ANALYSIS OF RULE-BASES IN HYBRID NEURAL NETWORKS FOR GEO-REFERENCING EARTH OBSERVATION IMAGERY

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ABSTRACT

The paper evaluates the performance of using both a neural network and a rule-base in developing a fully integrated geo-referencing routine. Aspects of hybrid neural network performance are reviewed, focussing on improved training times, improved geo-referencing precisions and overcoming convergence problems associated with stand-alone neural network processing models.

1. INTRODUCTION

A hybrid neural network is a network whose architecture consists of two or more separate processing structures. Hybrid neural networks consist of a neural network augmented with another processing structure (rule-base) which can be included within the system by running parallel to it, or in series with it. In addition to providing a more precise geo-referencing system, the hybrid architecture is highly parallel and ideally suited to parallel processing producing a highly effective and computationally efficient system.

1.1 Hybrid Neural Networks

The hybrid network technique adopted for this study is similar to that presented by *Bengio et al.* (1992). Hidden Markov Models have a proven success in the modelling of the temporal structure of speech, whereas the artificial neural network (and in particular the multi-layer perceptron) has a proven success in continuous function approximation. The system used by *Bengio et al. (ibid)* combines the advantages of the two independent techniques. A similar approach was used by *Burniston* (1994), consisting of a simple *rule-based* model to approximate the speech pattern. The multi-layer perceptron neural network was then used to identify and model the peculiarities and fine detail of the speech. This form of network construction removes the requirement for the network to learn the complete function. This allows the network to focus its ability on recognising the patterns which exist in the difference between the rule-based estimate and the true geographic coordinates of the training patterns. This is achieved in a learning process similar to that used in conventional neural network training algorithms (e.g, back-error propagation). The integration method adopted was through the use of a *rule-base* to assist the removal of the majority of the systematic errors within the geo-referencing process (Dumville, 1995).

1.2 The Rule Base

The Platform Trajectory Model combines satellite ephemeral information with ground control to create the geo-referencing model. Unlike popular geometric rectification algorithms the Platform Trajectory Model only requires a single ground control point (GCP). This point is used to anchor the image to the cartesian reference system to be used within the geo-referencing routine. The satellite ephemeris acts as the control for the orientation of the image and the timing information is used for the scaling of the image pixels. The ephemeral and timing information is made available within the header files of the satellite image.

2. THE TEST IMAGE

A Synthetic Aperture Radar (SAR) image of the North of Scotland from the European Remote Sensing Satellite, ERS-1, was used in this study. The image contains 8000 by 8000 pixels corresponding to a ground area of 100 km by 100 km. This area was selected as a test site due to the availability of the appropriate satellite imagery and the mapping of the region.

A relative GPS ground survey was carried to obtain ground control for geo-referencing the image. A set of eleven control points were observed after by identification of suitable features on the image (Putter, 1993).

3. NEURAL NETWORKS

The task facing the neural network is to perform the multiple transformation stages of the geometric rectification process. Firstly, a pixel's image coordinates need to be geo-referenced into a 3-dimensional geodetic coordinate system, from where they can be converted to local geodetic coordinates. Subsequently, the local ellipsoidal coordinates require projecting as grid coordinates. This form of direct rectification produces projection coordinates for each pixel in the image (Figure 1). This can often result in pixels being overlaid or missed in a rectified image and therefore requires a post-processing filter to be employed on the rectified image to solve these problems.

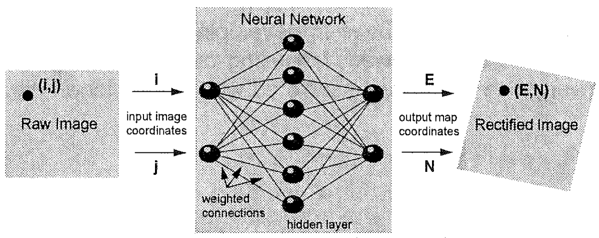

Figure 1 Geo-referencing Using Neural Networks

4. HYBRID NETWORKS

A hybrid network is required to learn a different mapping function to that learnt by the stand-alone neural network. From the exterior of a hybrid network there is no evident change of architecture from that of a stand alone neural network. The input and output are the same. However, internally the architecture of the two differ significantly. The neural network module of the hybrid network is used to provide corrections to the estimated geo-referenced coordinates produced from the rule-base that operates in parallel to the neural network module. The neural network performs a different task to that previously mentioned in §2, a different geo-referencing function is required, and therefore a new network topology is required.

