Intelligent recognition of RFID tag position

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The antenna height, read field length, and tag direction are very important factors in tag position recognition. Currently, the best tag position on the target objects is found by experimenting all possible cases with a trial-and-error method. Introduced is a method for identifying the best RFID tag position by employing an intelligent tag strength prediction approach using the backpropagation learning algorithm of neural networks. Experiments reveal that the proposed approach gives high prediction accuracy of mostly about 90%.

Introduction: In supply chain management and logistics, goods can be effectively tracked by attaching RFID tags to them [1]. Recognising the tags by the antenna of the RFID reader is a critical task [2–4]. However, there is no standard established for the tag position. As a result, the best position of the tag on the target object has been obtained by time-consuming trial-and-error approaches, and very little research on this has been reported so far. The strength of the tag signal determines whether or not a specific tag position is recognised. Therefore, in this Letter, an intelligent approach predicting the strength of the tag signal by using the artificial backpropagation learning algorithm of neural networks is proposed. The tag position of the target object with higher than a certain level of the predicted strength of the tag signal is considered to be sensed and recognised by the RFID reader. Experiments conducted on carton boxes stacked on a wooden pallet show that the proposed approach allows accurate tag recognition of higher than 90%. Thus the best tag position can be identified (or recognised) by the proposed scheme. The approach will significantly reduce the time and effort required to find the best tag position in the target object.

Factors influencing tag reading: In addition to tag direction, the factors influencing recognition of the tag position include the read field and reader antenna height. The distance over which the antenna and tag can communicate with each other is called the read field. The factors are controllable by the users, and therefore the three factors are selected as the variable parameters in the proposed model influencing the strength of the tag signal.

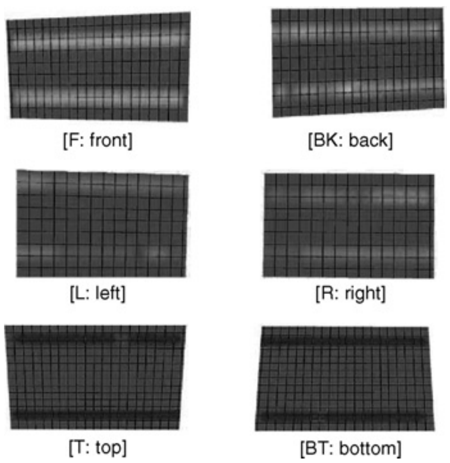

Fig. 1 *Picture of measured strength of tag signal from single carton*

Proposed approach: To train the neural network, some raw data on tag strength are required to be input to the network. The raw data are obtained through the time-consuming trial-and-error approach. In the experiment the target object is 40 cartons. Each carton box with a layer of 2×2 cartons stacked in 10 layers on a wooden pallet is packed with books. The size of a carton box is $52 \times 36 \times 22$ cm. There exist a total of 240 tag positions from the 40 cartons with six sides (directions) per carton (front(F), back(BK), left(L), right(R), top(T), bottom(BT)). In the experiment the RFID reader of 915 MHz with a reading rate of 50 tags/s is used. The single antenna of 865–928 MHz of vertical polarisation type allows 6 dBi gains. The RFID tag of 915 MHz frequency and EPC Class 1 Gen 2 is used. The tag strength for each position is measured by the Instant EPC Hotspot tag readability evaluation system. An example of visual representation of the tag signal strength measurements for a single carton box is shown in Fig. 1. Here the light stripes represent a strong tag signal. The front and back side tag turns out to allow the largest tag signal strength while the top and bottom side tags display the worst case. The measured tag signal strengths with the antenna height of 1.1m and read field length 1m are shown in Fig. 2. The shaded boxes indicate a recognised tag position. Here 'A' denotes a tag strength of higher than 6 dB, 'B' higher than 3 dB but lower than 6 dB, and 'C' lower than 3 dB, respectively. 'A' and 'B' are considered a successful tag position recognition while 'C' is failed recognition. We can observe from Fig. 2 that the tag positions of the top and bottom of a carton are not preferred at the antenna height and read field length.

