2 5 8 71021
 . . . . 1 . . 1 . . . . . . 1 2 . . 1 1 3 4 513 6
 . . . . . . . 1 1 . 1 . . . . . . 1 2 1 2 1 3 5 6
 . . 1 . . . . 1 . . . . . 2 . . . . . 1 2 1 3 2 9
 . . . . . . . . . 1 . . . . . . . . . 1 . 1 1 111
 . . . . . . . . . . . . . . . . . . . . . . 1 113
 . . . . . . . . . . . . . . . . . . . . . . . .25
 . . . . . . . . . . . . . . . . . . . . . . . . 3
```

correct : 77.8 (767) wrong : 22.2 (219)

Figure 4-3e. Scatter-plots for Continuous Data
Fuzzy Training Mean Square Error

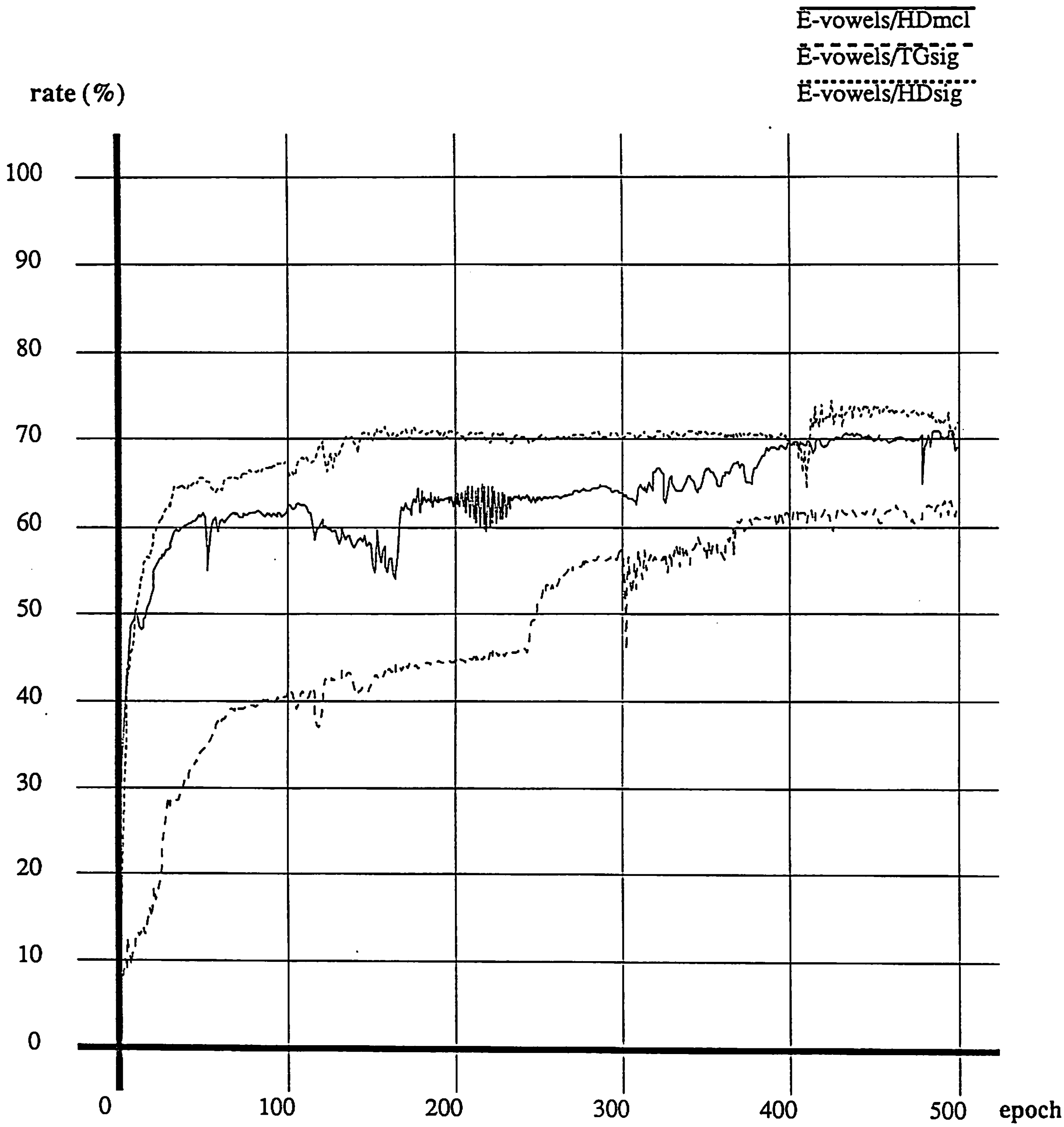


Figure 5. Convergence for English Vowel Training Data

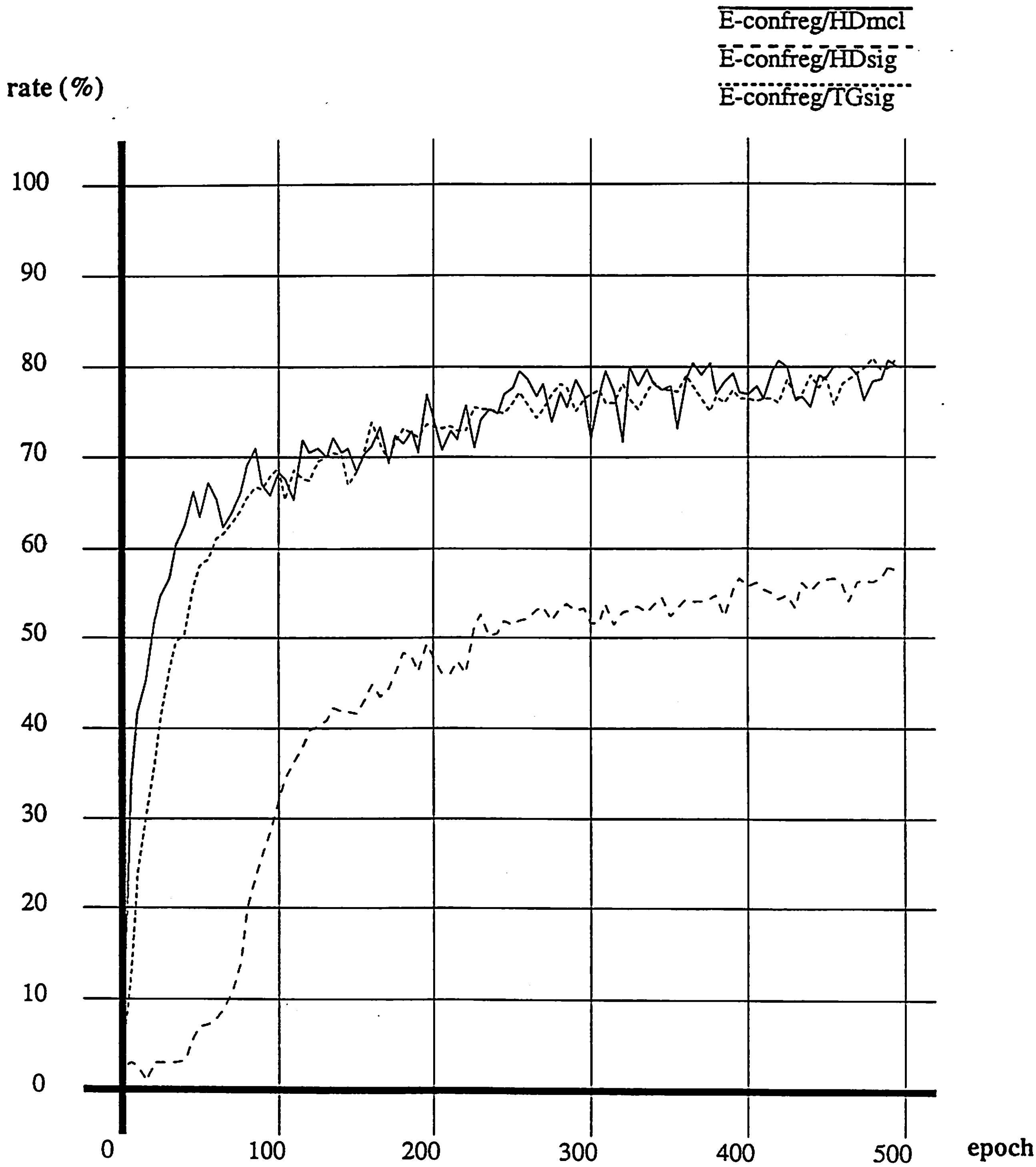


Figure 6. Convergence for English All Phoneme Training Data

```
 . . . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . . . . . . . . . . . . . . . . . . . .
 1 . . . . 1 . 2 . . . . . . . . . . . . . . . . .
 . 1 . . 1 . 2 . 2 . . . . . . . . . . . . . . . .
 3 1 1 . . . 2 2 . . . . . . . . . . . . . . . . .
 3 . . . . 1 1 3 1 . . . . . . . 1 . . . . . . . .
 2 . . . . . 1 1 . . . . 1 2 1 . . . . . . . . . .
 1 1 . 2 . . . . . 1 . 1 1 3 1 . 1 . . . . . . . .
 . . 1 1 . 2 1 1 . 1 2 1 1 2 3 1 . . . . . . . . .
 3 . 1 . . . 4 3 2 2 . 4 4 . 1 1 . . . . . . . . .
 5 . . 1 2 1 2 . 2 . . . . 1 . . 3 2 1 . 3 . . . .
 5 4 . . 1 . 3 1 2 . 1 . 2 2 1 2 2 1 . 1 1 1 . . .
 5 2 2 1 3 1 2 2 3 2 3 4 2 4 2 4 2 5 2 . 1 1 . . .
 4 3 3 1 . 7 3 3 4 2 7 5 1 2 1 3 3 3 . . 2 4 2 . .