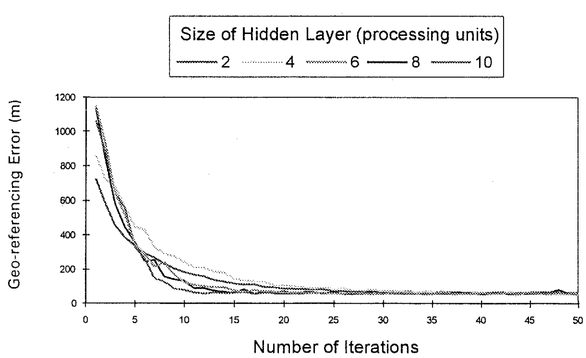

Figure 2 Hidden Layer Size Test Results

Tests were performed to decide upon the new topology and values for the new network parameters within the neural network module of the hybrid model. This included tests for the number of hidden layer units, the learning term and the momentum rate.

Figure 2 shows the effect of altering the number of the hidden layer processing units. From the figure it is evident that all five curves are highly correlated, possessing very similar characteristics. What is apparent from the figure is that the final result is approximately the same for all curves *independent* of the number of hidden layer units. This simple test demonstrates that a hybrid network, used for image geo-referencing, requires fewer processing units than a stand-alone network. This property of hybrid networks was also concluded by *Burniston* (1994), for the use of hybrid networks in speech approximation.

For geo-referencing tasks, the reduced number of hidden layer units can be attributed to the fact that the major rectification manoeuvres are performed by the rule-base and not the neural network module as was the case in §2.

Other network design tests were performed using the ERS-1 SAR image. The topology which provided the best results, in the design phase, was subsequently kept constant for all of the operational tests. The empirical tests for determining values of the learning term and the momentum rate yielded figures of 0.1 and 0.5 respectively. The design tests resulted in the network topology as illustrated in Figure 3, with the neual network module assembled from a single hidden layer, containing 6 hidden layer processing units.

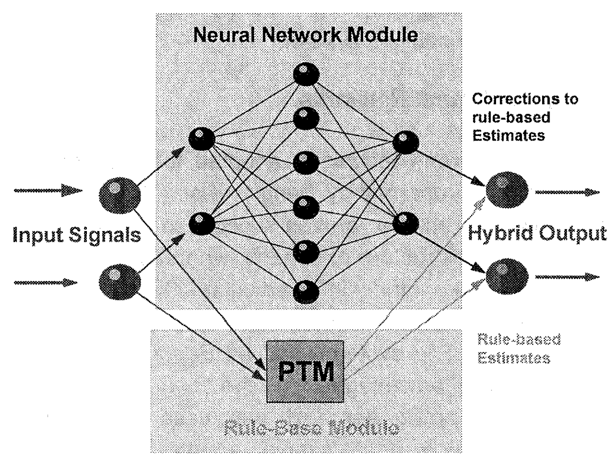

Figure 3 Hybrid Network Topology

The final hybrid network had the same neural topology as used for the stand-alone neural network but possessed different values for the learning term and the momentum rate.

4.1 Hybrid Network Geo-referencing

This section presents the results using the hybrid neural network to determine its learning ability, its performance ability and its merits compared to performing similar tasks using a stand-alone neural network model.

Table 1 presents results demonstrating the effect of altering the number of control points used in the hybrid network's training phase, on the geo-referencing precision.

