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Neural Networks for Transformation to Spectral Spaces

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ABSTRACT

This work is concerned with mapping between the CMYK colour space and spectral space using Artificial Neural Networks (ANNs). The dimensionality of the spectral space is high (typically 31) leading to a large number of weights (or free parameters) in the network. This paper explores the hypothesis that a computational advantage can be obtained, in these cases, by treating the reflectance at each wavelength as being independent of the reflectance at any other wavelength; the implication of this hypothesis is that instead of using a single large ANN, it is possible to use, for example, 31 separate networks, each of which maps to one dimension of the 31-d spectral space. The results showed that as the number of training samples is reduced the advantage of the population of single-wavelength networks over the standard neural network approach increased.

Keywords: colour space conversion, Artificial Neural Networks (ANNs), CMYK, printing

1. INTRODUCTION

Artificial neural networks (ANNs) are widely used in colour prediction and mapping between different colour spaces[1-3]. For example, mapping between camera RGB values and CIE XYZ values is an example of a mapping between two 3-d spaces. For a standard neural network, the performance difference with additional hidden layers can be very small; therefore, one hidden layer is sufficient for the large majority of problems. In order to predict spectral reflectance factors (at 31 wavelengths) from, for example, CMYK values then the network would have 4 input units and 31 output units with a single hidden layer of *N* units; we can therefore write the standard neural network architecture of 4-*N*-31 (Figure 1).

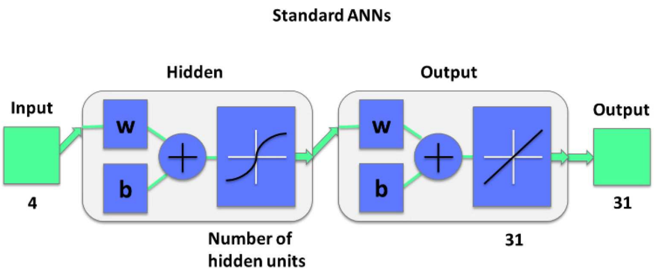

Figure **1**: Architecture of a standard neural network with a structure of *4-N-31*.

The network shown in Figure 1 has many weights (the free parameters that are optimised during network training). In fact, the network in Figure 1 has (5×N + (N+1) ×31) = 36N + 31 (when N = 10, for example, this is equal to 391). A number of researchers argue that the number of weights must be less than the number of samples that are used to train the network4 in order that the network is adequately constrained. In this work we introduce a new method for applying networks to colour transformations whereby instead of using a single large network to predict the reflectance at all wavelengths simultaneously, 31 smaller networks are used to predict reflectance at a single wavelength (see Figure 2). Even if the network in Figure 2 had 10 hidden the number of weights in each network would be 61. Although the total number of weights in the 31 networks is much larger than in the single large neural network, the ratio of training samples to weights is much larger for each of the smaller networks than it is for the single larger network.

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In this work, the single large network architecture will be referred to as a Standard ANN and the population of 31 networks will be called the Wave ANNs. The hypothesis that the Wave ANNs are more efficient than the Standard ANN is tested in this paper using a set of printed sample

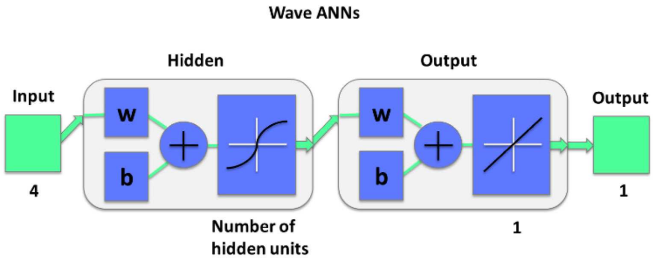

Figure **2**: Architecture of a single-wavelength neural network with a structure of *4-N-1*.

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2. EXPERIMENTAL

A set of 524 printed samples were prepared using a MAN ROLAND sheet-fed halftone offset 4-colour press. Double A Gloss paper coated with 80±5% gloss and 90% brightness, with a weight of 160g/m^2 was used as the substrate. The colour of the substrates was L^*= 94±3, a^*=2±2, and b^*= -7±2. Each sample was specified by an amount of cyan (C), magenta (M), yellow (Y) and black (K), each between 0% and 100%, ink. The spectral reflectance factors of each of the printed samples were measured at intervals of 10nm between 400 and 700nm. The 524 samples were randomly split into a training set of 300 samples and a test set of 224 samples. The training set was used to optimise the weights in various neural networks. During training 80% of the training set was used to optimise the weights and 20% was used as validation samples. Training continued until the error for the validation samples increased six times consecutively (this is to avoid over-training and to ensure good generalisation).

The standard neural network had four inputs (CMYK) and 31 outputs (the spectral reflectance factors). Networks were trained with different numbers of units in the hidden layer. Populations of wave ANNs were also trained so that each network in the population predicted reflectance at one of the wavelengths. Trained ANNs were tested by their ability to predict spectral reflectance for the training set (300 samples) and the test set (the remaining 224 samples) and errors were calculated in terms of CIELAB colour differences (illuminant D65 and 1964 CIE observer). Networks with fewer training samples were also tested by sub-sampling the full training set. All networks were implemented using MATLAB's Neural Network toolbox. Each network was trained six times, starting each time with a different random set of weights, and the average ΔE of these six trials is reported in the study.

Table **1**:Comparison on numbers of free parameters (weights) in the standard neural networks (4-*N*-31) and the single-wavelength neural networks (4-*N*-1) with different numbers of hidden units.

