CONTRIBUTED ARTICLE

Effects of Learning Parameters on Learning Procedure and Performance of a BPNN

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Abstract—We examined the effects of changing learning parameters on the learning procedure and performance of back-propagation neural networks used to pick seismic arrivals. The results show that such change mainly affects the speed of convergence of the learning procedures, and does not affect the BPNN structure and its overall performance. A relationship between the learning parameters and iteration number is obtained. This relationship may be used as a guide to check the convergence of the learning procedure and the BPNN performance. We also use a weight map of BPNN structure to analyze its interior and performance. Two BPNNs used to pick seismic arrivals from three-component and single-component seismograms have similar weight patterns and operate in a similar way, although they have different structures and trained by different training dataset. © 1997 Elsevier Science Ltd.

Keywords—Back-propagation neural network, Seismic arrivals picking, Pattern recognition, Learning procedure, Convergence.

1. INTRODUCTION

The back-propagation neural network (BPNN) trained by the *generalized delta rule* (Rumelhart, Hinton & Williams, 1986) is successfully used in many fields, especially for pattern recognition, due to its learning ability. However, one of its major disadvantages is that it looks like a “black-box” and provides no insight into the physics of its processing (McCormack, 1991). As a result, it is difficult to understand how it processes. Its performance is affected by many factors, such as the network structure (the numbers of input nodes, output nodes, hidden layers, and hidden nodes), and training parameters (the learning rate, momentum rate, and thresholds of system and pattern errors) which form components of the generalized delta rule. The range of choice of these factors results in a variable performance and, consequently, makes comparisons difficult. It is unclear if and when the optimum solution has been reached.

Although some efforts have been devoted to selecting optimal values (Gorman and Sejnowski, 1988; Dowla Taylor & Anderson, 1990; Fausett, 1994), such values can only be obtained by a process of trial and error which is often time-consuming and inconsistent. It makes the application of BPNNs difficult. There is a need to find an appropriate method which can efficiently select these factors and understand the BPNN performance. The most important selection of the training parameters of generalized delta rule are the learning rate η and momentum rate α . They may have different values depending upon the problems and the researcher's favourite choice. Usually, determination is arbitrary and their optimum values can only be obtained by a process of trial and error.

In order to investigate this effect, two questions should be answered: (1) how do they affect the training procedure? and (2) how do they affect the BPNN structure? The training procedure can be measured by using the *iteration number* for convergence. The trained BPNN structure can be measured by its *weight pattern* in a weight map which displays the distribution of weight values (Dai and MacBeth, 1994a). In this paper, we will investigate this effect by analyzing a BPNN specially applied to the problem of picking seismic arrivals from local earthquake data. We will introduce the approach for picking seismic arrivals, and analyze the effects of changing the learning parameters.

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FIGURE 1. Schematic diagram showing the method of using a BPNN to pick seismic arrivals. Here, the input of the BPNN is a segment of the modulus of three-component recordings (the low diagram). A trained BPNN is treated as a filter in a sliding window across through the entire modulus trace. The output of the BPNN (the upper diagram) yields a time series which enhances the changes in the modulus to indicate the arrival onset. P and S indicate the *P*- and *S*-arrivals.

2. SEISMIC ARRIVAL PICKING

Picking seismic arrival from background noise is a typical pattern recognition problem. In order to detect and locate a seismic event, the primary (*P*) and secondary (*S*) wave arrivals must be picked and their onset times must be measured. We have developed a BPNN approach to tackle this (Dai and MacBeth, 1995). This approach includes two phases: the *training (learning)* phase and the *testing (generating)* phase. In the training phase, some training dataset should be selected by an analyst using his experience and then be used to train the BPNN. After training, the BPNN is applied to the entire seismogram as a filter by using a sliding window along the entire modulus trace of three-component seismograms (Figure 1). The input of the BPNN is a segment of the modulus. The output of the BPNN then yields a time series which is interrogated for a decision regarding the seismic arrivals.

In such an application, the first task is to select a suitable BPNN structure, then a suitable training dataset, and also it is necessary to select suitable training parameters. In our early paper (Dai and MacBeth, 1995), we examined some factors which affect the performance. We found that: (1) a three-layer BPNN (with a single hidden layer) is sufficient; (2) there exist optimal numbers of both input nodes and hidden nodes and the input node number seems to have a large effect; (3) the performance is strongly dependent on the training dataset. A small training dataset may result in a poorly trained BPNN, and a large one may result in the learning procedure becoming too long. It seems better to train a BPNN with a small training dataset first, and then to improve its performance by subsequently adding more training dataset. Finally, by using a process of trial and error, we selected a three-layer BPNN which had an

input layer, a hidden layer and an output layer (Figure 2). The input layer has 30 nodes corresponding to the segment of the input characteristic function which is chosen to include several complete cycles of a wave in the sliding window, the hidden layer has 10 nodes, and the output layer has two nodes flagging the result, (0,1) for an arrival and (1,0) for pure background noise.

In this approach, the BPNN is applied to pick as many changes from the background noise as possible and discard those which are neither *P*- nor *S*-arrivals, so the training data should include the seismic arrival signal and background noise signal. Because both *P*- and *S*-arrivals appear to exhibit similar modulus characteristics, the training dataset only includes the

FIGURE 2. The structure of a BPNN for seismic arrival picking. It has three layers including an input layer with 30 nodes, a hidden layer with 10 nodes and an output layer with two nodes. The BPNN input is a segment of the modulus of three component seismograms. The two BPNN outputs indicate the input segment with (0,1) as a *P*-arrival and (1,0) as noise.

FIGURE 3. Nine P-arrival and nine background noise segments of the modulus of three-component recordings used for training a BPNN. Noise segments are extracted prior to the P-arrivals in the same seismograms. Arrows on P-arrival segments indicate arrival onset times used to train the BPNN, all at the eleventh sample. These segments are individually normalized before being input into the BPNN.

modulus segment of the *P*-arrivals and background noise which was extracted prior to the *P*-arrivals in the same seismograms. These segments are arranged so that the predicted onset time of every *P*-arrival lies at the eleventh sample. Finally nine pairs of *P*-arrivals and background noise segments (Figure 3) are selected for training in the study. With the above

BPNN structure and training dataset, this approach is applied to deal with several hundreds of three-component seismograms from a local earthquake network. It can detect 94% *P*-arrivals and 90% *S*-arrivals. 75% of the *P*-arrivals and 67% of the *S*-arrivals are estimated from their onset times within one sample increment (10 ms).