GCPs	Control Points (m)			Check Points (m)		
Used	Σ dE	Σ dN	RMSE	Σ dE	Σ dN	RMSE
1	0	0	0	20491	23805	2861
2	-1	0	3	-965	1338	247
3	18	-14	39	-276	-216	104
4	37	46	61	-50	50	71
5	24	42	61	132	67	73
6	55	150	67	-94	65	69
7	-121	-68	64	-63	8	73
8	-180	-129	65	-140	-13	77
9	81	2	59	-152	11	77
10	70	-232	61	-31	-10	32
11	212	-71	58			

Table 1 Hybrid Network Geo-referencing Results

Table 1 indicates that using only one GCP, for the geo-referencing process, there is insufficient information present in the single training pattern for the network to establish a link between the rule-base estimate and the true location of the training pattern. The introduction of a second GCP into the training process produces a significant improvement in the network's performance. This extra GCP enables the link to be identified and the hybrid network begins to function as an integrated system. Through the addition of more control information, the geo-referencing precision improves but reaches a threshold when using between 4 and 9 control points (RMSE ranges from 59 m to 67 m for the Control Points and ranges from 69 m to 77 m for the Check Points). The process does not improve or severely degrade when using 4, 5, 6, 7, 8 or 9, demonstrating that the geo-referencing function can be using fewer control points than would be required by a stand alone neural network.

The RMSE fit to the control points in the final two tests (i.e., using 10 and 11 GCPs) are in the same threshold region (~60 m) as in the previous tests. However, as little check point information is available for analysis these results should not be considered for performance evaluation, though they can be used in assessing the hybrid network's learning ability.

5. SUMMARY OF RESULTS

There follows a summary of the results achieved using the neural network approach (Figure 4), the rule-base approach (Figure 5) and the integrated hybrid network approach (Figure 6). The rule-base used for the tests in the hybrid approach was that of the platform trajectory model. Figure 4 presents the direction and magnitude of the geo-referencing RMSE residual vectors within the neural network process from a test that used 5 GCPs for training 6 check points for recall. The direction of the residual vectors associated with the GCPs appear unrelated to one another, with no distinguishable pattern. What is apparent, however, is the trend which exists in the residual vectors associated with the 6 check points.

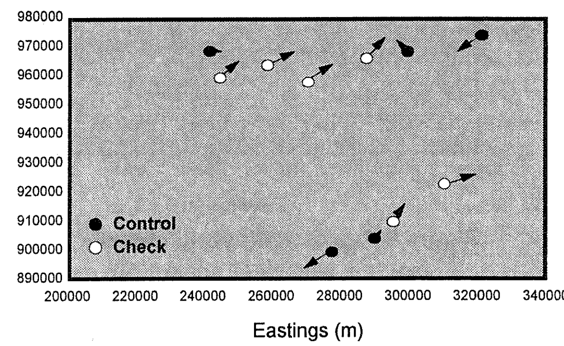

Figure 4 Residuals (neural network)
residual vectors @ scale 1:50

Figure 5 shows an example of the geo-referencing residuals present in the Platform Trajectory Model (PTM) approach to geo-referencing Earth Observation imagery. The image was geo-referenced using a single GCP. There is a clear trend in the directions of the residuals, in the Easterly direction. This could be attributed to; pixel dimensioning, reduction to the ellipsoid, Earth rotation or atmospheric effects, all of which effect the image in an along-track (Easterly) direction. Another distinctive feature within the figure is the size of the residuals in the bottom-right of the image as compared to those towards the top of the image. The larger residuals can be attributed to the propagation effects of the Platform Trajectory Model.

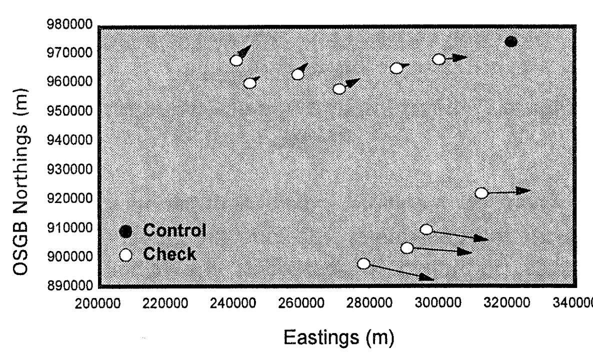

Figure 5 Residuals (rule base)
residual vectors @ scale 1:50

Figure 6 illustrates the performance of the hybrid network in the geo-referencing role. The plot contains the results of using 5 GCPs and 6 check points. It can be seen from Figure 6 that the resident systematic trends which were present in Figure 4 have now been removed. There are no visible patterns within the directions of the residual vectors. The RMSE for the control points is 61 metres and the RMSE for the check points is 73 metres. These values can be compared to those from Figure 4 of 156 m and 160 m for the control and check points respectively.