 5 2 3 2 4 1 2 2 5 5 2 1 3 1 2 2 5 4 1 3 1 3 1 . .
 8 6 6 2 2 3 4 6 3 1 2 1 . 1 2 2 4 2 . 4 . 6 2 1 .
15 4 2 1 . 5 3 6 3 6 4 4 8 4 1 3 3 4 1 2 3 4 1 . .
15 4 3 4 2 4 2 2 3 3 5 6 2 5 4 4 8 1 2 3 3 612 . .
11 . 3 7 4 8 2 3 7 5 9 7 6 2 5 3 6 .10 6 913 5 . .
10 3 6 4 7 2 4 8 3 6 4 510 . 7 5 6 5 6 2 5 3 2 . .
 8 4 6 1 8 4 3 3 8 . 5 2 7 3 4 1 4 3 5 5 3 8 1 1 .
21 4 3 8 7 5 3 2 5 6 5 8 1 3 3 1 3 1 4 4 . 1 2 1 1
14 5 5 4 3 6 4 3 3 3 2 4 4 1 1 7 2 3 3 2 1 3 . 5 1
 8 4 5 5 3 1 1 3 1 1 2 5 2 3 8 5 6 3 3 5 8 2 6 8 .
 1 1 2 . . . 2 . . . 4 . 1 3 2 4 3 . . 5 5 8 2 . .

 correct :  60.6 ( 758)  wrong   :  39.4 ( 493)
```

Figure 7-1a. Scatter Plot for English Vowels (train)
Conventional Training with Mean Square Error

```
 . . . . . . . . . . . . . . . . . . . . . . . . .
 1 . . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . . . . . . . . . . . . . . . . . . . .
 1 . 1 . . . . . . . . . . . . . . . . . . . . . .
 . 1 1 . . . 1 3 . 1 . . . . . . . . . . . . . . .
 1 . 2 . . . 1 . . . . . . . . . . . . . . . . . .
 1 . 3 . . . . . . . . . . . 1 . . . . . . . . . .
 3 . 1 1 . . 1 2 . . . . . 2 1 . . . . 1 . . . . .
 2 . 1 . 1 2 1 4 1 . 1 . . 1 . . . . . . . . . . .
 1 . . 1 . . 1 2 . . . . . 1 1 . . . . . . . . . .
 1 3 1 . 1 . 1 1 1 1 . 1 . 2 . . 1 . 1 . . . . . .
 1 . 1 3 . . 2 . . . 1 . . . 1 1 2 . 1 . . . . . .
 1 1 1 2 . 1 . 1 . . 1 . 1 1 . . 2 1 . . . . . . .
 2 1 . 1 . 2 2 . . 3 . . . . 1 . 1 . 1 . . 1 . . .
 . 2 2 1 . . 2 . . . . . 2 . . 1 1 . 1 . . . . . .
 3 2 1 . 1 1 . 1 1 . 2 1 . 1 . 1 1 . . 1 1 3 . . .
 2 1 1 . 2 1 . 1 1 2 1 1 . 2 1 . 2 2 1 . 1 2 4 1 .
 . 3 1 1 2 1 . 2 1 1 1 . 2 . . . 3 2 . . 2 1 4 . .
 4 . . 1 1 1 . 1 2 1 2 1 1 1 . 1 . . . 2 1 1 3 . .
 3 3 2 . 1 1 3 1 1 1 2 4 . 1 . 1 1 . 1 1 2 3 . . .
 8 4 . 2 3 1 1 1 2 1 1 . . . 1 1 2 1 . . 1 2 . . .
 3 1 3 . 2 2 1 . . . . 1 . . . 1 1 1 . 1 1 . . . 1
 3 2 4 4 1 1 3 2 1 . 2 . . . 1 . . . 3 1 1 . . . 1
 1 3 1 3 2 1 2 . 1 . . 3 1 2 . . 1 . 1 1 . . 2 1 .
 1 . 1 1 . . . . . . . . . . 1 . 1 . 1 . . 2 . . .

 correct :  52.7 ( 194)   wrong   :  47.3 ( 174)
```

Figure 7-1b. Scatter Plot for English Vowels (test)
Conventional Training with Mean Square Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
1 . . . . . . . . . . . . . . . . . . . . . . . .
1 . . 1 . 3 . . . . . . . . . . . . . . . . . . .
. . . 1 . . . . . . . . . . . . . . . . . . . . .
. 1 1 1 . . 1 . . . . . . . . . . . . . . . . . .
1 . . . 1 2 1 2 . . 3 . . . . . . 2 . . . . . . .
. . . 1 2 2 . 1 1 1 . . 2 . 1 . . 1 . . . . . . .
2 2 . 1 5 . 4 2 1 . 3 1 1 . . 1 . 1 2 . . . . . .
. . 2 1 2 3 2 5 . 1 3 2 1 2 . . 1 2 . . . . . . .
1 1 2 3 2 4 3 2 5 4 2 5 . 3 4 1 1 2 . . . . . . .
