is not significantly affected by the relative position of the two FSS layers.

The above position of the receiving antenna indicates that the measurements were made in the far field where the experimental results are the combination of aperture and FSS transmission. To investigate the effect of the aperture, the receiving antenna was placed closer to the FSS window at distances of 67 and 16 mm. The results, shown in Fig. 3, are not significantly altered by changing the receiver's position. Fig. 4 demonstrates the high optical transparency of the double layer ITO FSS window.

Fig. 4 *Double layer ITO FSS window on top of Radiocommunications Agency logo*

Conclusion: An optically transparent FSS structure based on highly conductive ITO is presented here for the first time. Comparative studies with a copper FSS structure showed that the performance of the ITO double layer FSS is very satisfactory and close to our 30 dB target. The current aim is to increase further the conductivity of the ITO. In general it is expected that any increase in the conductivity of the ITO would result in a concomitant decrease in its optical transparency. There are indications, based on in-house laboratory experiments and published literature, that the conductivity can be improved further without severely affecting the high optical transparency [2 – 4].

Acknowledgments: This work was performed under Radiocommunications Agency contract AY3365.

11 September 2001
Electronics Letters Online No: 20010979
DOI: 10.1049/el:20010979

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Classification of vintages of wine by artificial nose using time delay neural networks

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A pattern recognition system for an artificial nose is presented. It is composed of artificial neural networks with time delay taps on their inputs. For the classification of vintages of wine, it achieves better results (mean classification error of 4.32%) than those obtained by networks without delay taps (42.79%).

Introduction: The two main components of an artificial nose are the sensor and the pattern recognition systems. Each odorant substance presented to the sensor system generates a pattern of resistance values that characterises the odour. This pattern is often first preprocessed and then given to the pattern recognition system, which in its turn classifies the odorant stimulus [1]. Sensor systems have often been built with polypyrrole-based gas sensors. Some advantages of using such a kind of sensor are [2]: (i) rapid adsorption kinetics at the environment temperature; (ii) low power consumption, as no heating element is required; (iii) resistance to poisoning; and (iv) the possibility of building sensors tailored to particular classes of chemical compounds. Artificial neural networks (ANNs) have been widely applied as pattern recognition systems in artificial noses [1]. Implementing the pattern recognition system with ANNs has advantages such as [3]: (i) the ability to handle nonlinear signals from the sensor array; (ii) adaptability; (iii) fault and noise tolerance; and (iv) inherent parallelism, resulting in high speed operation. The type of neural network most commonly used for odour classification in artificial noses has been the multi-layer perceptron (MLP), together with the backpropagation learning algorithm [4]. Such networks are usually constrained to deal only with static patterns. In contrast, in this Letter we propose an odour recognition system for artificial noses, which takes into account the temporal properties of the sensor signals. This is accomplished by using ANNs with time delay taps on their inputs.

Problem and data description: The aim is to classify odours from three different vintages (years 1995, 1996 and 1997) of the same wine (Almadém, Brazil). A prototype of an artificial nose was used to acquire the data. This prototype is composed of six distinct polypyrrole-based gas sensors, built by electrochemical deposition of polypyrrole using different types of dopants. Three disjointed data acquisitions were performed for every vintage of wine, by recording the resistance value of each sensor at every half second during a five minute interval. Therefore, this experiment yielded three data sets with equal numbers of patterns: 1800 patterns (600 from each vintage). A pattern is a vector of six elements representing the values of the resistances recorded by the sensor array. The patterns in every set of vintage have been ordered according to the sequence in which they were obtained. Thus, there is a curve (resistance against time) associated with each sensor.

Experiments: In this Letter, a pattern recognition system for an artificial nose is proposed. The system comprises a time delay neural network (TDNN) [5], which allows for the handling of the temporal features in the signals generated by the sensors.

The data for training and testing the network were divided as follows: the first data acquisition was assigned to the training set, the second to the validation set, and the last was reserved to test the network. This partitioning has been chosen so that the temporal behaviour of the patterns within each set could be kept, allowing the presentation of these patterns in the same order as they originally occurred. The patterns were normalised to the range [–1, +1], for all network processing units implemented by hyperbolic tangent activation functions. All networks analysed were TDNNs with only a single hidden layer, but with different numbers of tap delay lines and hidden nodes. The first group of TDNNs had six units in the input layer: one for each sensor – in fact this group of topologies had no delays, for the classification is based on only the current input. Conversely, the second group of TDNNs had twelve units in the input layer: six units representing the pattern currently presented and the other six units for the pattern shown at the previous time step. For both groups of topologies, the network output was represented by a 1-of-*m* code – one unit for each vintage of wine (i.e. three output nodes). All networks contained all possible feedforward connections between adjacent layers, having no connection between non-adjacent layers. For each group of TDNNs, six different topologies (2, 4, 8, 12, 16 and 20 hidden units) were trained. The training algorithm is a version of the Levenberg-Marquardt method [6]. For each topology, 10 runs were performed with different random weight initialisations, and the maximum number of epochs allowed was 100. Training was stopped if: (i) the GL_5 criterion defined in Proben1 [7] was satisfied twice (to avoid stopping training because of initial oscillations in the validation error); or (ii) the training progress criterion given was met, with $P_5(t) < 0.1$ [7]; or (iii) a maximum number of 100 epochs was achieved.