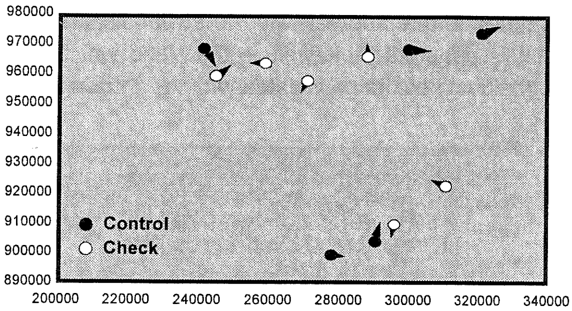

Figure 6 Residuals (hybrid network)
residual vectors @ scale 1:50

5.1 Learning versus Recall for Hybrid Networks

Figure 7 presents three curves illustrating the nature of how the geo-referencing error decreases with the amount of training. The first curve shows the progress in network learning using 4 control points for the neural network training. This curve starts with the largest error, however after 20 000 iterations the error has reduced to a similar value as the curve displaying the check point residual **RMSE** using 7 check points.

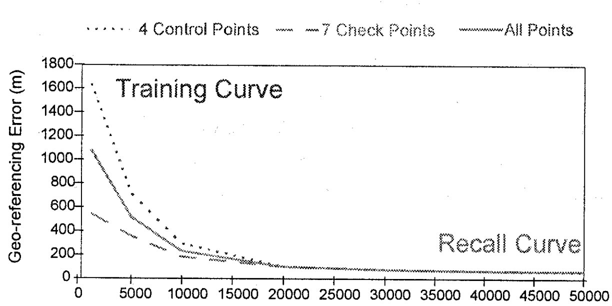

Figure 7 Learning and Recall Curves for Hybrid Network

The check point curve is indicative of the network's ability to recall the geo-referencing function should the training process be halted. It represents the hybrid network's ability to approximate the geo-referencing function up to 50 000 training iterations. The graph closely resembles that of the training curve. Initially, the recall curve produces less error than the training curve that uses the control points. This feature is, however, only present over a limited domain (up to 20 000 iterations) and once the curves begin to flatten off, they both stabilise to the same geo-referencing error of ~60 m.

The rule base estimate was produced using **GCP** 1 (as highlighted in Figure 5). The set of eleven GCPs were used in the training process for both network architectures, hence no check point data was available. The results are presented in Table 2. The table compares the two architectures' ability to learn the function and not to recall the function.

GCP	Neural Network (m)			Hybrid Network (m)		
Nor	dE	dN	dL	dE	dN	dL
1	-140	-203	247	87	15	88
2	-74	-102	126	-20	-39	44
3	-208	-201	289	62	50	80
4	186	68	198	18	-72	74
5	-117	-25	120	-70	6	70
6	56	46	72	39	23	45
7	60	24	65	7	-47	47
8	83	12	84	46	-3	46
9	7	-36	37	61	12	62
10	-34	-57	67	-8	-18	19
11	50	56	75	-8	2	9
	mean dE	mean dN	mean dL	mean dE	mean dN	mean dL
	-12	**-38**	**125**	**19**	**-6**	**53**

Table 2 Comparing the Stand-Alone Neural Network with the Hybrid Neural Network in Learning

Despite the **mean** values for **dE** being of similar magnitudes for the two types of network, inspection within the table, reveals a much reduced variance on the individual dE values when using the hybrid network as opposed to the stand-alone network. Furthermore, the **mean** value for **dN** is far less for the hybrid network than it is for the stand-alone counterpart (-6 m compared to -38 m for the stand-alone network). This feature also applies to the mean residual, **dL**, which amounts to 53 m for the hybrid network and 125 m for the stand-alone neural network.