. 1 1 2 2 4 5 1 3 6 5 4 8 9 2 3 . 2 1 . . . . . .
1 . 1 5 3 5 4 6 4 6 4 9 6 412 6 1 . 1 . 1 . . . .
. 3 3 1 2 1 6 5 6 4 6 7 7 8 7 81510 2 . . . . . .
. 1 2 1 2 2 5 8 811 7 5 9 61214 9 2 3 1 . . 1 . .
2 2 3 5 2 2 2 3 5 61010 910 810 6 1 4 1 1 1 . . .
1 3 2 1 4 3 2 3 4 6 91010 7 7 3 4 7 9 5 1 2 . . .
. . 3 . 2 4 4 3 2 4 4 9 6 3 4 5 8 911 311 3 . . .
1 5 1 . . 2 1 1 1 8 911 9 6 9 71111121114 6 2 . .
. . . 2 2 1 1 1 4 4 6 4 5 7 7 8 8 9101510 9 2 6 .
. . 1 1 . . 4 2 3 . 4 4 8 1 2 4 1 4 6 7 610 812 1
. . . . . . 1 1 . . 1 2 5 1 . 3 . 3 3 8 6 7102114
. 1 . . . . . . . . 1 1 . . . . . 1 . 2 3 7 7 4 3
. . . . . . . . . . . . . . . . . . . . . . 1 1 .
. . . . . . . . . . . . . . . . . . . . . . . . .

correct :  69.3 ( 867)  wrong   :  30.7 ( 384)
```

Figure 7-2a. Scatter Plot for English Vowels (train)
Conventional Training with McClelland Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . 1 . 1 . . . . 1 . . . . . . . . . . . . . . .
1 . . . . . . . . . . . . . . . . . . . . . . . .
1 1 . 1 . . . . . . . . . . . . . . . . . . . . .
. 1 . . 2 . . . . . . . . . . . . . . . . . . . .
. . . . 1 . . . . . 1 . . . . . . . . . . . . . .
. 2 . 1 . . . . . . . . 1 . . . . . . . . . . . .
. . 1 . 1 . . . . . . 1 . . . . . 1 . . . . . . .
1 . . 1 2 1 . 1 1 1 1 2 2 1 . 1 1 . 1 . . . . . .
1 1 . 1 2 1 1 1 2 1 2 2 2 . . . . . . . . . . . .
2 1 . 1 1 1 . . 1 1 5 2 1 3 1 1 . . . . . . . . .
1 . 2 . . 1 2 . 2 . . 1 . . 1 2 3 . . . . . . . .
3 1 . . . 2 2 1 1 2 . . 3 2 3 2 . . . . . . . . .
. 1 1 4 . 1 . 4 1 3 2 3 . 3 4 1 1 2 . . . . . . .
2 . 1 . 2 . 1 . 1 . 2 4 . 3 1 2 4 . . 1 . . . . .
2 4 . . 1 1 3 . . . 2 3 3 7 . 3 2 3 1 4 1 . . . .
. 1 1 2 . 1 . 2 2 6 . 2 . . 7 . . 5 4 . . . . . .
. . 1 . . 1 . 1 2 . . 1 2 . 2 2 2 3 3 2 2 2 . . .
. . . 1 1 1 . 3 1 . . . 1 . 2 . 4 . 3 3 7 4 . . .
. . 2 . . . 2 1 1 . 1 . 1 1 2 . . 4 2 . 3 7 1 . 1
. . . . . . 2 1 . . . 3 . . 2 1 1 . 2 1 1 1 . 2 .
. . . . . . . . . 1 1 . 1 2 . 1 . . . 1 . 2 1 4 6
. . . . . 1 . . . . . . . . . . . . . . . . . 2 1
. . . . . . . . . . . . . . . . . . . . . . . 1 .
. . . . . . . . . . . . . . . . . . . . . . . . .

correct :  59.8 ( 220)  wrong   :  40.2 ( 148)
```

Figure 7-2b. Scatter Plot for English Vowels (test)
Conventional Training with McClelland Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . 1 1 . . 1 . . . . 1 . . . . . . . . . . . . .
. 1 . . 1 2 . . 1 . . . . . . . . 1 . . . . . . .
. . . . . . . 1 . 3 2 . . . . . . . 4 . . . . . .
. . . . 1 . . . 1 1 . . . . . . . 1 1 . . . . . .
. . . . 1 3 1 . . . 1 . . . 1 3 1 2 1 3 1 . . . .
1 . 2 . . 1 1 1 1 1 . 1 . . 1 5 4 4 3 2 . . . . .
1 1 . 2 . 3 1 3 4 2 1 2 . 3 311 8 7 5 7 1 1 . . .
1 . . 1 2 . 1 5 2 2 2 2 4 1 5 5101013 4 3 . 2 . .
. 1 . 4 2 5 1 3 . 3 2 1 3 5 2 1 612 8 6 . . . . .
1 1 1 . 4 5 4 2 5 2 1 5 6 4 5 8 8 813 9 1 . 1 1 .
