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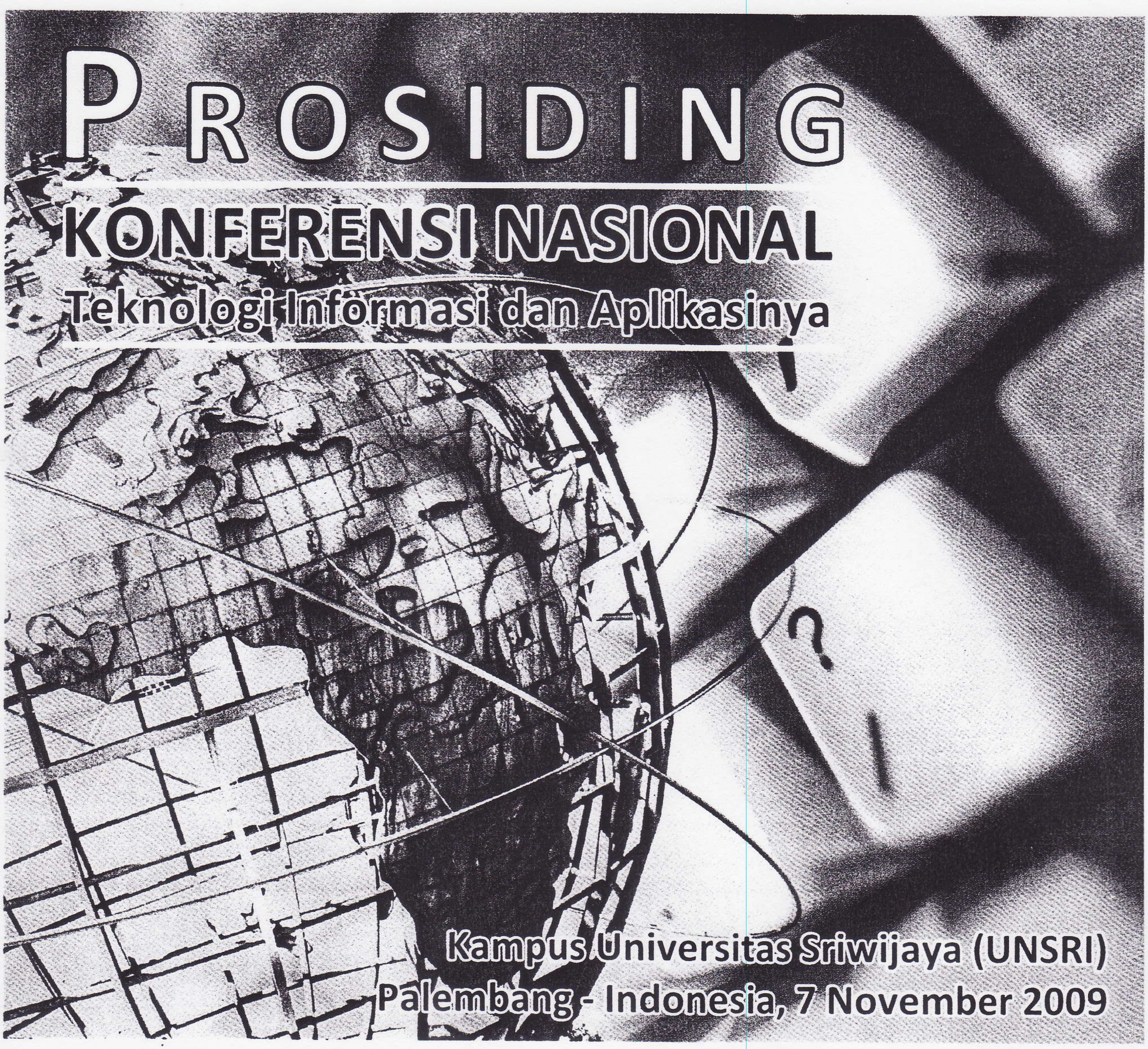