Layer	Front left box						Front right box						Back left box						Back right box					
	F	BK	L	R	T	BT	F	BK	L	R	T	BT	F	BK	L	R	T	BT	F	BK	L	R	T	BT
1	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C
2	B	C	C	B	C	C	B	C	C	B	C	C	C	C	C	B	C	C	C	C	C	B	C	C
3	A	A	A	A	C	C	A	A	A	A	C	C	A	A	B	A	C	C	A	A	A	B	C	C
4	A	A	A	A	C	C	A	A	A	A	C	C	A	A	B	A	C	C	A	A	A	B	C	C
5	A	A	A	A	C	C	A	A	A	A	C	C	A	A	B	A	C	C	A	A	A	B	C	C
6	A	A	A	A	C	C	A	A	A	A	C	C	A	A	B	A	C	C	A	A	A	B	C	C
7	A	A	A	A	C	C	A	A	A	A	C	C	A	A	B	A	C	C	A	A	A	B	C	C
8	A	A	A	A	C	C	A	A	A	A	C	C	A	A	B	A	C	C	A	A	A	B	C	C
9	B	C	C	B	C	C	B	C	C	B	C	C	C	C	C	B	C	C	C	C	C	B	C	C
10	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C	C

Fig. 2 *Mmeasured tag signal strengths with antenna height of 1.1 m and read field length 1 m*

Modelling for intelligent recognition: The backpropagation is a supervised learning algorithm adopted in artificial neural networks. It is used to calculate the stochastic gradient of the error of the network with respect to the modifiable weights of the network, i.e. the gradient is used for minimising the error [5]. The node value is calculated forward while the weight of the network links is backpropagated to be modified. The proposed backpropagation neural network training model is shown in Fig. 3. The neural network consists of five input layer nodes (the height of antenna, length of read field, position of layer, position of a box in a layer, and side of a box) and one output layer node to determine if the tag position is recognised ('A' or 'B') or not ('C'). The number of the hidden layer nodes ranging from two to nine is tested to obtain the best solution. The error used to modify the weights by backpropagation for the target pattern corresponding to the input training pattern can be computed as in (1):

$$\delta_k = (t_k - y_k) f'(y\_in_k) \tag{1}$$

such that $f'(y\_in_k) = f(y\_in_k)[1 - f(y\_in_k)]$ and $f(y\_in_k) = 1/(1 + e^{-(y\_in_k)})$. k is the output node number (each grid), t_k is the target value (measured tag strength), y_k is the output value (calculated output tag strength), y_in_k is the net input value to output unit k, and $f(y\_\mathrm{in}_k)$ is the sigmoid activation function allowing saturation. The Nguyen-Widrow weight initialisation [6] is applied instead of the common random weight initialisation for much faster learning as shown in (2):

$$\beta = 0.7(p)^{1/n} \tag{2}$$

where n is the number of input units, p the number of hidden units, and β the scale factor. The initial weights are generated between $-\beta$ and β. The learning rate of 0.01 was used and the learning epochs were stopped when the mean square error becomes smaller than 0.08. A total of 4800 datasets are used to train the backpropagation model and a total of 960 datasets are applied to verify the prediction. The backpropagation model is simulated using Matlab V. 7.

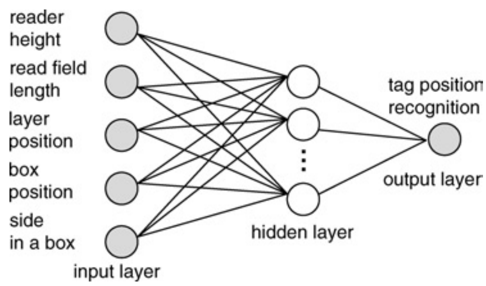

Fig. 3 *Proposed backpropagation neural network training model*

Results: With the trained neural network, the accuracy of the proposed tag strength prediction approach is validated with the new six different antenna height-read field length combinations which have never been used in training: (0m, 1.3 m), (0 m, 1.7 m), (1.1 m, 1.3 m), (1.1 m, 1.7 m), (2.2 m, 1.3 m) and (2.2 m, 1.7 m). The accuracy of the proposed approach is the portion of tag positions out of 160 positions for the predicted tag strength obtained by the proposed method that matches the measured one by the trial-and-error approach. We use 160 positions (240 – 80 = 160) for the accuracy calculation instead of 240 positions because the strength of all the top and bottom positions is always ‘C’, which is meaningless. It turns out that the three backpropagation neural network models with six, seven and eight hidden layer nodes, respectively, provide better results than others as given in Table 1. We can see the distribution of the tag strength prediction accuracy with variable antenna height and read field length combinations in Fig. 4 and among the three, the model with seven hidden layer nodes gives the best results. We observe that the prediction accuracy is between 89 and 96%. The prediction accuracy with antenna height of 0 m and read field length of 1.3 m is the highest, 96.25%. The prediction accuracy with the antenna at the middle height, 1.1 m, is lower compared to the bottom and top height. This is because only half of the tags are exposed to the radio waves when the antenna is located at the top or bottom height of the box stack, i.e. the more the number of tags gives more variable and unpredictable tag strengths, so possibly less accuracy. If the predicted tag signal strength is ‘A’ or ‘B’, we can find out that the tag position is recognised and conclude that the position is the best.

