Proceedings of the 1997 IEEE
International Conference on Robotics and Automation
Albuquerque, New Mexico - April 1997

An Approach to Integrated Tactile Perception

D. Taddeucci*, C. Laschi*, R. Lazzarini*, R. Magni*, P. Dario*, A. Starita°

*ARTS Lab - Scuola Superiore Sant'Anna
via Carducci 40 - 56127 Pisa, Italy
Phone: +39-50-883207, Fax: +39-50-883215
E-mail: {davide, cecilia, lazzarini, ric, dario}@arts.sssup.it

°Dipartimento di Informatica, Università degli Studi di Pisa
Corso Italia 40 - 56127 Pisa, Italy
Phone: +39-50-887215, Fax: +39-50-887226
E-mail: starita@di.unipi.it

Abstract

This paper presents an integrated approach to tactile perception, both in terms of data acquisition and of data interpretation.

In humans, touch sensing is implemented through a number of different sensing elements embedded in: the skin. The interpretation of perceived data to the level of detection of basic features, such as material, shape of surface, shape of contact, is achieved by integrating the different sensorial inputs at a low level, with no involvement of high level cognitive processes.

The approach we propose in this paper follows this anthropomorphic model of tactile perception, by including, on one hand, a miniature fingertip integrating different sensors and, on the other hand, a parallel data interpretation module, implemented through a fuzzy neural-network, which processes all the different inputs at the same level.

The paper describes the characteristics of the integrated fingertip sensor and of the neuro-fuzzy system, and discusses experimental results achieved during exploratory tasks on a set of common object are discussed in detail in the following.

1. Introduction

A key issue in modern robotics both involves the robot capability of dealing with uncertainties, in the working environment and in the behavior to adopt according to current circumstances. This is particularly true in the emerging field of service robotics, where robots interact with humans and deal with unstructured environments. For these reasons, the capability of perceiving the external environment and of planning and modifying behavior according to the perceived features is of main concern in robotics.

Tactile perception is an important tool for extracting information by means of direct interaction with objects, especially if different sensory modalities are integrated, such as dynamic, thermal, force, torque and contact [1]. In recent years many efforts have been devoted to the development of sensors for tactile probes and grippers [2] [3] [4]. These sensors have been developed using different approaches and technologies, with the common aim of improving robot performance in two main kinds of operations: "exploratory" tasks and "manipulative" tasks.

Although these types of actions are performed simultaneously in most practical cases, they can be considered conceptually as separated for the sake of clarity. According to this classification, the primary goal of recognition and exploration tasks by touch is to provide the robot system with information on the physical properties of surfaces and objects. This knowledge is useful to characterise more accurately the robot workspace (in most cases along with the information provided by vision and by range sensing) and may be used for subsequent manipulative tasks. To this aim, the robot end effector should be capable of gathering as much and as varied information as possible on the explored object. Thus the main technical problem in recognition and exploration is to design a tactile sensor with multiple sensory capabilities. If the model from which the designer can take inspiration is the biological one (a reasonable choice for robots intended to operate, for example, in the service field) it is not necessary to fabricate sensors extremely accurate. In this context, tactile sensors should be regarded as tools useful to extract qualitative or semi-quantitative information, rather than precision instruments.

In parallel with the advances in tactile sensing technology, important results have been achieved in the field of tactile data interpretation. Starting from the paradigm of 'Active Perception' [5] and from studies on human perception [6], typical exploratory procedures have been formulated for tactile exploration of object [7] [8]. The problem of object recognition through perception has usually been faced by integration of different sensor modalities, such as vision and touch [9] or different touch modalities [10]. Furthermore, interesting results have been achieved in robot sensory-motor co-ordination [11][12].

The aspects of noise robustness, adaptability, parallel processing, low level integration and ability to learn, typical of human tactile perception have suggested the implementation of neural networks and fuzzy systems for tactile models in robotics [12] [13].

In this paper, an integrated tactile sensor, including a custom tactile array, a thermal sensor and a dynamic sensor, is presented. This sensor is the core of a robotic system for investigating tactile perception. A neuro-fuzzy approach to data interpretation is then discussed and experimental results are reported, for the case of an object sorting problem. Finally, hints for future research and experiments to be carried out on the proposed sensor are given and conclusions are drawn on the validity of the proposed approach.