	Free Parameters	
Hidden Units	Standard ANNs	Wave ANNs
1	67	7
2	103	13
3	139	19
4	175	25
5	211	31
7	283	43
9	355	55
10	391	61
11	427	67
15	571	91
20	751	121
25	931	151

30	1111	181

Table 1 lists a number of hidden units with their corresponding free parameters in both standard neural network and in single wavelength neural network. Although we have used different sets of hidden units for Standard ANNs and Wave ANNs, it clearly shows in Figure 3 that the ratios of the number of training data to the number of free parameters are inevitably greater for Wave ANNs than for Standard ANNs. So the training data will be more likely to be adequate in the single-wavelength network with less probability of the network being over-trained than in the standard network.

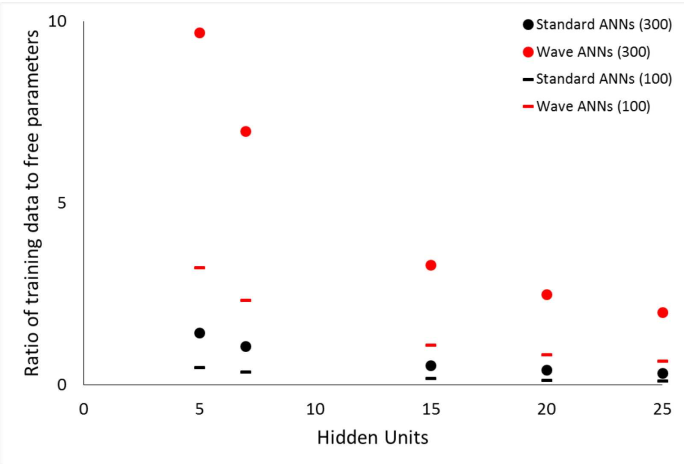

Figure **3**: Comparisons of ratios of training data to free parameters between standard ANNs and single-wavelength ANNs with 300 and 100 training data.

3. RESULTS

Mean values of ΔE were calculated for the Standard ANN and the Wave ANN both trained with the same 300 training data. The ΔE was plotted against the number of hidden units in Figure 4. The optimal umber of hidden units was determined as that which gives the lowest error for the test set and this was mean ΔE =1.62 (25 hidden units) for the standard ANN and ΔE =1.55 (11 hidden units) the Wave ANNs.

As the number of training data reduced from 300, the number of weights in the standard network is large and over-training is more likely to occur. Figure 5 summarises performance (the number of hidden units was determined in the same way as for Figure 4 but was different in each case) on the training as test set as the number of training samples is reduced.

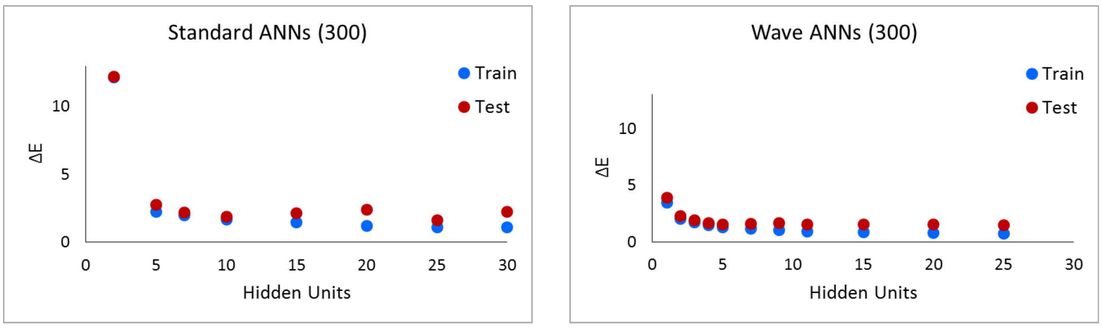

Figure **4**: A comparison of ΔE between standard neural network and single-wavelength neural network.

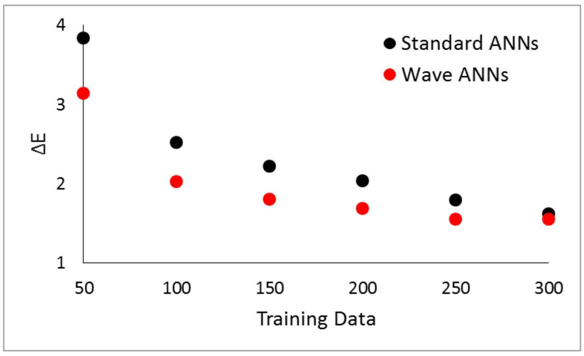

Figure **5**: A comparison of ΔE between Standard ANNs and Wave ANNs with different number of training data

4. DISCUSSION

When mapping between the CMYK and the spectral colour space, the number of weights in the neural network is inevitably large due to the high dimensionality of the spectral space (typically 31). A standard neural network requires a large number of training data in order to train the network sufficiently. When the number of training data is less or equal to the number of weights in the network, over-training is possible to occur. Alternatively, instead of using a single large ANN, it is possible to use, for example, 31 separate networks, each of which maps to one dimension of the 31-d spectral space. The number of weights in the network will be greatly reduced and the ratio of number of training samples to the number of weights in the network will larger. In that way, we can obtain a more reliable network with a better representation. The results proved that single-wavelength neural network outperformed standard neural network even with reduced numbers of training samples. However, further work is required to find out whether the difference is significant. Other numerical methods should also be further explored as a comparison to the Wave ANNs in order to find out the optimal solution for mapping between these colour spaces.

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