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KATA PENGANTAR

Konferensi Nasional Teknologi Informasi dan Aplikasinya (KNTIA) merupakan pertemuan ilmiah di bidang teknologi informasi (TI) yang bertaraf nasional, dimana di dalamnya para peneliti dan praktisi dapat mendiseminasikan hasil-hasil penelitian terkini mereka dan sekaligus mendiskusikan isu-isu terkini di bidang TI. Konferensi juga ini merupakan wadah berkumpulnya ide-ide dari para pemikir yang dapat berupa pemikiran yang bersifat murni dan terapan. Beberapa peneliti yang akan mendiseminasikan hasil penelitian mereka berasal dari berbagai perguruan tinggi ternama di Indonesia dan negara tetangga Malaysia.

Kumpulan makalah dikemas dalam bentuk prosiding dan dikelompokkan sesuai dengan bidang kajian antara lain Soft Computing, Rekayasa Perangkat Lunak, Data Mining dan Data Warehouse, IT Governance dan IT Management,, Komunikasi Data dan Jaringan Komputer, Pembelajaran Berbasis Komputer serta Sistem Kendali..

Makalah yang diterima berasal dari seluruh Indonesia dan negara tetangga Malaysia. Makalah yang dimuat dalam prosiding KNTIA 2009 telah melalui tahapan evaluasi oleh reviewer-reviewer yang berkompeten di bidangnya. Panitia mengucapkan selamat dan terima kasih atas keikutsertaan dan dimuatnya makalah dalam prosiding KNTIA 2009. Panitia juga mengucapkan terima kasih kepada Pemerintah Daerah Sumatera Selatan dan semua pihak yang telah mendukung serta partisipasi aktif dalam mensukseskan acara konferensi nasional ini.

Saran dan kritik demi menuju kesempurnaan prosiding KNTIA 2009 sangat diharapkan. Semoga prosiding ini dapat digunakan sebagai salah satu acuan dalam pengembangan teknologi dan peningkatan pembelajaran di bidang Teknologi Informasi dan Aplikasinya.

Palembang, 2 Oktober 2009

Ketua Panitia,

Fathoni, MMSI

DAFTAR ISI

WEIGHTLESS NEURAL NETWORK CLASSIFIER

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ABSTRACT

Learning and reasoning, in a digital hardware, may lead to adaptation and reconfiguration. Neural network have shown to be well suited to learn from examples and adapt to non-linear environments, but many variants are rather resource intensive and therefore prohibitive in practical embedded applications. However, one class of neural networks is more suited to implementation in hardware - the so-called weightless neural networks (WNNs) can be well matched to RAM (Random Access Memory) because their learning and recognition algorithms are mainly associated with reading from and writing to memory. In this paper the technique is being developed for classification mobile robot environment. In this way, the operation of the WNNs that would take hundreds of lines of code to be implemented can be executed with one single instruction that reads the command byte in the memory. It can make the classifier work hundreds of times faster.

Keywords: Weightless Neural Network, environment recognition, random access memory.

I. INTRODUCTION

Modern multiple classifier systems are being increasingly employed in practical application domains where the required performance level exceeds that achievable from a single pattern classifier. These systems typically employ concurrently a number of distinct classifiers, each of whose defining characteristics are able to address an aspect of the pattern classification task as a part of the overall problem domain in question.

Autonomously recognizing in mobile robot is a prominent example of difficult realistic problems, and has long attracted the application of a wide range of powerful classification methods [18]. It is a very difficult problem needing a lot of computational power, and giving not so much accurate results in terms of robot pose estimation [19].

Mainstream artificial neural network (ANN) models are based on weighted-sum-and-threshold artificial neurons, as the pioneering *Threshold Logic Unit*, of McCullogh and Pitts [10]. The biological analogy behind this model lies on the mapping of the synaptic strength between the output produced and transmitted by the neuron's axon and the input of a post-synaptic neuron, into pseudo-continuous numerical weights [11]. Nevertheless generalizations of artificial weighted-sum-and-threshold neurons, such as Sigma-Pi units, do exist, this means that the dendritic tree, the mostly noticeable morphological structure of the neuron cell, is not being taken into account in mainstream ANN paradigms [11].