2. Design Concepts

The approach we propose to tactile perception in robotics starts from considerations on the human tactile system and perception model. Tactile sensing, in humans, is achieved through a number of different sensing elements, corresponding to different sensor modalities, physically integrated into the skin, a miniature support allowing sensors to perceive external environment and to be protected, at the same time. The perceived signals are acquired in parallel, in humans, and integrated at a low level, with no involvement of high level cognitive processes. Furthermore, the human tactile system shows high noise robustness and high adaptability and learning capabilities.

Based on these considerations, we propose a tactile model including an integrated miniature fingertip sensor and a neuro-fuzzy processing system.

The integrated fingertip sensor has novel technological features, such as the use of space-variant sensor geometry and the partial integration of the pre-processing electronics, which alleviate some serious practical problems, like the number and encumbrance of electrical wiring. These features reflect consideration for mechatronic and (in the near future) micromechatronic design concepts and fabrication technologies. Furthermore, the unique "anthropomorphic" features of the fingertip sensor may open new opportunities for fundamental research on tactile perception. The fingertip sensor was developed with support from the Korean Institute of Science and Technology (KIST) in the framework of the "CENTAUR" Project [14].

The proposed approach aims at integrating tactile perception, by allowing a supervisor-control system to evaluate contact conditions through several parameters. Different sensors have been integrated into one sensory system, including a miniature control electronics, such as to be physically assembled onto an anthropomorphic fingertip, with sensors on the external surface and electronics inside.

The proposed solution includes three different types of sensors:

- a Tactile Array sensor, to determine contact patterns;
- a Dynamic sensor, to detect micro-vibrations due to stick-slip movements;
- a Thermal sensor, to detect thermal conductivity of contact object surfaces.

The electronic circuitry that interfaces and acquires the signals of the sensors has been purposely designed to allow fabrication by SMD technology: it yields to completely embed the interface and acquisition electronics inside the fingertip. Specific software has been developed for the management of the acquisition modalities and data transfer.

The resulting sensory system is an integrated anthropomorphic sensorised fingertip with contact, dynamic and thermal sensor capabilities and data acquisition functionality.

A short description of the fingertip different sensors is given in the following section, though further technical details can be found in [14]

The neuro-fuzzy system we propose is based on a multi-layer feed-forward neural network comprising two level of features extraction and classification.

From the tactile and dynamic signals, the first level was able to extract two fuzzy values about the degree of curvature and roughness of an object surface. Together with temperature and shape, these values were used to train the final network to classify different sensed objects.

We focus our attention on the choice of a neural network as a classifier system for the high parallel nature of the algorithm that has to process parallel signals. Furthermore, the complexity of the recognition task is significantly reduced via the iterative learning supervised process, that, in the meanwhile, allows a robust and distributed knowledge representation and treatment.

3. The Integrated Fingertip

The integrated fingertip comprises the "Tactile Array sensor" ,the "Dynamic sensor" and the "Thermal sensor".

The "KIST" Tactile Array sensor is an evolution of the ARTS Tactile Sensor, previously designed by some of the authors and described in [15]. The sensor reflects the unique space-variant disposition of the sensing sites, aiming to increase the size of the tactile sensing area and reproducing the concept of tactile "focus of attention" at the fingertip (very similar to the analogous well known concept of foveal vision [16]), though it has been reduced in size in order to be integrated in the fingertip; in particular, site number has decreased from 256 to 64 and the connection "tail" has been reduced to a compact connector.

Fig.1 depicts the Tactile sensor stand-alone and mounted on the robotic fingertip.

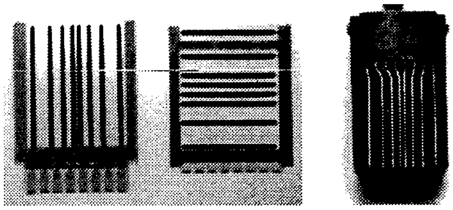


Fig.1 The Tactile array sensor

The Dynamic sensor is based on a bimorph piezo-ceramic element, generating a signal related to applied stress. Further technical details on the design and development of the Dynamic sensor can be found in [14].

The Thermal sensor is composed of two miniature resistors embedded in thermally conductive rubber: one is for heating the sensor and the other is for detecting temperature variations. So, the sensor requires two phases: the heating phase and the measuring phase.