Table 1: Prediction accuracy with different number of hidden layer nodes

(Antenna height, read field length)	Number of hidden layer nodes		
	6	7	8
(0m, 1.3 m)	95.00	96.25	94.38
(0m, 1.7 m)	93.13	93.75	92.50
(1.1m, 1.3 m)	88.75	89.38	89.38
(1.1m, 1.7 m)	83.75	89.38	89.38
(2.2m, 1.3 m)	93.13	92.50	89.38
(2.2m, 1.7 m)	83.13	92.50	86.25

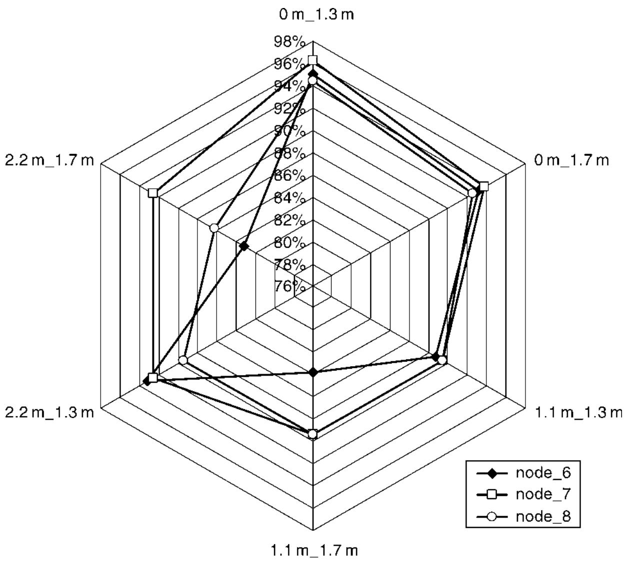

Fig. 4 *Distribution of prediction accuracy with variable antenna height and read field length combinations*

Conclusion: The approach presented in this Letter predicts the strength of the tag signal and based on the predicted strength, determines which tag position of the target object can be recognised or not by the RFID reader. Using the trained neural network, the strength of the tag signal is predicted under five different conditions of reader height, read field length, layer position in the stack, box position in a layer, and side of a box. We have verified the prediction accuracy by comparing the predicted data obtained by the proposed approach with measured data by the trial-and-error method, which results in mostly above 90%. The proposed approach gives a possibility to find the best RFID tag position by avoiding the time-consuming trial-and-error approach. We will further investigate the proposed approach for the cases of different content type, work environment, and antenna type.

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References

1 Gadh, R.: ‘The State of RFID: ‘Heading toward a wireless internet of artifacts’, *Computerworld*, August 11, 2004

2 Flores, J.L.M., Srikant, S.S., Sareen, B., and Vagga, A.: ‘Performance of RFID tags in near and far field’. 2005 IEEE Int. Conf. on Personal Wireless Communications, (ICPWC 2005), New Delhi, India, January 2005, pp. 353–357

3 Jiang, B., Fishkin, K.P., Roy, S., and Philipose, M.: ‘Unobtrusive long-range detection of passive RFID tag motion’, *IEEE Trans. Instrum. Meas.*, 2006, **55**, (1), pp. 187–196

4 Techsolutions: Application Note: ‘RFID Solutions for Pallet Tracking’ http://www.techsolutions.co.za/PDF/Application%20Note%20Pallet%20TrackingV1_3.pdf# search=%22RFID%20tag%20location%20distance%20direction%22

5 Rumelhart, D.E., and McClell, J.L.: ‘PDP Research Group “Parallel distributed processing: explorations in the microstructure of cognition” (MIT Press, Cambridge, MA, 1986), Vol. 1

6 Nguyen, D., and Widrow, B.: ‘Improving the learning speed of two-layer neural networks by choosing initial values of the adaptive weights’. Int. Joint Conf. on Neural Networks, San Diego, CA, USA, 1990, Vol. III, pp. 21–26