3. LEARNING PARAMETERS AND LEARNING CONVERGENCE

The generalized delta rule which is used to train BPNNs can be mathematically written as:

$$\Delta w_{ijk}(n+1) = \eta \delta_{ik} o_{ij} + \alpha \Delta w_{ijk}(n), \quad (1)$$

where η is the *learning rate* and α the *momentum rate*. Δw_{ijk} is the change of the weighted connection between n_{ij} (n_{ij} is defined as the j th node in the i th layer) and n_{i+1k} , o_{ij} the output of n_{ij} , and δ_{ik} the change in error as a function of the change in the network input to the n_{i+1k} . The quantity $(n+1)$ indicates the $(n+1)$ th step. This equation means the change of weights at the $(n+1)$ th step should be similar to the change of weights undertaken at the n th step.

To train a BPNN, the first input pattern is presented to an initially randomized BPNN, and the weights (including thresholds of nodes) adjusted in all the connections. Other patterns are then presented in succession, and the weights adjusted from the previously determined values. This process continues until all patterns in the training set are exhausted (*an iteration*). The final solution is generally independent of the order in which the example patterns are presented. However, a final check can be performed by looking at the *pattern error*, E_p , the sum of squares of the difference between desired output and BPNN output for each pattern, and *system error*, E_s , the average of all pattern errors, to determine whether the final BPNN solution satisfies all of the patterns presented to it within a certain error.

TABLE 1

Iteration number		α										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
η	0.1	7248	6523	5799	5074	4350	3625	2900	2175	1451	730	NC
		2.69	2.69	2.69	2.70	2.70	2.70	2.70	2.70	2.70	2.69	
		7248	6523	5798	5074	4349	3624	2899	2174	1450	725	
	0.2	3634	3274	2910	2547	2183	1819	1455	1091	728	368	NC
		2.70	2.69	2.70	2.70	2.71	2.71	2.72	2.72	2.72	2.71	
		3624	3262	2899	2537	2175	1812	1449	1087	725	363	
	0.3	2435	2191	1948	1705	1462	1218	974	729	486	247	NC
		2.70	2.70	2.71	2.71	2.72	2.73	2.74	2.75	2.74	2.75	
		2416	2174	1932	1691	1450	1208	966	725	483	242	
	0.4	1834	1651	1468	1285	1102	918	734	550	366	188	NC
		2.70	2.71	2.71	2.72	2.73	2.74	2.74	2.76	2.77	2.81	
		1812	1631	1449	1269	1087	906	725	544	363	181	
	0.5	1474	1327	1180	1033	886	739	591	443	295	151	NC
		2.70	2.71	2.72	2.73	2.74	2.75	2.77	2.78	2.79	2.87	
		1450	1304	1159	1015	870	725	580	435	290	145	
	0.6	1234	1111	989	866	743	620	496	372	248	124	NC
		2.70	2.71	2.72	2.73	2.75	2.76	2.78	2.80	2.80	2.97	
		1208	1087	966	846	725	604	483	362	242	121	
	0.7	1063	957	852	746	641	535	428	321	215	102	NC
		2.70	2.71	2.72	2.74	2.75	2.77	2.79	2.82	2.81	3.19	
		1035	931	828	724	621	518	414	310	207	104	
	0.8	935	842	750	657	564	471	378	284	190	85	NC
		2.69	2.71	2.72	2.74	2.76	2.78	2.80	2.81	2.84	3.45	
		906	815	725	634	543	453	362	272	181	91	
	0.9	836	753	670	588	505	422	338	254	171	73	NC
		2.68	2.98	2.72	2.73	2.75	2.78	2.81	2.83	2.86	3.57	
		805	725	644	564	483	403	322	242	161	81	
	1.0	756	681	606	532	457	382	307	231	156	67	NC
		2.68	2.70	2.72	2.73	2.76	2.78	2.81	2.83	2.97	3.52	
		725	652	580	507	435	362	290	217	145	73	
	1.1	691	622	554	486	418	350	281	212	143	65	NC
		2.67	2.69	2.71	2.73	2.76	2.78	2.81	2.83	2.90	3.37	
		659	593	527	461	395	329	264	197	131	66	

The iteration number for training with different learning rate η ranged from 0.1 to 1.1 and momentum rate α ranged from 0.0 to 1.0. In each cell, the top number is the number of training iteration, the middle one is the system error ($\times 10^{-5}$), and the bottom one is the predicted iteration by using eqn (2). NC means non-convergence. This BPNN is trained with seven pairs of P-arrival and background noise segments.

The convergence speed (iteration number) of the training procedure is obviously dependent on the learning rate η , and momentum rate α . Naturally, the higher the learning rate is, the larger the change in the weights. For practical purposes, it should be chosen to be as high as possible. However, if the learning rate is too large, it will lead to unstable oscillation (Pao, 1988). This oscillation might be filtered out by the *momentum term*. However selecting them is somewhat difficult as their values depend on the nature of the problem. Here we attempt to obtain a relationship between the learning parameter and the iteration number by analyzing the BPNN used in the above approach.

3.1. Relationship between Learning Parameters and Learning Convenience

We use different values of learning rate η and momentum rate α to train the same BPNN by using seven pairs of *P*-arrival and background noise segments (Figure 3). Table 1 shows the iteration number required in training this BPNN as a function of η and α , but with the same pattern error threshold (0.0001) and system error threshold (0.00001) which are used to terminate the training

procedure. A relationship between the iteration number and η and α can be obtained from this table:

$$\text{Iteration_Number} = IN_0 * \frac{(1 - \alpha)}{10 * \eta}, \quad (2)$$

where IN_0 is the iteration number at $\eta = 0.1$ and $\alpha = 0.0$. In order to verify this equation, we calculate the iteration number by using this equation with the same IN_0 (Table 1). The calculated iteration numbers fit well with the real numbers. For example, the maximum relative error is 10% at $\alpha = 0.9$ and $\eta = 0.9$ with an absolute error of 8 iterations.