1 2 . . 2 2 2 4 4 3 4 7 3 6 4 8 7 7 8 8 2 2 1 . 1
. . 1 1 3 3 3 4 3 3 . 6 4 4 6 5 813 1 4 7 6 1 1 .
1 2 2 . 4 1 1 5 2 7 6 3 7 4 81311 4 6 1 9 3 3 . .
1 2 3 . 1 1 2 2 1 2 8 1 7 5 9 712 7 8 3 6 4 1 . 1
. 1 3 1 . 2 2 2 4 5 3 7 7 4 7 2 8 510 6 7 4 6 1 .
. . 1 2 . 1 5 1 1 4 4 1 8 1 4 4 412 8121312 8 2 .
. . . . 1 . 1 . 3 1 2 4 4 4 8 4 7 8 5 5 916 4 5 2
. . . . 1 2 1 1 3 1 1 3 2 3 1 4 4 5 6 910 62212 1
. . . . . 1 . 1 1 2 1 1 1 3 2 1 2 1 1 314 415 9 .
. . . . . . 2 . . . 3 . 1 1 1 . . 1 3 2 1 3 7 9 .
. . . . . . . . . . . 1 . . . . . 2 1 . 3 1 2 4 .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .

correct :  70.2 ( 878)  wrong   :  29.8 ( 373)
```

Figure 7-3a. Scatter Plot for English Vowels (test)
Fuzzy Training with Mean Square Error

```
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
1 . . . . 1 . 1 . . . . . . . . . . 1 . . . . . .
. . 1 . . 1 . . . . 1 . . . . . . . . . . . . . .
. . 1 . . . . . 1 . . . . . . . . 1 2 . . . . . .
1 . . 1 . . . . . 1 1 . . . . 2 1 . . . . . . . .
. 2 . 1 1 1 . 2 . 1 . . 1 . 1 1 . . 1 3 3 . . . .
. . 1 2 . 1 . 1 1 . 1 . 1 . . . 1 1 . 2 1 . . . .
2 . . . . . 1 2 . 1 1 . 2 4 1 . 3 4 5 1 3 . . . .
. . . 1 2 . 2 1 3 . . 1 . . . 2 1 3 1 3 1 . . . .
1 . . . . 1 2 . 3 . . 2 3 2 . 2 2 3 3 . . 1 . . .
1 . . 1 . 2 . 1 1 2 1 2 2 1 1 . 2 . 1 2 1 1 . . .
. 1 . 1 . . . . 1 2 2 . 2 . 2 1 1 2 . 1 1 . 2 . .
. 1 4 1 . . 3 2 1 2 1 1 2 . 1 2 2 7 . 2 2 1 . 1 .
. . . . . 1 2 . . 2 2 2 2 2 . . 2 3 1 3 1 . . . 1
. 1 2 1 1 1 . . 2 3 1 2 1 1 2 2 2 3 3 1 1 3 1 . .
. . . . 1 2 . 1 2 1 . . . 2 1 1 3 2 3 1 4 2 3 . 1
. . . 1 . 1 . 1 4 2 . . 1 1 1 . 3 3 . 1 1 3 2 . 1
. . . . . 2 1 . . 2 1 . . . 2 . 1 1 2 1 2 3 1 2 .
. . . . . . 1 . 1 . 1 . . . . . . 1 3 3 1 2 1 3 .
. . . . . . . . . . 1 . . . . . . . . 1 . 1 3 1 .
. . . . . . . . . 1 . . . . 1 . . . 1 . 1 . 1 1 .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . . . .

correct :  62.0 ( 228)  wrong   :  38.0
```

Figure 7-3b. Scatter Plot for English Vowels (train)
Fuzzy Training with Mean Square Error

```
 .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .  .
 5 2 2 1 . 1 . . 1 . . . . . . . . . . . . . . . .
 7 1 1 1 . . . . . 1 . . . . . . . . . . . . . . .
 8 3 1 3 . . 1 . . 1 1 . . . . . . . . . . . . . .
 7 1 2 1 3 1 . . . . . . . 1 . . . . . . . . . . .
 8 . 3 2 1 3 . . . 1 . . . . . . 1 1 . . . . . . .
 9 6 1 . 2 6 3 1 1 . . . . . . . . . . . . . . . .
16 4 6 2 6 3 7 1 2 1 . 1 . . . . . . 1 . . . . . .
16 4 1 3 4 3 3 2 . 1 . 1 1 1 1 . . . . 1 . . . . . .
15 7 3 1 1 3 610 2 . 2 1 . . . . . . . . . . . . .
16 7 4 2 7 1 2 4 5 1 2 2 . 1 . . 1 . . . . . . . .
19 3 . . 1 3 2 1 . 1 . . 6 . . . . . . . . . . . .
16 8 2 4 3 1 3 . . 4 4 2 3 1 1 1 1 1 1 2 2 2 . . .
27 4 1 3 . 3 3 2 1 2 3 . 3 3 1 1 2 3 . 2 5 . . 1 .