In the heating phase the heating element is powered on, thus heating the sensor up to an appropriate temperature.

In the measuring phase the heating element is powered off, the thermal sensor assembly is put in contact with the object surface and the NTC sensor measures the temperature versus time variations. This function is related with the thermal flow between the sensor assembly and the object.

A proper interface electronics acquires the signals from the sensor and put them in numerical format.

The integrated fingertip is contained in a compact and lightweight assembly of 27.4 x 25 x 52 mm that can be mounted on a commercial hand (Barrett Hand, by Barrett Technology Inc., Cambridge, MA); the Tactile Sensor and the Thermal Sensor are placed on the contact surface, while the Dynamic Sensor leans out from the fingertip upper side. In order to limit possible damages to the dynamic sensor during grasping operations, the sensor stick may glide into the fingertip structure.

The electronic boards for data acquisition are embedded inside the fingertip structure, too; the tactile acquisition electronics is connected to the Tactile Sensor through a connector that is supported by the small custom made mechanical assembly.

4. Tactile Information

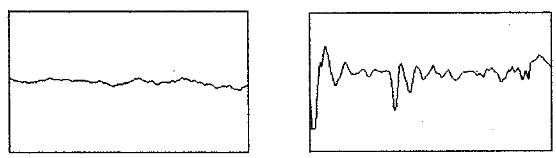
The integration of different sensory modalities in the fingertip sensor provides rich information, which gives indications on a variety of features, such as material, shape of the surface, roughness, curvature, and kind of contact with the fingertip. By detecting the normal forces applied at a number of different sites of the surface of the fingertip, an indication on the shape of contact can be extracted, together with the position of contact with respect to the fingertip. Furthermore, the force values that the sensor detect for each active site allow to recover rough information on the curvature of the object. Fig.2 shows typical tactile images for a spherical (a) and a flat (b) object.

(a) *(b)*

Fig.2. Typical tactile images for a spherical (a) and a flat (b) object.

The particular anthropomorphic fovea-like structure of the tactile array allows to collect information on a wider area, respect to the number of active sites; though high definition information is available at the central part of the array, further rougher information is also available on a wider area of the object surface, so that indications on ‘what is next’ (especially helpful for directing exploratory research) are also given. A well-suited application of this particular sensor feature is in edge tracking, as indications on the prosecution of edge can be extracted from the rough sensor area information during the detection of an edge in the high definition area.

The Dynamic sensor provides important information during tactile exploratory actions, when the sensor is being moved along the contact surface. The perceived information gives indications both on the surface roughness and on the slippage between fingertip and object surface. Fig.3 shows typical outputs for a smooth (a) and a rough (b) surface.



(a) *(b)*

Fig.3. Typical dynamic responses for a smooth (a) and a rough (b) surface.

By detecting the thermal conductivity of the object in contact, the information provided by the Thermal sensor especially concern the material it is composed of.

The integration of the different kinds of data detected by the integrated fingertip sensor gives an overall perception which is similar to what, in humans, is detected and integrated at a low level, with no involvement of high level cognitive processes.

5. Use of integrated fingertip data

The multi-sensorial nature of the integrated fingertip sensor makes its use possible in different robotics research and application areas, specifically in *manipulation strategy* and *object recognition.*

These areas are strictly dependent; for instance, when we want to grasp an unknown object, the first attempt is to manipulate it in some manner in order to acquire information about the weight, the surface, the material and then, using these instances, we calibrate our fingers to obtain a stable grasp. General computational geometry, computer vision methods and mathematical model of the sensed surface have been applied for object recognition applications, relaying on the assumption of a completely known object representation; in contrast, real-time robotic tasks in unstructured environments require a more suitable "fuzzy" object representation without reference to *a priori* models.

In this paper we focus our attention onto the problem of object recognition by the design of a neural based system.

Our framework can be modelled as an integrated system of neural networks and fuzzy logic combining the artificial neural network ability to learn and to adapt itself with noise robustness to new environmental information, especially at the low-level, with the attitude of fuzzy-logic to treat incomplete knowledge.

The innovative aspect of our approach is the parallel nature of the entire process of data acquisition and data processing.

In our past work [8] [17] for instance, we sequentially acquired the different sensorial components of the object to be identified and then we used a sequential algorithm based on a decisional tree for the classification task.