This equation shows that: (1) the iteration number is inversely proportional to α . Note that α must be less than 1.0, otherwise the learning procedure does not converge. (2) the iteration number is the reciprocal of the η , and naturally, η cannot be zero. Due to the nature of the reciprocal function, large η cannot reduce the iteration number too much. For example, when η is increased from 0.1 to 0.2, the iteration number is reduced by 50%, but when η is increased from 0.7 to 0.8, the iteration number is reduced by 12.5%.

The iteration number is also related to the system error. It seems that the deviation of iteration number is

FIGURE 4. The space of η and α for a BPNN with seven training datasets. A is the stable area where the fitness between real iteration number and the one calculated is accurate and the system error is stable with a relative change of less than 10%; B is the unstable area where the fitness is not accurate and the system error is unstable; and C is the misfit area where the learning does not converge or take too many iterations, and the system error is unstable.

TABLE 2

Iteration number		α										
		0.90	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.0
η	0.1	730	659	587	516	445	375	308	201	139	NC	NC
		2.69	2.69	2.69	2.69	2.69	2.72	2.82	3.76	2.29		
		725	652	580	507	435	364	290	218	146		
	0.2	368	333	297	262	228	188	138	85	100	NC	NC
		2.71	2.71	2.73	2.75	2.81	3.16	3.63	2.74	1.79		
		363	326	290	254	217	181	145	108	73		
	0.3	247	223	2.97	177	147	105	73	NC	NC	NC	NC
		2.75	2.78	2.73	2.91	3.33	3.83	3.09				
		242	2.17	193	1.69	145	120	97				
	0.4	188	171	152	127	97	70	49	83	NC	NC	NC
		2.81	2.86	2.99	3.40	3.69	3.18	3.09	1.99			
		181	163	145	127	109	91	72	54			
	0.5	151	135	116	92	68	49	46	107	NC	NC	NC
		2.87	2.97	3.21	3.50	3.36	3.19	3.70	1.49			
		145	130	116	101	87	72	58	43			
	0.6	124	108	86	67	52	47	54	NC	NC	NC	NC
		2.97	3.15	3.61	3.64	3.15	2.59	2.21				
		121	109	97	85	72	60	48				
	0.7	102	85	67	52	42	42	54	NC	NC	NC	NC
		3.19	3.56	3.80	3.55	3.17	2.59	2.21				
		104	93	82	72	62	51	41				
	0.8	85	69	56	41	41	50	124	NC	NC	NC	NC
		3.45	3.79	3.70	4.46	2.92	2.18	2.07				
		91	81	72	63	54	45	36				
	0.9	73	61	50	46	80	132	NC	NC	NC	NC	NC
		3.57	3.74	3.72	3.10	2.04	2.45					
		81	72	64	56	48	40					
	1.0	67	58	50	64	100	NC	NC	NC	NC	NC	NC
		3.52	3.64	3.58	2.61	2.10						
		72	65	58	51	43						
	1.1	65	59	57	65	83	55	NC	NC	NC	NC	NC
		3.37	3.36	3.18	2.28	1.86	2.46					
		66	59	53	46	40	34					

The iteration number for training with different learning rate η ranged from 0.1 to 1.1 and momentum rate α ranged from 0.9 to 1.0 for the same BPNN as in Table 1. Notations are the same as in Table 1.

proportional to the deviation of the system errors related to that at $\eta = 0.1$ and $\alpha = 0.0$. In the training procedure, we have mainly used the pattern error to terminate the training procedure. The training procedure stops when all training patterns have an error less than 0.0001, but the system error, varying with different learning parameters, does not need to reach its threshold (0.00001). A small system error corresponds to a long learning procedure. It seems that a better fit between the real and calculated data is obtained if the same system error is used to terminate the training procedure.

The above results only limit $\eta < 1.1$. In order to obtain a complete image of the effect of η and α , we have examined the details of fitness between eqn (2) and the real iteration on the above BPNN when $\eta > 1.1$ and α varies between 0.9 and 1.0 at small intervals. Tables 2 and 3 show the results in which, as the η and α increase,

the system error unstably deviates from the system error at $\alpha = 0.0$ and $\eta = 0.1$ and the real iteration number also deviates from the calculated one, and as η increases, the value of α , when the non-convergence occurs is decreased. The iteration number and system error, as the functions of α and η , can be divided into three areas (Figure 4): A is the stable area where the fitness between real iteration number and calculated one is accurate and the system error is stable; B is the unstable area where the fitness is not accurate and the system error is unstable; and C is the misfit area where the learning does not converge or take too many iterations, and the system error is unstable.