Weightless neural networks (WNNs) are based on networks of Random Access Memory (RAM) nodes. WNNs are a variant of artificial neural networks that are trained to recognize a pattern based on lookup tables that store neuronal functions. They do not have multiplicative weights between nodes, hence the name [6].

The use of RAM nodes in pattern recognition problems is dating 50 years by the work of Bledsoe and Browning [1]. These networks are typically used in pattern recognition applications because of their small size and computational requirements [4]-[5]. Some years later, Aleksander introduced Stored Logic Adaptive Microcircuit (SLAM) and *n*-tuple RAM nodes as basic components for an adaptive learning network [12]. With the availability of integrated circuit memories in the late 70s, the WiSARD (Wilkes, Stonham and Aleksander Recognition Device) was the first artificial neural network machine to be patented and produced commercially [13][14]. Other WNN models followed, such as PLNs [15], GSNs [16] and GRAMs [17].

Many researcher using this technique in mobile robot application indicates this approach maybe successful such as, [2],[3],[7],[8],[9]. This paper demonstrates the potential technique of WNNs in embedded mobile robot for recognizing and classify the environment. In the paragraphs that follow, the WNNs structure and application in mobile robot will be presented.

Results of experiments that measure classification of environment will also be given.

II. WNNs STRUCTURE

The main component of the WNN is the ensemble of class discriminator (Figure 1). A discriminator consists of a series of address spaces similar to Random Access Memory (RAM) components that are attached to each of the n-tuples, where the value of the n-tuple is employed as the address of the RAM location, being incremented when the network is trained. The neuron inputs are connected in a random sequence to the feature vector, each neuron is a binary pattern recognition device. Each discriminator consists of *M* RAM-like neurons (weightless neurons) with n address lines, 2^n storage locations (sites) and 1-bit word length. Each RAM randomly samples n bit of the input pattern. Each pattern must be sampled by at least one RAM.

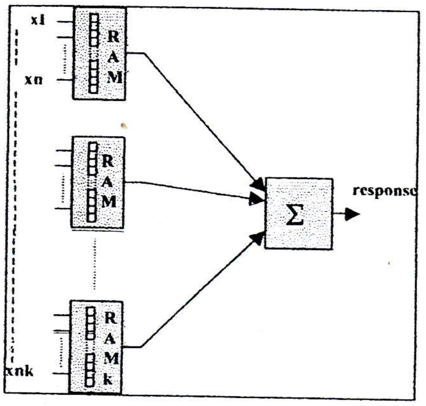

Figure 1. RAM Discriminator

For an input vector of size *K*, the number of necessary neurons *J* of connectivity *N* that should be used to cover all inputs of the input vector should satisfy: $J \times N > K$. This neuron group is called a discriminator and its response is produced by connecting an adder that sums the neuron outputs, counting the number of active neurons (neurons outputting "1") in the group [6]. This response vector can be regarded as a feature vector that measures the similarity of an input pattern to all classes. In the WNN, a Winner-Takes-All-Block can be attached to the adder outputs to choose the discriminator containing the greater number of active neurons, pointing to the winning classes. Each pattern will produce a feature vector that describes its similarity to all classes.

II.1. Learning Phase

The input address vector is presented to the network. The desired output of every cell in is the *same* as the desired output. If the desired output at the input layer is **1**, the addressed location is incremented by one. If the desired output is **0**, the location is decremented by one. The learning algorithm then involves calculating the address vectors for the next layer, moving towards the output

II.2. Recalling Phase

During the recall phase, again, the content of each addressed location, starting from the input layer, is interpreted as U (undefined), 0, or 1 as the counter value is zero, negative, or positive respectively. During recall, we can clearly see that the output of each cell might propagate forward an undefined output. In the output cell, we determine, for each U location addressed, the nearest address up to a Hamming distance measure of *d* to a defined location's address (either 0 or 1). We continue to run through the training set in this way until all U's are replaced by 1's or 0's in the output layer. The size of *d* should be less than half the cell size. We have found that the overall classification result improves significantly.