In the present paper, we exploit the multi-sensorial nature of integrated fingertip sensor to obtain in a parallel way the features input vector of the neural networks. The vector has thermal, dynamic and tactile components. We validated our approach through an experimental trial on common object recognition during exploratory procedures.

5.1 Experimental scenario

The experiment consisted in the recognition of a typical shopping bag with 14 objects, including vegetables, fruits, cans and bottles. The neural net (NN) learns via an iterative process how to distinguish between the thermal, tactile, visual and dynamic features of the objects. In the choice of the training objects, we put attention to have little but meaningful variations from one object to another in order the network to be able to discriminate. For instance the orange and the apple have the same visual, thermal and tactile characterisation but different dynamic texture; the black and the green olive cans differ only for the material they are made out of and so on. The successful convergence of the final neural network indicates the ability of this computing model to replicate also the classic decision tree [17], with stronger robustness and generalisation ability.

The integrated fingertip sensor was mounted on a PUMA robot arm; simple compliant control algorithm was used to slide the sensor over the surface of different objects with constant pressure, speed and inclination. At the same time the three different sensorial modalities were acquired and a camera took the object image.

5.2 Data acquisition and system description

The system global architecture is depicted in Fig. 4.

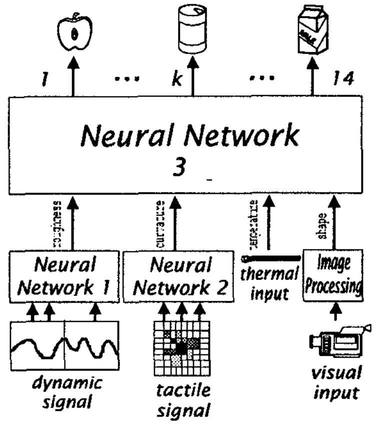


Fig. 4. Global system architecture design

For each object, the signals were acquired twice: the first signals were for the training set while the second for the validation test set.

The system comprised two levels of NN: the first was aimed at features extraction from the tactile and dynamic signals; and the second, fed by the output of the previous NN, the output of the visual recognition module and by the direct thermal sensor output, was aimed at recognition. All of the inputs to the NNs were first normalised. Since the output of the NN is computed by a sigmoidal function limited between 0 and 1, we assume that the 0 was represented by the value 0.1 and 1 by the value 0.9.

At the first level, two windows of 256 dynamic samples each (512 input nodes) were taken from the dynamic sensor and sent to a first NN. This NN (NN1) was trained to produce as output a fuzzy value in the range [0.1 ... 0.9] were the left extreme represents a smooth surface and the right value a very irregular one. At the same level, a single stable tactile 8x8 image was sent to a second parallel NN with the task of classifying the surface curvature. As output, the NN (NN2) produced a single fuzzy value in the range [0.1 ... 0.9], where 0.1 was for planar surface and 0.9 for curved surface.

In Table 3 the values used for each object in the training are presented.

	Dynamic score	Thermal score	Tactile Score	Visual Score
barley-coffee (can)	0.15	0.5	0.8	1
green olives (glass)	0.1	0.3	0.9	1
black olives (can)	0.1	0.1	0.9	1
peaches (can)	0.7	0.1	0.85	1
peeled tomatoes (can)	0.9	0.1	0.8	1
orange fruit	0.7	0.3	0.75	4
apple fruit	0.2	0.3	0.7	4
sponge	0.95	0.7	0.2	1
soap bar	0.15	0.9	0.1	1
zucchini	0.3	0.3	0.8	2
cucumber	0.6	0.3	0.8	2
glass bottle	0.1	0.3	0.75	3
plastic bottle	0.85	0.9	0.2	3
milk (box)	0.15	0.5	0.2	1

Table 3

The visual image of the object was analysed by a separate module able to distinguish, in our examples, between four basic shapes of the objects included in our scenario: regular parallelepiped (1), elongated parallelepiped (2), bottle (3) and circle (4).

The thermal output was sent directly to the second level NN after a delay and a normalization procedure.

In the second level, a final NN (NN3) is fed by a seven mixed values vector x=[x1,x2,x3,x4], were x1 is the fuzzy dynamic value, x2 the fuzzy tactile value, x3 the thermal value and x4 a four binary component describing the shape of the object.