3.2. Analysis about other BPNNs

Although the performance of this BPNN is good, we still

TABLE 3

Iteration number	α										
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	7248	6523	5799	5074	4350	3625	2900	2175	1451	730	NC
	2.69	2.69	2.69	2.70	2.70	2.70	2.70	2.70	2.70	2.69	
	7248	6523	5798	5074	4349	3624	2899	2174	1450	725	
1	756	681	606	532	457	382	307	231	156	67	NC
	2.68	2.70	2.72	2.73	2.76	2.78	2.81	2.83	2.97	3.52	
	725	652	580	507	435	362	290	217	145	73	
2	391	353	316	277	239	202	164	124	87	53	NC
	2.62	2.64	2.67	2.71	2.75	2.79	2.83	2.85	2.87	2.40	
	362	326	290	254	217	181	145	109	72	36	
3	258	234	211	188	163	136	109	84	46	42	NC
	2.77	2.78	2.80	2.84	2.91	3.01	3.10	3.17	3.64	2.06	
	242	216	192	108	144	120	96	72	48	24	
4	187	172	157	139	119	99	78	55	47	NC	NC
	3.01	3.03	3.06	3.13	3.24	3.38	3.65	4.06	2.70		
	181	162	144	126	108	90	72	54	36		
5	149	137	123	108	92	76	58	43	34	NC	NC
	3.15	3.22	3.31	3.41	3.59	3.80	4.21	4.78	3.47		
	145	131	116	102	87	73	58	44	29		
6	124	113	101	88	74	66	68	57	51	NC	NC
	3.30	3.40	3.48	3.66	4.06	4.06	3.03	2.88	2.30		
	121	109	97	85	73	60	48	36	24		
7	107	96	85	74	62	67	44	54	NC	NC	NC
	3.41	3.50	3.83	4.34	4.94	3.62	5.48	1.68			
	104	94	83	73	62	52	41	31			
8	93	88	74	66	57	65	82	45	NC	NC	NC
	3.65	3.88	4.42	5.04	5.47	3.95	2.59	4.01			
	91	82	73	64	55	46	36	27			
9	86	81	73	68	71	58	118	48	NC	NC	NC
	4.09	3.81	4.45	5.03	4.00	3.26	1.95	1.73			
	81	73	65	57	49	40	32	24			
10	83	80	73	66	73	54	45	NC	NC	NC	NC
	4.19	3.79	3.54	4.01	3.37	4.56	3.14				
	73	65	60	52	45	37	30				
11	76	70	71	89	118	48	87	NC	NC	NC	NC
	4.22	3.80	3.74	3.94	2.24	3.42	1.88				
	66	57	51	44	38	31	24				

The iteration number for training with different learning rate η ranged from and 1 .0 to 11 .0 with an interval of 1 .0 and momentum rate α ranged from 0.0 to 1 .0 for the same BPNN as in Table 1. Notations are the same as in Table 1.

seek the possibility to improve its performance by adding new training data. A new BPNN is finally trained by nine pairs of *P*-arrival and background noise segments (Figure 3) and has an improved performance than the original one (Dai and MacBeth, 1995). Here Tables 4–6 shows the iteration numbers required in training this BPNN. These tables also show the prediction from eqn (2) which provides a satisfactory fit. It also shows that the system error is more stable for this BPNN. Figure 5 shows the same features of η and α as Figure 4. It seems that this better fit corresponds to the improved performance of the later BPNN.

We also examine another BPNN which is used to pick seismic arrivals from vertical component seismograms

(Dai and MacBeth, 1994b). In this case the BPNN also has three layers, but with 40 input nodes. To train this BPNN, 10 pairs of *P*-arrival and background noise segments of absolute values of vertical component recordings are selected (Figure 6). Tables 7–9 and Figure 7 show the results. Due to an unstable system error, its fit is not as good as that of the two previous BPNNs.

3.3. Discussion

By analyzing three BPNNs, we obtain a general relationship (eqn (2)) between the learning parameters (η and α) and the iteration number. The iteration number depends on two factors: the system error and the learning

TABLE 4

Iteration number											
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	8991	8096	7201	6304	5406	4507	3606	2703	1799	893	NC
	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.03	
	8991	8092	7192	6294	5396	4496	3596	2697	1798	899	
0.2	4483	4046	3596	3150	2702	2253	1803	1351	898	443	NC
	1.05	1.05	1.04	1.04	1.04	1.04	1.04	1.04	1.03	1.02	
	4496	4046	3596	3152	2698	2248	1798	1349	899	450	
0.3	2981	2688	2394	2098	1800	1502	1202	900	596	291	NC
	1.05	1.05	1.05	1.05	1.05	1.04	1.04	1.04	1.03	1.01	
	2997	2697	2397	2101	1798	1499	1199	899	599	300	
0.4	2230	2012	1792	1572	1349	1126	901	674	445	213	NC
	1.05	1.05	1.05	1.05	1.05	1.04	1.04	1.04	1.03	1.01	
	2248	2023	1798	1576	1349	1124	899	674	450	225	
0.5	1779	1606	1431	1256	1078	900	720	538	354	165	NC
	1.06	1.05	1.05	1.05	1.05	1.05	1.04	1.04	1.03	1.03	
	1798	1618	1438	1261	1079	899	719	538	360	180	
0.6	1479	1335	1191	1045	898	749	599	447	294	135	NC
	1.06	1.06	1.05	1.05	1.05	1.05	1.05	1.04	1.04	1.08	
	1499	1349	1199	1051	899	749	599	450	300	150	
0.7	1264	1142	1019	894	768	641	513	383	251	112	NC
	1.06	1.06	1.06	1.06	1.06	1.05	1.05	1.04	1.03	1.16	
	1284	1156	1027	899	770	642	513	385	257	128	
0.8	1104	997	890	781	671	561	448	334	219	96	NC
	1.07	1.06	1.06	1.06	1.06	1.05	1.05	1.05	1.04	1.23	
	1123	1011	899	788	674	562	450	337	225	112	
0.9	980	885	790	693	596	498	399	297	195	81	NC
	1.07	1.07	1.06	1.06	1.06	1.06	1.05	1.05	1.04	1.34	
	999	899	799	700	599	499	400	300	200	100	
1.0	891	796	710	624	536	448	359	267	177	67	NC
	1.07	1.07	1.07	1.06	1.06	1.06	1.05	1.05	1.04	1.53	
	899	809	719	630	540	450	360	270	180	90	
1.1	802	723	645	567	488	408	326	244	164	64	NC
	1.07	1.07	1.07	1.07	1.06	1.06	1.06	1.05	1.04	1.58	
	817	736	654	573	490	409	327	245	164	82	

The iteration number for training with different learning rate η ranged from 0.1 to 1.1 and momentum rate α ranged from 0.0 to 1.0. This BPNN is trained with nine pairs of P-arrival and background noise segments. Notations are the same as in Table 1.

parameters (η and α). The fit between the real number and the calculated number is related to the system error change. The system error is affected by the learning parameters, however, it seems that there is no regular rule. Although for a well trained BPNN, it should be stable. The learning parameters have only a minor effect on the fitness when η and α in the stable area are small. In contrast, when the η and α are large, the effect is also large. The differences increase as η increases. For example, on the column $\alpha = 0.1$ of Table 1, although the system errors are the same when $\eta = 0.1$ and $\eta = 1.1$, the real iteration number at $\eta = 1.1$ is still larger than the calculated one. This reflects the fact that a large deviation can take place in the weight space with a high η in the training procedure (Pao, 1988). During the learning procedure with high η , the weight changes might rise

above the desired weight state and necessitate a re-search. As a result, the learning procedure requires more iterations to reach this state. Although using the momentum term can reduce this jump, it cannot be totally overcome. Therefore, a large training parameter may not necessarily result in a short learning procedure.