Table 1: Mean and standard deviation for the results of the first system (with 6 input units) for each topology

Hidden nodes	Training error		Validation error		Test error		Classification error		Epochs	
	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.
2	237.82	180.23	307.60	99.89	254.27	149.52	0.4474	0.1981	13	12
4	250.26	88.82	289.05	137.26	283.05	75.79	0.5904	0.2179	12	9
8	188.29	80.55	259.71	124.20	230.08	63.95	0.4333	0.0929	16	11
12	151.70	74.16	242.48	118.34	214.94	48.06	0.5053	0.1776	17	8
16	66.19	64.56	141.14	85.37	131.19	53.44	0.3219	0.1750	11	4
20	45.69	48.99	106.69	61.29	118.63	34.73	0.2692	0.1001	19	13

Results: The error measures analysed were the percentage mean squared error [7] (for training, validation and test sets) and the classification error (for the test set only). The latter is equal to the number of incorrectly classified examples divided by the total number of patterns. The results for the first system (TDNNs with six input units and no tapped delay lines) are shown in Table 1. For each topology, the mean and standard deviation of the results obtained for the set of ten runs are presented. As can be seen, values for the test set classification errors were high: for instance, the mean classification error for all topologies is 42.79%. For the 2-hidden-node topology, the smallest classification error in the set of ten runs was about 13.61%. For the 4-hidden-node topology, this value was about 27.50%, and for the topologies with 8, 12, 16 and 20 hidden nodes, this error was about 22.61%, 31.01%, 11.01% and 8.61%, respectively.

Table 2: Mean and standard deviation for the results of the second system (with 12 input units) for each topology

Hidden nodes	Training error		Validation error		Test error		Classification error		Epochs	
	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.	Mean	S. dev.
2	14.15	43.23	158.54	18.05	20.61	38.28	0.0336	0.1053	8	4
4	0.38	0.14	154.55	9.74	2.99	5.32	0.0002	0.0005	7	2
8	0.23	0.08	157.46	14.84	2.64	2.01	0.0000	0.0000	8	6
12	0.19	0.03	158.77	10.99	3.47	3.31	0.0000	0.0000	6	1
16	26.69	60.01	176.45	43.06	24.54	53.32	0.0642	0.1608	6	1
20	53.34	85.87	192.90	56.16	64.27	81.43	0.1611	0.2495	26	39

The results for the second system (TDNNs with 12 input units – one tapped delay line) are shown in Table 2. As can be seen, the use of time delays for temporal processing improved classification performance. For this approach, the mean classification error is 4.32%. For example, the 2-hidden-node topology had only two runs with non-zero test set classification error. For the 4-hidden-node topology, only one run obtained a non-zero classification error. The topologies with 8 and 12 hidden nodes attained 0% classification error on the test set. For the 16-hidden-node topology, only two runs achieved non-zero classification errors. The largest topology, with 20 hidden units, had four runs with non-zero classification errors on the test set. These results have already been compared to those obtained by MLP networks [8], which showed worse performance than the proposed system for the same data.

Conclusion: In this Letter, results for a pattern recognition system in an artificial nose have been presented. Such a system is implemented by using TDNNs [5], which allows temporal processing. For the case of classification of vintages of wine, the system proposed was shown to achieve better results than those obtained by using networks without time delay taps. While the mean classification error of the former was 4.32%, this error for the latter was 42.79%. Thus, it has been shown that temporal processing (i.e. taking into account the changes in the sensor signals during data acquisition) improves odour classification. Possible future work includes the investigation of other neural network approaches for the odour recognition problem and the optimisation and hardware implementation of the proposed networks.

Acknowledgments: The authors would like to thank CNPq and Finep (Brazilian Agencies) for their financial support.

15 August 2001
Electronics Letters Online No: 20010985
DOI: 10.1049/el:20010985

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800 Gbit/s (80 × 10.664 Gbit/s) WDM transmission over 5200 km of fibre employing 100 km dispersion-managed spans

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80 × 10.664 Gbit/s wavelength division multiplexed transmission over 5200 km of fibre with 100 km amplified spans and 50 GHz channel spacing is demonstrated. Error-free operation of all 80 channels is achieved by using dispersion-managed fibre spans, distributed Raman amplification, and forward error correction.

Introduction: Increasing demand for high capacity data pipes connecting the world's largest cities implies that transmission distances of the order of 2000 to 5000 km without electronic regeneration will be required to cross continents with no intermediate traffic drop [1, 2]. Ultra-long haul terrestrial DWDM transmission requires novel concepts to allow optimal trade-off between the major limiting factors such as chromatic dispersion, accumula-