2914 6 2 3 4 1 5 1 2 2 3 1 2 3 2 3 1 . 1 . 1 1 . .
4712 5 3 5 4 4 2 3 3 3 4 6 2 1 5 3 3 6 3 5 4 4 1 .
451011 710 5 1 1 3 3 4 2 . 5 3 4 5 3 5 5 3 . 1 2 .
521511 610 6 2 4 2 7 4 3 9 8 8 510 410 2 4 7 2 3 .
64141014 6 6 2 1 . 7 9 6 6 6 7 6122414 7 4 8 2 3 1
4622 7 9 7 3 2 8 . 3 9 7 4 6 615 8243625121111 7 1
741417 8 810 4 6121210 911 8 911 916 71110181511 4
882818 6 7 4 610 712 810 6171111 61415261110294618
**23222515 8 617 9 2 7 9 6 4 9 713 826172317548425
**18171910 8 3 4 81318 7 611 7 413 613121922402730
45 7 1 3 3 1 1 . 1 1 1 2 . . . 4 1 2 1 3 4 8 610 .

 correct :  53.7 (1851)  wrong   :  46.3 (1598)
```

Figure 8-1a. Scatter Plot for English Phoneme (train)
Conventional Training with Mean Square Error

```
 2 1 1 1 . . . . . . . . . . . . . . . . . . . . .
 3 5 3 . 1 . . . . . . . . . . . . . . . . . . . .
 4 1 1 2 1 1 2 . . . . . . . . . . . . . . . . . .
 9 . 1 1 1 3 . . . . 1 . . . . . . . . . . . . . .
 6 5 1 2 1 . . . . . . . . . . . . . . . . . . . .
 8 . 5 4 1 2 . 1 . . . 1 . 1 . . . . . . . . . . .
 7 5 . 1 3 2 . . . . . . . . . . . . . . . . . . .
 9 1 . 1 . 1 1 1 . 1 . . . . . 1 . . . . . . . . .
 9 1 1 2 2 . 1 2 1 . . . . . . . . . . . . . . . .
 9 4 5 . 1 1 . 1 . . . . . . . . . . . . . . . . .
 5 2 2 1 1 1 1 1 1 1 . . . . . . . . 1 . 1 . . . .
 4 . . . 1 4 . 2 . 1 1 1 . . . . . 2 . 1 1 . . . .
11 8 2 . . 1 . 1 1 2 . . . 1 1 . . . . . . 2 . . .
 9 1 . 1 . . . 1 . . 3 3 1 . . 1 1 . . . . . . . .
10 4 2 3 3 . . 2 2 . . . . 1 . . . 1 . . . . 2 . .
15 4 . 2 3 1 1 . 1 1 . . 2 . 1 . . . . . . . . . .
16 3 . . 3 . 1 1 1 2 . . 2 1 2 2 1 . 1 3 . . . . .
 9 6 4 1 1 . 2 . 2 2 2 1 . . 3 3 3 . . 1 3 1 1 1 .
17 7 4 1 . 3 4 . 1 . . . 1 1 3 1 4 6 2 1 3 2 . 4 .
23 7 2 . 3 1 1 . . 2 1 1 2 1 . 4 4 724 8 3 2 3 . 2
26 4 8 5 4 1 2 4 2 4 6 6 4 4 1 4 2 . 3 1 2 3 2 3 8
27 7 4 7 4 2 2 7 5 3 4 2 4 2 2 4 2 3 3 4 5 4 3 7 5
35 5 714 2 2 3 1 3 1 2 3 2 . 3 . 4 5 9 5 8 9 624 9
39 3 2 2 1 . 1 3 2 2 8 3 . 2 . 1 1 2 3 3 3 9 6 8 .
10 2 . 1 1 . . . 1 . . 1 1 . . . . . . 1 1 . 2 1 .

 correct :  46.0 ( 495)  wrong   :  54.0 ( 580)
```

Figure 8-1b. Scatter Plot for English Phoneme (test)
Conventional Training with Mean Square Error

```
. . 1 . . . . . . . . . . . . . . . . . . . . . .
. . . . 1 1 . . . . 1 . . . . . . . . 1 . . . . .
. . . . 1 . 1 2 1 1 . . . . . . . . . . . . . . .
. 3 1 1 . . 1 . 3 1 . 1 2 . 2 . . . . . . . . . .
. 2 1 1 2 1 2 3 . 2 1 1 2 1 1 . . 1 1 . . . . . .
. 2 1 . . 1 3 . 1 . 1 4 . 2 1 1 . . . . . . . . .
3 1 . 5 2 2 5 1 4 4 2 3 1 1 4 2 3 1 . . 1 . . . .
. 1 2 3 3 6 4 5 7 5 . 2 6 2 6 . . . 5 1 . 2 . 1 1
. 2 1 4 5 7 1 3 3 3 5 7 4 1 4 4 1 2 4 4 2 . 1 2 1
2 3 5 4 6 4 4 4 8 5 1 4 3 8 4 2 4 1 2 2 . 3 . . .