The space of η and α can be divided into three areas for the iteration number and system error (Figs 4 and 5 and Figure 7). It seems the shape of the areas reflects the BPNN's performance. For a BPNN with good performance, the stable area (A) should be large as in Figure 5. However, the other two BPNNs have a smaller stable area with lower performance. This may be used to check the performance during training of a BPNN. In addition, when using large η and α to train a BPNN, the iteration number should not deviate far from the

TABLE 5

Iteration number	α										
	0.9	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.0
0.1	893	803	712	621	529	433	326	195	106	786	NC
	1.03	1.03	1.03	1.03	1.03	1.03	1.05	1.36	1.63	0.96	
	899	809	719	629	539	450	360	270	180	90	
0.2	443	398	351	303	251	194	134	89	246	NC	NC
	1.02	1.02	1.02	1.02	1.03	1.14	1.43	1.65	0.97		
	450	405	360	315	270	225	180	135	90		
0.3	291	259	226	190	151	102	66	72	187	NC	NC
	1.01	1.01	1.01	1.04	1.17	1.45	1.87	1.35	2.27		
	300	270	240	210	180	150	120	90	60		
0.4	213	187	159	128	91	63	51	47	451	NC	NC
	1.01	1.01	1.05	1.15	1.35	1.65	1.47	1.74	1.92		
	225	203	180	158	134	112	89	67	44		
0.5	165	143	119	92	68	56	49	66	NC	NC	NC
	1.03	1.07	1.16	1.30	1.53	1.57	1.68	1.71			
	180	162	144	126	108	90	72	54			
0.6	135	116	94	74	59	50	34	477	NC	NC	NC
	1.08	1.16	1.30	1.52	1.82	1.52	4.01	1.91			
	150	135	120	105	90	75	60	45			
0.7	112	96	84	61	60	50	107	NC	NC	NC	NC
	1.16	1.26	1.39	1.88	1.57	2.55	1.39				
	128	115	102	90	77	64	51				
0.8	96	83	60	57	62	75	95	603	NC	NC	NC
	1.23	1.37	1.90	1.84	1.66	1.25	1.52	0.98			
	112	101	90	78	67	56	45	34			
0.9	81	63	53	57	63	39	36	467	NC	NC	NC
	1.34	1.72	2.17	2.01	1.57	1.57	2.08	2.04			
	100	90	80	70	60	50	40	30			
1.0	67	56	51	67	40	34	60	708	NC	NC	NC
	1.53	1.99	2.56	1.40	1.73	1.80	1.73	2.20			
	90	81	72	63	54	45	36	27			
1.1	64	57	52	69	37	36	96	NC	NC	NC	NC
	1.58	2.04	2.55	1.37	1.82	2.10	1.67				
	82	74	66	57	49	41	37				

The iteration number for training with different learning rate η ranged from 0.1 to 1.1 and momentum rate α ranged from 0.9 to 1.0 for the same BPNN as in Table 4. Notations are the same as in Table 1.

predicted value. If this is so, it seems that either the BPNN is not well designed or the training dataset is not well selected.

This feature may also be used as a guide to select η and α values. The η and α values should be in the stable area (A) and near its boundary where the iteration number is smaller. In order to reduce the iteration number to a value as small as possible, the optimum choice for η is 0.7 and for α is between 0.8 and 0.9 (must be less than 0.9), or 0.6 and 0.9 for a well designed BPNN.

4. WEIGHT PATTERN ANALYSIS

The above analysis shows that learning parameters (η and α) greatly affect the convergent speed of the learning procedure. Here we will examine their effect on the

BPNN structure. In order to examine this effect, we introduce a weight map of the BPNN structure which is produced to show the BPNN weight patterns, then analyzes this weight pattern.

4.1. Weight Map

The weight map of a BPNN structure shows the magnitudes of each weight connecting to the different layers in the BPNN. Figure 8 shows an example of a weight map of a BPNN trained with nine pairs of training dataset. For this three-layer BPNN, this map includes two plots: (1) the mapping of weights between the input layer and the hidden layer; and (2) the mapping between the hidden layer and the output layer. In each mapping, solid circles are shaded on a grey scale corresponding to a magnitude

TABLE 6

Iteration number	α										
	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	8991	8096	7201	6304	5406	4507	3606	2703	1799	893	NC
	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.04	1.03	
	8991	8092	7192	6294	5396	4496	3596	2697	1798	899	
1.0	891	796	710	624	536	448	359	267	177	67	NC
	1.07	1.07	1.07	1.06	1.06	1.06	1.05	1.05	1.04	1.53	
	899	809	719	630	540	450	360	270	180	90	
2.0	475	423	374	326	281	230	196	149	97	122	NC
	1.05	1.06	1.06	1.06	1.05	1.05	1.03	1.02	1.11	1.04	
	450	405	360	315	270	225	180	135	90	45	
3.0	342	305	271	240	211	181	151	133	101	34	NC
	1.06	1.06	1.06	1.06	1.06	1.06	1.09	1.15	1.50	2.16	
	300	270	240	210	180	150	120	90	60	30	
4.0	263	239	218	198	179	161	147	91	33	245	NC
	1.16	1.16	1.16	1.16	1.16	1.19	1.22	1.34	2.43	0.91	
	2.25	2.03	180	158	135	113	90	68	45	23	
5.0	213	196	183	175	164	135	112	73	100	NC	NC
	1.26	1.27	1.27	1.25	1.24	1.33	1.42	1.61	1.73		
	180	162	144	126	108	90	72	54	36		
6.0	184	171	167	167	146	120	126	58	68	NC	NC
	1.33	1.35	1.31	1.26	1.39	1.64	1.65	1.81	2.64		
	150	135	120	105	90	75	60	45	30		
7.0	164	156	164	156	129	104	80	108	57	NC	NC
	1.38	1.42	1.39	1.51	1.74	2.00	1.83	1.81	1.66		
	128	115	102	90	77	64	51	38	26		
8.0	147	144	155	135	125	40	57	57	NC	NC	NC
	1.52	1.65	1.60	2.01	1.42	2.37	2.91	2.91			
	112	101	90	67	56	45	34	34			
9.0	125	103	128	123	101	81	81	45	NC	NC	NC
	1.50	1.93	1.77	1.50	2.48	1.51	1.63	2.45			
	100	90	80	70	60	50	40	30			
10.0	113	127	116	114	110	71	45	327	NC	NC	NC
	1.46	1.31	2.20	1.52	2.05	2.55	1.67	1.40			
	90	81	72	63	54	45	36				
11.0	126	105	93	72	86	40	72	312	NC	NC	NC
	1.94	2.58	1.43	2.50	1.67	3.44	2.23	1.52			
	82	74	66	57	49	41	33	25			