5.3 Neural Network description

The neural network was implemented by the well known Back Propagation (BP) algorithm [18], with the momentum variation [19]. Back Propagation is a supervised learning algorithm able to train a feed-forward network to be an universal approximator of any mapping functions from a N-dimensional input to a M-dimensional output; at each iteration the network is presented with the actual input and the expected target value. Since at the first iteration the net internal parameters (connection weights) are generated randomly, the approximation error would be large. Thus the learning algorithm operates a gradient descent on the surface of the error with an iterative process moving along the negative derivative until the error is significantly reduced to a tolerance value specified by the user. That is when for each input the net produces a near approximation of the expected output. In our experiments, all the NNs included three levels of units: INPUT, HIDDEN and OUTPUT units. The first level received the inputs, the last produced the output and the hidden level operated non-linear transformations. Table 4 shows the dimensions of the different NNs used in our experiments.

	Dynamic NN1	Tactile NN2	Recognition NN3
Input units	512	64	7
Hidden units	150	20	12
Output units	1	1	14
Tolerance	0.05	0.05	0.1

Table 4

Each units is fully connected to the following level and each connection has a weight parameter. The hidden and output level units perform a weighted sum of their input and the result is transformed by a sigmoid function. The learning algorithm changes the weights associated to each units by back propagating the error from the output level to the hidden level. A momentum variation was introduced in order to speed up the convergence time. The variation adds to each weight a fraction of the previous variation to enhance the direction of the gradient descent. The BP with momentum variation algorithm is the following:

$$w(t+1) = w(t)+\Delta w+k_1 w_{old}$$
$$\Delta w = k_2 \delta_{error} inp$$

where **w** is the weight vector, $\mathbf{k_1}$ and $\mathbf{k_2}$ constant, $\boldsymbol{\delta_{error}}$ is an error function proportional to the negative gradient and **inp** is the node input.

After the training phase, we made a validation phase to test the NN capability to generalise and to discriminate patterns never seen before.

5.4 Discussion

The NN1 network has a large number of input and hidden nodes, so that the simulation takes many hours to learn how to perform the dynamic analysis of the surface (on a PC Pentium 166MHz). However in the validation phase the NN1 network showed high tolerance to noise.

The NN2 network has lower performance since the tactile image does not have a good resolution. However the training made it able to perform the required task with a sufficient precision.

The NN3 network has few nodes and reached the convergence in 855 iterations, in a time of 44 s and an error tolerance of 10%. The network has an output node for each object to recognise, each one with its ordinal number. If the output unit with the major activation value (about 0.9) is N, the object class is N and the other 13 units have a small value (near 0.1); so tolerance level of 10% is very large.

The validation phase consisted in testing the NN system with the validation set (with which the network was not trained). In this test, recognition was obtained with a success of 100%. In fact, thanks to the robustness of a distributed system like this, the generalisation capability is remarkable. This was evident when in the test, the thermal and visual value remained almost the same, while the dynamic and tactile values varied with less or more slight changes: the NN3 network was yet able to reach a total success classifying in the right way the new sensed object.

In our NN simulations, the use of fuzzy output gave us further information about the nature of the signal under examination. In fact, we interpret the final net result as the node with the higher activity (first hypothesis); in the meanwhile, if the other nodes have a low activity the first hypothesis is the only acceptable for the network, otherwise significant activities (>0.5) in the other output nodes can suggest secondary hypothesis about the class membership of the sensed object. For instance, when we analyse the net result with the values of cucumber obtained in the training phase as input, its related output node has an activity of 0.91 and the others are at 0.1/0.25, but when we perturbate lightly the roughness fuzzy value (moving it towards the zucchini relative value) we obtain 0.9 for cucumber output node and 0.7 for zucchini output node: "it is probably a cucumber, otherwise a zucchini" (which are actually very similar).

6. Conclusions

In this paper we presented an integrated approach to tactile perception, by describing the design and development of an integrated miniature tactile sensor and the implementation of a neuro-fuzzy network for data acquisition and interpretation. Innovative aspects of the proposed approach especially regard the integration of tactile perception at low level, according to the anthropomorphic model of tactile sensing. Experimental trials, carried out in the case of object sorting, demonstrated the validity of the proposed integrated approach, showing a high tolerance to noise and a high generalisation ability given by the neuro-fuzzy structure.

Future developments of the proposed work concern the planning of proper motor strategies, based on tactile feedback, for purposive exploration of objects and for object manipulation.