. 4 7 7 3 7 6 4 9 7 6 4 9 3 5 7 5 7 3 4 4 2 1 2 .
2 3 6 7 6 310 7 710 7 9 7 3 3 5 5 7 8 3 112 5 . 1
2 4 3 5 2 1 8 3 5 4 4 4 5 5 2 4 6 410 7 6 5 6 2 .
2 1 6 3 6 7 7 8 9 91410 7 4 7 214 5 8 511 6 7 2 1
1 410 6 5 710 611 9 6 6 7 9 9 81110 810 913 6 6 7
1 3 3 2 1 812 7 7 710 815 9 8 91311 811 812 9 5 5
. 6 2 4 3 6 610 7 8 814 6 811 5 713152018181 7 412
1 3 3 4 6 7 9 911 3 81012 812 9171314192114 81411
1 1 3 3 6 2 3 8 7 7 714 6121117141321263024181127
. . 2 7 1 2 7 5 6 6 911 812101213182119242232244 2
3 . 2 . 3 2 7 6 5 4 7 310 914171019282722273442 52
. 1 1 1 . 2 2 4 . 6 2 6 312 510121514 81930315160
. . . . . 2 2 . 5 2 3 3 . 3 4 6 7 712111621274771
. . 1 . . 1 . . 2 . 1 2 1 . . 2 4 1 4 4 6 9234498
. . . . . . . . . . . . . . . 1 . . 1 . . 1 4 727

correct :  76.7 (2647)  wrong   :  23.3 ( 802)
```

Figure 8-2a. Scatter Plot for English Phoneme (train)
Conventional Training with McClelland Error

```
4 1 . . . . 2 . . . . . . . . . . . . . 1 . . .
1 1 4 . . . . . 2 . . . . . . . . . . 1 . . . .
7 1 . 5 . 2 2 2 . . . . . 2 . . . . . . . 1 . .
3 . 1 2 1 . 1 1 . . . . . . . 1 . . . . . . 2 .
5 1 2 . 3 . 2 2 . . 1 1 . . . . . . . . . . . 2
5 2 1 2 1 1 3 4 1 . . 1 . 1 . . 1 . . . 1 . . . .
5 2 4 1 1 1 2 2 1 2 1 1 . 2 . . 1 . . . . . 1 . 1
3 2 4 3 . 2 . . 1 1 1 4 . . 2 . . 1 2 . . 1 . 1 1
7 . 2 3 7 3 2 1 1 3 . . . . 2 1 . 1 1 2 . . . 1 2
2 2 5 1 1 2 4 . 1 1 . 1 1 . 2 1 . . 1 . . . . . 1
5 5 4 2 2 3 3 1 1 3 4 2 2 . . . 3 . . . 2 1 2 . 1
4 2 4 3 2 3 3 . 2 1 1 3 1 3 1 . 2 3 1 . 1 . 2 . 1
4 1 1 1 1 5 1 . 2 3 . 3 1 2 4 2 3 2 1 . 1 . 1 2 .
4 6 4 3 8 1 2 1 2 2 2 2 2 2 4 5 4 1 2 2 1 1 1 2 1
5 6 2 2 3 4 3 2 8 . 3 1 1 3 3 1 1 . 2 . 4 2 1 . 1
3 3 1 6 3 2 2 2 2 5 3 3 5 5 3 5 2 4 2 5 2 6 3 1 4
6 4 1 4 5 1 5 . 2 1 5 2 3 3 3 2 4 4 5 3 2 4 6 1 2
4 1 2 . 1 4 . 3 . 1 . 3 3 6 3 3 3 4 3 2 1 . 3 1 .
4 4 2 2 . 1 3 3 1 2 3 1 6 2 2 5 2 4 4 . 3 4 1 3 7
1 6 3 3 2 2 . 1 . 3 1 1 2 4 6 4 3 3 4 5 4 7 2 2 2
. 1 . 1 . . . 2 3 . 1 . 4 1 5 2 1 5 1 3 8 3 712 5
1 . . . . 2 . . . . 2 2 . 1 3 1 5 3 5 3 811 5 820
3 . 1 1 . . 1 . . . . . 1 . . 2 1 3 3 3 5 6 8 422
. . 1 1 . . . . . . . . . . 1 . 1 . . . . 1 . 2 724
. . . . . . . . . . . . . . . . . . . 1 . . 1 2 4

correct :  57.1 ( 614)  wrong   :  42.9 ( 461)
```

Figure 8-2b. Scatter Plot for English Phoneme (test)
Conventional Training with McClelland Error

```
 . . . . . . 1 . . . . 1 . . . . . . . . . . . . .
 . . . . . 1 1 . . 1 . . . . . . . . . . . . . . .
 . . . . . . 1 1 . 1 1 . 1 . . . . . 1 . . . . . .
 . 2 . 1 . 1 1 6 1 1 . . . 1 . . . . 1 . . 1 . . .