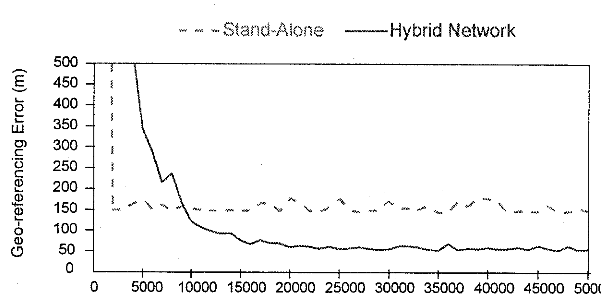

Figure 8 Learning Curves for both Stand-Alone and Hybrid Neural Network Models

The enhanced performance of the hybrid network can also be shown by comparing its progress (in training) with that of the stand-alone neural network. Figure 8 presents the learning curves of the two networks in their training phase. The training set, once again, contained the complete set of eleven control points. The curves therefore reflect the manner in which the two networks learn the function.

The two curves in Figure 8 are clearly distinguishable, each possessing different features peculiar to their method of learning. The stand-alone network, after 1000 iterations, has a geo-referencing error of 2000 m. For clarity, this is off the figure in order to show the lesser undulations within the learning curve. From the geo-referencing error of 2000 m the stand-alone network is quick to learn the hidden patterns within the geo-referencing function and swiftly progresses to errors of around 150 - 200 m level after 2000 iterations. The slight perturbations around the 150 m level are a feature of the noise added to the network to avoid the occurrence of the network falling into a *false well.*

The hybrid network curve within the figure shows a much smoother learning path in contrast to the stand-alone network. This curve has a geo-referencing error of 1150 m at 1000 iterations, again for clarity, this is off the graph. This initial value is almost half that of the other network. However, using the hybrid approach the network fails to learn the function at such a rapid rate. The learning curve is gradual and only approaches a stable value of about 50 m at 25 000 iterations (taking over 10 times as long as the stand-alone model to stabilse). Though the two graphs cross at approximately 8000 iterations the remaining 17 000 iterations have the effect of gradually reducing the geo-referencing error in the hybrid network which ultimately results in a final geo-referencing error 2.5 times smaller than that of the stand-alone model.

5.2 Benefits of Hybrid Networks over stand-alone Networks

The final test was to try to achieve similar geo-referencing precisions to the hybrid network using a stand-alone neural network model. The only variable to be altered in the tests was the number of hidden processing units within the single hidden layer. The learning term and the momentum rate were kept at the constant values of 0.15 and 0.6 for all stand-alone neural network topologies and 0.1 and 0.5 for all hybrid network topologies. This was necessary to keep the number of tests to a realistic amount. Tests were performed using between 2 and 44 hidden layer units. Some typical results from the tests have been selected and presented in Figure 9. The tests were performed to the exhaustive limit of 100000 iterations.

Some of the statistics from the tests are presented in Table 2. From Figure 9 and Table 2 the noise within the learning process can be quantified by examining the standard deviation (**std dev**) of the scatter from the stable region of the curve. Despite the network achieving precisions of the order of 70 m (for 20 hidden units) the standard deviation of 12.3 m indicates quite large deviations from a smooth learning curve. This quantity of noise is also present on the remaining two curves (those for 6 and 10 hidden units). The curves suggest the stand-alone neural network is capable of producing comparable results to the hybrid network (i.e., 70 m level of precision). However to achieve this, the network requires additional processing units within the hidden layer (e.g., from Table 3 the number of units required is 20) and hence additional computational time to learn the function, even then there is a large uncertainty, i.e, 12.3 m, associated with the geo-referencing precision.

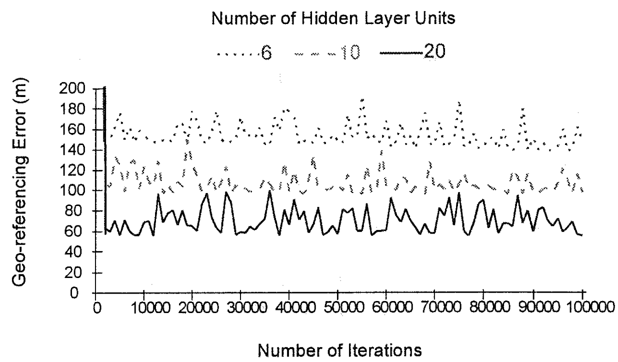

Figure 9 Geo-referencing Error against number of iterations for different Stand-Alone Network Topologies

No of Hidden Units	Stand-Alone Network mean (m)	std dev (m)
6	153	12.1
10	107	11.4
20	70	12.3

Table 3 Statistics of the Learning Curves in Figure 9

Similar tests were performed for the hybrid network to see if prolonged training would lead to improved geo-referencing. The results are presented in Figure 10. The most noticeable feature is that all three curves produce similar geo-referencing errors.