Possible applications are all fields involving robot capability of exploration and manipulation, such as service robotics (personal assistance, medical care), surgery, industrial assembly/disassembly processes. The integrated fingertip can also be improved as a prosthetic sensor.

References

[1] Howe, R.D., and Cutkosky, M.R. 1992. "Touch Sensing for Robotic Manipulation and Recognition", in O. Khatib, J.J. Craig and T. Lozano-Perez (Eds) *"The Robotics Review 2"*, pp. 55-112, MIT Press, Cambridge, MA.

[2] Dario, P. 1989. "Tactile Sensing for Robots: Present and Future", in O. Khatib, J.J. Craig and T. Lozano-Perez (Eds) *"The Robotics Review"*, pp. 133-146, MIT Press, Cambridge, MA.

[3] Russel, R.A. 1990. *Robot Tactile Sensing*, Prentice Hall, New York, NY.

[4] Bicchi, A., Salisbury, J.K., and Brock, D.L. 1993. "Contact sensing from force measurement", *International Journal of Robotics Research*, 12 (3): pp.249-262.

[5] Bajcsy, R. 1988. "Active Perception", *Proceedings of the IEEE*, 76 (8), pp.996-1005.

[6] Ledermann, S.J., and Klatzky, R.L. 1987. "Hand movaments: a window into haptic object recognition", *Cognitive Psychology*, 19, pp.342-368.

[7] Stansfield, S.A. 1990. "Haptic perception with an articulated, sensate robot hand", SANDIA Report 0085, UC-406, Sandia National Laboratories, Albuquerque, NM, USA.

[8] Dario, P., Ferrante, P., Giacalone, G., Livaldi, L., Allotta, B., Buttazzo, G., Sabatini, A.M. 1992. "Planning and executing tactile exploratory procedures", *Proc. of the International Conference on Intelligent Robots and Systems (IROS '92)*, Raleigh, NC, USA, July 1992, pp.1896-1903.

[9] Bajcsy, R.K., and Allen, P.K., 1986. "Multisensor integration", *Encyclopedia of Artificial Intelligence*, Wiley, New York, pp.632-638.

[10] Hager, G.D. 1990. *Task-directed sensor fusion and planning*, Kluwer, Boston.

[11] Beger, A., and Khosla, P. 1991. "Using tactile data for real-time feed-back", International *Journal of Robotics Research*, 10(2), pp.88-102.

[12] Rucci, M., and Dario, P. 1994. "Development of Cutaneo-Motor Co-ordination in an Autonomous Robotic System", *Autonomous Robots*, pp. 93-106, Kluwer Academic Publishers, Boston, MA.

[13] Gaudiano, P., and Grossberg, S. 1991. "Vector associative maps: unsupervised real-time error-based learning and control of movement trajectories", *Neural Networks*, 4, pp.147-183.

[14] Dario, P., Lazzarini, R., Magni, R., Oh, S.R. 1996. "An integrated miniature fingertip sensor", *accepted for the 7th International Symposium on Micro Machine and Human Science (MHS '96)*, Nagoya, Japan, October 2-4.

[15] Lazzarini, R., Magni, R., Dario, P. 1995. "A tactile array sensor layered in an artificial skin", *Proc. of the International Conference on Intelligent Robots and Systems (IROS '95)*, Pittsburgh, Pennsylvania, USA, August 5-9, pp.114-119.

[16] Sandini, G., Dario, P., De Micheli, M., Tistarelli, M. 1993. "Retina-like CCD sensor for active vision", *Robots and Biological Systems*, P. Dario, G. Sandini, P. Aebischer Eds., Berlin-Heidelberg, Springer-Verlag, pp. 553-570

[17] Dario, P., Rucci, M., Guadagnini, C., Laschi, C., 1994. "An investigation on a robot system for disassembly automation", *Proc. of the 1994 IEEE* International *Conference on Robotics and Automation*, San Diego, California, USA, may 8-13, pp.3515-3521.

[18] Rumhelhart, D., Mc Clelland, J. 1986. *Parallel Distributed Processing*, Cambridge, Massachusetts, MIT Press.

[19] Freeman, J., Skapura, D. 1991. *Neural Networks: Algorithms, Applications and Programming Techniques*, Reading, Massachusetts, Addison Wesley.