 2 1 . . . . 1 3 1 1 . 1 1 1 3 2 . 2 1 . . . . . .
 1 2 2 . 2 1 4 4 2 5 3 3 1 2 3 1 1 2 . . . . . . .
 2 1 1 1 2 . 4 3 6 2 3 6 4 7 3 3 5 6 . 1 . . 1 . .
 2 1 1 5 . 3 5 1 5 5 7 4 8 3 8 5 7 8 2 2 3 . . . .
 . 1 2 4 . 3 6 3 6 7 7 5 8 7 9 5 6 8 4 3 . 1 . . .
 2 1 3 4 6 2 510 4 7 81110 5 9 91010 5 2 3 . . . .
 1 3 5 5 2 5 8 511 6 510 610 81711 911 6 6 . 2 . .
 4 6 4 8 5 5 41011 5 9 311 612 613 81315 3 4 . . .
 3 1 2 8 5 5 9 31113 6 4 5 613 915111915 8 3 4 2 .
 1 2 2 610 8 3 511 6 616101013131315141817 4 6 3 2
 2 7 2 6 5 71113111012111217161518151627141 3 9 1 2
10 6 4 5 8 3 9 8 7 81411122416122129242315 16 7 8 1
 1 2 5 5 4 5 911 9 81617101218211826232223 22 7 8 1
 2 1 3 2 2 8 9 8 41214 61515141621242527332915 12 2
 9 5 3 6 2 1 4 7 7 4 9 611 81919222225242430242 5 3
 2 3 1 4 2 4 1 6 5 4 4 6 5 91316182329292935312 6 4
 1 1 . 1 . . 2 5 3 . 4 4 1 7 6 912 9 9213039313712
 6 . . . . 1 . . 1 2 1 6 . 1 5 5 5 2 4121424294316
 . . . 1 . . . . . . . . . 1 1 . 2 1 1 . 2 2 6 517
 . . . . . . . . . . . . . . . . . . . . . . . . 2
 . . . . . . . . . . . . . . . . . . . . . . . . .

 correct :  71.7 (2474)  wrong   :  28.3 ( 975)
```

Figure 8-3a. Scatter Plot for English Phoneme (train)
Fuzzy Training with Mean Square Error

```
 . 1 . . . . . . . . . . . . . . . . . . . . . . .
 . 2 . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . 1 . 2 1 . . . . . . . . . . . . . . .
 . 3 2 1 . 2 . 1 1 1 1 . . . . . . . . . . . . . .
 2 5 . 2 . . . 1 . . 1 . 1 . 1 . . . . . . . . . .
 . . 2 3 1 2 . 1 . 1 3 1 . 4 2 . . . . . . . . . .
 2 . 1 . 1 3 1 2 2 2 . 1 1 1 1 . . 1 1 . . . . . .
 1 1 1 2 1 1 2 1 2 4 3 1 2 1 2 1 1 1 . . . . . . .
 3 2 1 3 9 2 . 4 2 1 4 2 1 2 2 3 2 2 . . . . . . .
 2 1 . 3 3 3 4 1 1 1 1 5 4 . 4 . 4 3 3 3 1 . . . .
 4 6 5 2 2 5 2 3 1 2 1 4 2 2 . 4 4 6 1 3 4 1 . 2 .
 4 2 4 3 2 2 5 4 3 4 1 4 2 4 2 3 7 2 7 . 1 1 . . .
 3 1 3 1 4 2 3 1 . 3 4 2 2 1 2 1 1 4 3 2 1 1 . . .
 8 1 7 4 3 4 4 2 1 4 . 7 2 4 4 2 5 5 7 6 2 . 3 1 .
 . 1 5 2 4 5 3 6 7 1 4 4 2 7 1 5 6 8 7 4 5 2 3 2 .
 . 1 3 1 5 . 1 4 310 3 . 5 2 2 3 7 2 7 5 3 3 2 . .
 1 1 4 3 3 2 2 5 4 2 5 5 4 4 4 4 5 7 5 715 4 2 4 .
 1 3 1 5 1 2 . 6 2 2 1 4 3 4 6 1 2 5 4 415 9 1 3 .
 1 3 . 6 2 3 . 1 . 2 4 3 5 9 3 4 5 4 2 3 910 5 4 1
 2 2 1 1 3 1 2 . 4 1 1 1 1 2 3 3 3 4 2 8 71310 4 1
 . . . . . 2 1 2 2 . 1 1 . 1 1 2 4 3 3 610 9 610 1
 . . . . . . . 1 . . . 2 1 . . . . 3 1 2 2 1 3 9 1
 . . . . . . . . . . . . . . . . 1 . . . 1 1 . 1 2
 . . . . . . . . . . . . . . . . . . . . . . . . .
 . . . . . . . . . . . . . . . . . . . . . . . . .

 correct :  58.1 ( 625)  wrong   :  41.9 ( 450)
```

Figure 8-3b. Scatter Plot for English Phoneme (test)
Fuzzy Training with Mean Square Error