Figure 10 demonstrates that when using a hybrid network the final geo-referencing error is less dependant upon the topology of the neural network. However, as can be seen within Table 4, the final result may be similar for all hybrid network configurations (i.e., 6, 10 or 20 hidden units) but the noise in the learning curve gets progressively worse the more redundant hidden layer processing units the network possesses.

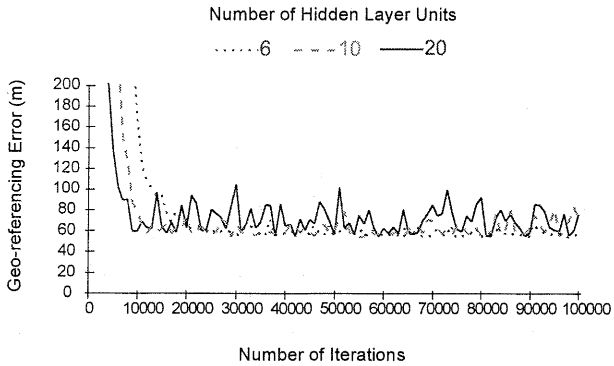

Figure 10 Geo-referencing Error against number of iterations for different Hybrid Network Topologies

No of Hidden Units	Hybrid Network mean (m)	std dev (m)
6	59	3.7
10	62	6.9
20	71	12.1

Table 4 Statistics of the Learning Curves in Figure 10

The results in Table 4 using 20, closely resemble the results for the same test using the stand-alone neural network in Table 3, however, the stand-alone neural network does not achieve the levels of precision achieved by the hybrid network (i.e., 59 m using 6 units) irrespective of the number of iterations and number of hidden layer processing units used in training.

Unfortunately, the hardware used in this work restricted the exploitation of the parallel structure of the neural network and hybrid network algorithms. The total time taken to geo-reference the complete ERS-1 SAR image (8000 x 8000 pixels) was approximately 3 hr 30 mins. The time taken to geo-reference the complete image, and the geo-referencing precision of the hybrid network, are compared to those of the Platform Trajectory Model rule base and to those of the stand-alone neural network in the following section.

6. SUMMARY

The paper has analysed the functionality of a Platform Trajectory Model approach (§2) a neural network approach (§3) and a hybrid network approach (§4) for image geo-referencing. The results of this latter approach have shown that a hybrid network can achieve better precisions, while at the same time, remove a significant proportion of the unmodelled, undetected systematic errors which exist when geo-referencing earth observation imagery using neural networks.

Figure 11 illustrates the relationships when comparing the geo-referencing precisions and times taken to geo-reference the complete image using the three approaches; the Platform Trajectory Model, the stand-alone neural network and the hybrid network. It must be borne in mind that it takes more time to train the network than it does to use it.

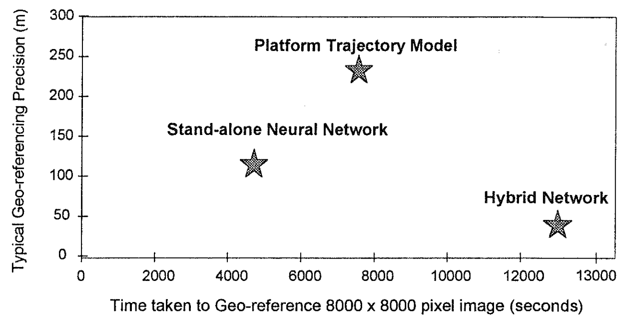

Figure 11 Comparison of Geo-referencing Techniques

The tests presented in this paper were not designed to provide an optimised geo-referencing tool for the geometric rectification of earth observation imagery. The tests were performed to analyse the behaviour of an integrated rule base / neural network processing model. Similar network architectures, to those presented, may be used in any area of image processing where there is the requirement for improving the function mapping ability of a neural network.

7. ACKNOWLEDGEMENTS

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