The iteration number for training with different learning rate η ranged from 1.0 to 11.0 with an interval of 1.0 and momentum rate α ranged from 0.0 to 1.0 for the same BPNN as in Table 4. Notations are the same as in Table 1.

range indicated by the key, with the top row of circles in map (1) and far right row of circles in map (2) representing the nodal thresholds. This method can be applied to any BPNN application, enabling illumination of the “black-box” approach of BPNN analysis and examination of the BPNN function. For example, this weight map shows that the weight pattern between the input nodes and hidden nodes can be divided into two portions with different patterns at the tenth input nodes. We can expect that for the BPNNs with the same structures, if they have the same weight patterns, they should have the same performance.

Visual checking of the weight maps of BPNNs training

with different parameters shows that with the same training dataset, they have similar weight patterns. The weight map between the input nodes and hidden nodes can be divided into two portions at the tenth input node. Weights connected to nodes between the first to tenth nodes show a “high contrast” pattern, in which most of the weights have large absolute values. Weights connected to nodes between the eleventh and thirtieth nodes show a “low contrast” pattern in which most of the weights have small absolute values. Although a few weights show some changes as η and α alter, the whole pattern is similar. Therefore, these trained BPNNs with similar weight patterns should have similar performances.

FIGURE 5. The space of η and α for a BPNN with nine training datasets. Notations as in Figure 4.

4.2. Weight Pattern Analysis

In order to understand how the trained BPNN picks seismic arrivals, further study is required to view the mechanism by which the trained BPNN performs its classification. Before training, the weights and thresholds in Figure 8 are randomly initialized between -0.5 and $+0.5$, and after training their values range from -2.12 to $+2.02$. It appears that the pattern of weights connecting the input layer to the hidden layer is divided into two portions at the *tenth* sample, corresponding to the *P*-arrival onset in the input signal in which before the onset the signal energy is low and after the onset the signal energy is high. The first portion between the *first* and *tenth* nodes shows a “*high contrast*” weight pattern in which the absolute values of most weights are large: most weights connected to the *first* and *seventh* hidden nodes are negative large values, and most weights connected to the *fourth* hidden node are positive large values. The second portion between the *eleventh* and *thirtieth* nodes shows a “*low contrast*” weight pattern in which the absolute values of most weights are small. The weight pattern between the hidden nodes and the output nodes is related to the pattern between the input node and hidden node. For example, the weights connected to the *first* and *seventh* hidden nodes have large negative values when they connect to the *noise*

output node and large positive values when they connect to the *P* output node, and the weights connected to the *fourth* hidden node have a large positive value when they connect to the *noise* node and large negative values when they connect to the *P* node. It seems the *first*, *fourth* and *seventh* hidden nodes are more active in the performance because the weights assigned to them have larger values than others.

According to the sigmoidal function of nodes and the input signal which contains all positive values which are normalized between 1 and 0, a negative weight decreases the node output and a positive weight increases the node output. In the case of a background noise segment being fed into the BPNN, because all values are high and the weights are large in the first portion and play the principal role, the weights in the second portion will be neglected. The *first* and *seventh* hidden nodes give low output and the *fourth* hidden node gives high output. So the final output will be (high, low) values for the noise. However, in the case of a *P*-arrival segment being fed into the BPNN, because of the low values before the *P*-onset, the weights in the first portion can be neglected. The weights in the second portion play the principal role in the BPNN output which will be (low, high) values according to the training. As the sliding window moves along the seismogram, once the onset of an arrival passes into the input window, the values of the input samples

FIGURE 6. Ten pairs of P-arrival and background noise segments with absolute values of vertical component recordings used for training a BPNN. Noise segments are extracted prior to the P-arrivals in the same seismograms. Arrows on P-arrival segments indicate arrival onset times used to train the BPNN, all at the twenty-first sample. These segments are individually normalized before being input into the BPNN.

before the onset decrease, and the first portion will lose its effect on the output which attempts to reach the (low, high) state indicating a *P*-arrival. At the stage of the onset at the eleventh node, the output should reach the peak of the (low, high) state. However, as the onset moves into the position before the tenth nodes, the input values before the 10 nodes increases, so that the first portion will strengthen its effect on the output which attempts

to reach the (high, low) state indicating background noise. It is too complex to show the numerical results, however, this simple analysis gives a clear image of the details of BPNN performance under different conditions.