III. ENVIRONMENT RECOGNITION USING WNNs

III.1. Classification

We considered the common target that there exist in real environment of mobile robot applications such as plane, edge, corner with angle 90 degree, acute corner with angle 60 degree. Length of plane is about 45 cm and other objects are of similar size. These objects at four distances: 10, 20, 30, 40 cm. Also angle between the head of mobile robot and these objects is assumed to be -30, -20, -10, 0, 10, 20, 30 degree. Fig. 2, show the environmental classification at these nine classes environment.

The WNNs is designed to identify the current environment by recognizing typical patterns. To implement the network, 8 bit data from eight ultrasonic sensors is used to determine the direction of the obstacle. The combination of them appearance in the seven directions makes up different input pattern such as, front, right front, left front, right front side, right back side left front side and left back side. The winner-takes-all decision chooses that has more active neurons and encodes it.

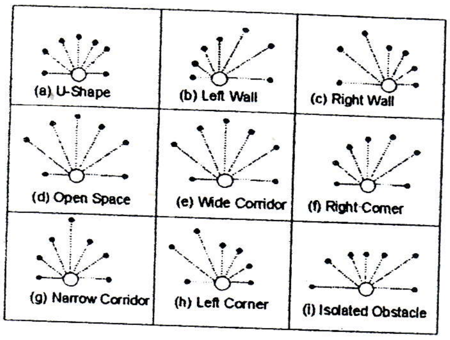

Figure 2. Environmental classification

III.2. Learning Strategy

Here we use patterns with a single far, medium, or near obstacle to train the neural network. At a time the obstacle is placed in different directions and in difference distance. The WNNs then is taught that the obstacle at left side, right side or forward. Using this technique, the value distinguishing distance an obstacle has to be obtained first. In this experiment, the variable sensors are single byte that holds the sensor readings. In the evaluation phase, the WNNs by generating all the possible input combination. The number of possible combination is 2^8= 256 combination. Then, each output for all input possibilities was written to a lookup table, representing the neuron combination.

The calculation of this value is based on the distance from an obstacle to the robot, Using on this calculation, the threshold values for distance of the robot are 00100010 (30 cm) indicates the obstacle is far, 00010111(20 cm) the obstacle is medium, and 00101111 (10 cm) the obstacle is near and 0100,011 (75 cm) no obstacle is detected.

IV. EXPERIMENTAL RESULT

Experiment is conducted to demonstrate the ability of a mobile robot to react to various unknown environment. The result is based on the environment classification. Table 1 has shown using 10 experiment data, winner take all learning algorithm has achieved 95 % recognition for obstacle and 94 % classification. How ever the poorest result was if the robot closes the object, where the scanning sensory sector of the robot was quite high and some noise has still interfered in echo signal.

Table. 1 Critical Class of Environment Recognition

Actual Place	Distance (cm)	Refe-Rence (hex)	Result (hex)
Convex (90°)	20	12h	12h
	30	0bh	0bh
	40	05h	0dh
Concave (270°)	10	06h	00h
	20	0eh	00h
	30	00h	00h
Plane (180°)	10	03h	07h
	20	0ch	0ch
	30	15h	15h
	40	1eh	1eh
Left-corner (180°)	10	03h	07h
	20	0ch	0ch
	30	15h	15h
	40	1eh	1eh
Right-corner (180°)	10	03h	07h
	20	0ch	0ch
	30	15h	15h
	40	1eh	1eh
Corridor (0°)	10	03h	07h
	20	0ch	0ch
	30	15h	15h
	40	1eh	1eh
U-shape (180°)	10	03h	
	20	0ch	
	30	15h	
	40	1eh	

V. CONCLUSIONS

The operation of the WNNs classifier that would take hundreds of lines of code to be implemented can be executed with one single instruction that reads the command byte in the memory. The classification is stimulated with every possible input and a corresponding output table is written. The network was implemented with very modes microcontroller system 20 Kbytes ROM,-small amount of data memory about 256 bytes and 10 Kbytes source code program using the microcontroller assembler and mobile robot was able to detect an environment in a real time.