It is interesting to note that hidden nodes have different activities according to the values of weights connected to them. It seems that active hidden nodes (e.g. the first, fourth, and seventh nodes) can recognize the main

TABLE 7

Iteration number	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	10134	9124	8116	7108	6098	5089	4080	3069	2058	1045	NC
	2.53	2.53	2.52	2.52	2.51	2.50	2.49	2.47	2.43	2.31	
	10134	9120	8107	7093	6080	5067	4053	3040	2026	1013	
0.2	5093	4588	4084	3579	3074	2569	2063	1557	1050	541	NC
	2.51	2.50	2.50	2.49	2.48	2.46	2.44	2.40	2.33	2.12	
	5067	4560	4053	3547	3040	2533	2026	1520	1013	506	
0.3	3416	3079	2741	2404	2067	1730	1393	1054	714	371	NC
	2.49	2.48	2.47	2.46	2.44	2.42	2.38	2.34	2.25	1.99	
	3378	3040	2702	2364	2026	1689	1351	1013	675	338	
0.4	2580	2326	2072	1819	1565	1312	1058	804	548	292	NC
	2.47	2.45	2.44	2.42	2.40	2.37	2.33	2.27	2.15	1.85	
	2534	2280	2026	1773	1520	1267	1013	760	506	253	
0.5	2081	1876	1672	1469	1265	1062	859	655	450	240	NC
	2.44	2.43	2.41	2.39	2.36	2.32	2.27	2.19	2.04	1.76	
	2027	1824	1621	1418	1216	1013	810	608	405	202	
0.6	1751	1579	1407	1237	1067	897	726	556	385	203	NC
	2.41	2.39	2.37	2.35	2.31	2.27	2.21	2.12	1.96	1.71	
	1689	1520	1351	1274	1013	844	675	506	338	169	
0.7	1518	1368	1219	1072	925	779	632	486	338	173	NC
	2.37	2.35	2.34	2.31	2.27	2.22	2.15	2.04	1.88	1.74	
	1448	1302	1158	1013	868	723	579	434	289	145	
0.8	1346	1212	1080	950	820	691	563	434	300	153	NC
	2.32	2.31	2.29	2.26	2.22	2.17	2.08	1.97	1.84	1.67	
	1267	1140	1013	886	760	633	506	380	253	126	
0.9	1214	1092	973	856	739	624	509	393	272	144	NC
	2.28	2.27	2.24	2.21	2.17	2.10	2.02	1.91	1.78	1.53	
	1126	1013	901	788	676	563	450	337	225	112	
1.0	1111	998	889	782	675	570	466	359	253	136	NC
	2.22	2.21	2.19	2.16	2.12	2.05	1.96	1.86	1.72	1.52	
	1013	912	811	711	608	507	409	304	203	101	
1.1	1029	923	821	722	624	527	430	331	243	126	NC
	2.16	2.16	2.14	2.10	2.06	1.99	1.91	1.82	1.60	1.44	
	921	829	737	644	552	460	360	331	184	92	

The iteration number for training with different learning rate η ranged from 0.1 to 1.1 and momentum rate α ranged from 0.0 to 1.0. This BPNN is trained with 10 pairs of *P*-arrival and background noise segments of vertical component. Notations are the same as in Table 1.

features of an input segment and other hidden nodes may improve the BPNN performance by recognizing the subtle features of the input signal.

4.3. Weight Pattern Analysis for Another BPNN

For the BPNN used to pick seismic arrivals from vertical component recordings, a similar weight pattern (Figure 9) is obtained, although this BPNN with 40 input nodes was trained by 10 pairs of *P*-arrival and background noise segments.

Before training, the weights and thresholds were randomly initialized between -0.5 and $+0.5$. After training, the values of weights and thresholds range from -2.41 to 2.26 . This pattern also shows that the weights connecting the input layer to the hidden layer are divided

into two portions at the twentieth sample, corresponding to the *P*-arrival onset in the input signal where before the onset the signal energy is low and after the onset the signal energy is high. The first portion between the first and twentieth nodes also shows a ‘‘high contrast’’ weight pattern, but the second portion between the twenty-first and fortieth nodes shows a ‘‘low contrast’’ weight pattern. Comparing with the weight map in Figure 8, two BPNNs have similar weight patterns, although their structure and the training dataset are quite different. Their similar weight pattern means that they operate in the same way and can do the same work. The significant feature in the two weight maps is that each of them is divided into two portions at the onset of the training *P*-arrival segments. These two portions have different functions in doing the ‘‘picking work’’. For example,

TABLE 8

Iteration number	α										
	0.90	0.91	0.92	0.93	0.94	0.95	0.96	0.97	0.98	0.99	1.0
0.1	1045	944	843	742	641	541	443	368	215	NC	NC
	2.31	2.28	2.24	2.19	2.12	2.02	1.88	1.63	2.07		
	1013	918	810	709	608	507	405	304	203		
0.2	541	490	439	389	338	293	261	184	304	NC	NC
	2.12	2.08	1.94	1.94	1.86	1.76	1.72	2.51	1.27		
	506	455	354	354	304	253	202	125	101		
0.3	371	337	304	275	254	211	159	103	169	NC	NC
	1.99	1.94	1.89	1.81	1.70	1.82	1.97	2.70	3.54		
	338	304	270	237	203	169	135	101	68		
0.4	292	268	246	221	184	144	99	77	337	NC	NC
	1.85	1.80	1.73	1.69	1.79	2.06	3.40	3.18	5.09		
	253	228	202	177	152	127	101	76	51		
0.5	240	219	195	166	135	105	83	63	NC	NC	NC
	1.76	1.72	1.72	1.78	1.91	2.53	2.80	1.77			
	202	182	162	141	121	101	81	61			
0.6	203	181	154	128	104	83	63	86	506	NC	NC
	1.71	1.72	1.78	1.75	1.97	2.33	2.34	1.71	1.04		
	169	152	135	118	101	85	68	51	34		
0.7	173	150	129	107	90	70	89	424	NC	NC	NC
	1.74	1.71	1.55	1.56	1.86	2.17	1.59	2.11			
	145	131	126	102	87	73	58	44			
0.8	153	135	116	99	77	79	142	NC	NC	NC	NC
	1.67	1.49	1.33	1.70	2.24	1.58	1.50				
	126	113	101	98	86	73	60				
0.9	144	127	108	93	74	173	NC	NC	NC	NC	NC
	1.53	1.41	1083	2.07	2.41	1.67					
	112	101	90	78	67	56					
1.0	136	119	103	90	68	52	328	NC	NC	NC	NC
	1.52	1.47	1.67	1.78	2.03	2.57	1.31				
	101	91	81	71	61	50	40				
1.1	126	111	95	75	53	78	490	NC	NC	NC	NC
	1.44	1.31	1.20	1.19	1.43	1.26	1.68				
	92	83	74	64	55	46	37				

The iteration number for training with different learning rate η ranged from 0.1 to 1.0 and momentum rate α ranged from 0.9 to 1.0 for the same BPNN as in Table 7. Notations are the same as in Table 1.

the ‘‘high contrast’’ portion has a strong effect on picking P -arrival and the ‘‘low contrast’’ portion has a strong effect on picking background noise. The hidden nodes in this BPNN also have different activities. The *first*, *fifth*, and *sixth* hidden nodes are active in the performance because the weights connected to them have larger values than others. Comparing two BPNNs, the sequence number of the active hidden nodes are different. The active hidden nodes and their attributes depend on the initial values of weights which are randomly generated.