Acknowledgments

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REFERENCES

[1] W.W. Bledsoe and I. Browning, Pattern Recognition and Reading by Machine, *Proceedings of the Eastern Joint Computer Conference,* Boston, pp. 225-232, 1959.

[2] R. J. Mitchell, D. A. Keating, and C. Kambhampati, "Neural network controller for mobile robot insect," Internal report, Department of Cybemetics, University of Reading, April 1994.

[3] Y. Zhou, D. Wilkins, R. P. Cook, "Neural network for a fire-fighting robot," University of Mississippi.

[4] I. Aleksander, W. V. Thomas, P. A. Bowden, "Wisard: A radical step forward in image recognition." Sensor Review, pp 120-124, July 1984

[5] J, Austin, "A Review of RAM-Based Neural Networks". Proceedings of the Fourth International Conference on MICRONEURO94, pp. 58-66, 1994.

[6]. L. Teresa et al, "Weightless Neural Models: A Review of Current and Past Works", Neural Computer Surveys v. 2,pp. 41-61, 1999.

[7]. Simoes, E. D. V., Uebel, L. F., and Barone, D. A. C., Hardware Implementation of RAM Neural Networks. In Pattern Recognition Letters, n. 17, pp. 421-429, 1996.

[8] Botelho, S. C., Simoes, E. D. V., Uebel, L. F., and Barone, D. A. C., High Speed Neural Control for Robot Navigation. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, Beijing, China, pp. 421-429, 1996.

[9] Q. Yao, D. Beetner, D.C. Wunsch, and B. Osterloh., "A RAM-Based Neural Network for Collision Avoidance in a Mobile Robot", IEEE, 2003.

[10]. McCulloch, W. and Pitts, W., A logical calculus of the ideas immanent in nervous activity, *Bulletin of Mathematical Biophysics*, 7, pp. 115-133, 1943.

[11]. I. Aleksander, "Weightless Neural Network", proceedings, European Symposium on Artificial Neural Networks - Advances in Computational Intelligence and Learning, Belgium, 2009.

[12]. I. Aleksander, Ideal neurons for neural computers, in: Parallel Processing in Neural Systems and *Computers*, North-Holland, Amsterdam, pp. 225-228, 1990.

[13] I. Aleksander and T.Stonham, Guide to pattern recognition using random-access-memoriesComputer and Digital Techniques, 2, pp. 29-40, 1979.

[14] I. Aleksander, W. Thomas, and P. Bowden, WISARD, a radical new step forward in image recognition, *Sensor Rev.*, 4(3), pp. 120-124, 1984.

[15] I. Aleksander and W.W. Kan, A Probabilistic Logic Neuron Network for Associative Learning, IEEE Proceedings of the First Int. Conf. on Neural Networks, pp. 541-548, 1987.

[16] R. G. Bowmaker and G. G. Coghill, Improved recognition capabilities for goal seeking neuron, IEE Electronics Letters, 28, pp. 220-221, 1992.

[17] I. Aleksander, Ideal neurons for neural computers, in: Parallel Processing in Neural Systems and Computers, North-Holland, Amsterdam, pp. 225-228, 1990.

[18] Borenstein, J., Everett, H.R., Feng, L.: Navigating Mobile Robots: Systems and Techniques. A. K. Peters, Ltd., Natick, MA, USA.,1996.

[19] Thrun, S., Burgard, W., Fox, D.: Probabilistic Robotics (Intelligent Robotics and Autonomous Agents). The MIT Press, 2005.