5. SUMMARY

In this paper, we have examined the effect of training parameter (η and α) on the BPNN learning procedure and its performance. The results show that the training para-

meters mainly affect the convergence of learning procedure and do not affect the structure of the trained BPNNs too greatly, therefore, these BPNNs should have similar performance. As a result, we do not need to put too much effort into selecting their optimum values in each case. This will allow us to devote our attention only to the performance of the trained BPNN and can make a complex problem simple. It is important for the case where a large BPNN and a large training dataset are involved. In order to obtain a quick learning procedure, we need to select the learning parameter to be as large as possible. However the learning procedure might be unstable and the weights of BPNN might be trapped in a local minimum by using too large a value of η (Rumelhart et al., 1986). The suggested value for η is 0.7, and α between 0.8 and 0.9 (less than 0.9) or $\eta = 0.6$ and $\alpha = 0.9$. This is

TABLE 9

	Iteration number	α										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
η	0.1	10134	9124	8116	7108	6098	5089	4080	3069	2058	1045	NC
		2.53	2.53	2.52	2.52	2.51	2.50	2.49	2.47	2.43	2.31	
		10134	9120	8107	7093	6080	5067	4053	3040	2026	1013	
	1.0	1111	998	889	782	675	570	466	359	253	136	NC
		2.22	2.21	2.19	2.16	2.12	2.05	1.96	1.86	1.72	1.52	
		1013	912	811	711	608	507	409	304	203	101	
	2.0	655	584	516	451	391	338	293	250	172	52	NC
		1.68	1.69	1.70	1.70	1.68	1.61	1.49	1.32	1.31	2.61	
		507	456	406	355	304	254	203	152	102	51	
	3.0	465	427	391	356	321	284	244	178	111	92	NC
		1.59	1.53	1.48	1.43	1.36	1.32	1.28	1.69	2.77	1.68	
		338	304	270	237	203	169	135	101	68	34	
	4.0	414	387	355	317	280	271	226	163	47	45	NC
		1.45	1.39	1.34	1.30	1.30	1.56	2.41	2.54	2.69	1.53	
		253	228	202	177	152	126	101	76	51	25	
	5.0	392	368	332	290	249	245	233	153	73	56	NC
		1.31	1.27	1.27	1.28	1.37	2.14	2.12	2.18	2.20	2.73	
		202	182	162	141	121	101	81	61	40	20	
	6.0	371	343	304	270	233	194	172	105	122	710	NC
		1.23	1.21	1.23	1.24	1.26	1.51	2.10	1.60	1.35	1.85	
		169	152	135	118	101	85	68	51	34	17	
	7.0	351	336	305	256	195	155	120	112	89	NC	NC
		1.17	1.17	1.18	1.19	1.27	1.32	2.87	2.14	1.92		
		145	131	116	102	87	73	58	44	29		
	8.0	352	327	274	226	211	102	147	49	464	NC	NC
		1.14	1.13	1.16	1.16	1.73	2.42	1.20	2.83	0.82		
		127	114	102	89	76	64	51	38	25		
	9.0	329	301	255	221	210	144	42	102	198	NC	NC
		1.11	1.11	1.13	1.14	1.11	1.66	3.07	2.03	2.55		
		113	102	90	79	68	57	45	34	23		
	10.0	116	274	126	66	176	177	98	57	NC	NC	NC
		2.24	1.13	1.68	2.53	1.33	1.90	2.00	1.98			
		101	91	81	71	61	51	40	30			
	11.0	86	74	74	230	227	90	192	142	64	NC	NC
		2.58	2.58	2.82	1.15	1.21	1.71	2.03	1.64	2.17		
		92	83	74	64	55	46	37	28	18		

The iteration number for training with different learning rate η ranged from 1 .0 to 11 .0 with an interval of 1 .0 and momentum rate α ranged from 0.0 to 1 .0 for the same BPNN as in Table 7. Notations are the same as in Table 1.

slightly different from other authors' suggestions that the suggested value is $\eta = 0.7$ and $\alpha = 0.9$ (McClelland and Rumelhart, 1988; Pao, 1988; Demuth and Beale, 1993).

In this paper, we use the "weight map" as a tool to investigate the interior and performance of BPNNs. For the BPNNs which are used to pick arrivals, although their structure and training dataset are different, they have similar weight patterns, which are divided into two portions corresponding to the onset of training P -arrivals and having different functions in the picking work. Changing learning parameters does not change the weight pattern of a trained BPNN. Although it is not

possible to fully understand the logic underlying the BPNN solution by visually inspecting these weight patterns, and the weight combinations in this map are not as easily distinguished as the parameter estimates, the weight map may still lend some perspective as to which aspects of the seismic waveform which are more relevant to its solution than others, and thus be of benefit to further processing schemes or studies.

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FIGURE 7. The space of η and α for a BPNN with 10 training datasets. Notations as in Figure 4.

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FIGURE 8. Weight map for a trained BPNN: (1) the mapping of weights between the input layer and the hidden layer; (2) the mapping between the hidden layer and the output layer. Shaded circles represent the weights and the contrast in each circle indicates the value of a weight. The top row of circles in (1) and the right row of circles in (2) represent the node thresholds. This BPNN is trained with nine pairs of /J-arrival and background noise segments.

FIGURE 9. Weight map for a trained BPNN with 40 input nodes with notations as in Figure 8. This BPNN is trained with 10 pairs of P-arrival and background noise segments of vertical component recordings.