A&QT-R 2002 (THETA 13)
International Conference on Automation, Quality and Testing, Robotics
May 23 – 25, 2002, Cluj-Napoca, Romania

COMPETITIVE PYRAMIDAL NEURAL NETWORKS OF PROBABILISTIC LOGIC NODES PLN AND THEIR APPLICATIONS AS MEDICAL IMAGING TOOLS

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Abstract. The paper analyses the applications of artificial intelligence represented by competitive pyramidal neural networks of probabilistic logic nodes PLN on the newest Medical Imaging noninvasive techniques and tools. The paper presents the training algorithm of PLN pyramidal nets with specific images of lesions obtained using the noninvasive tools Magnetic Resonance Imaging MRI, Computed Tomography Imaging CTI and Multislice Spiral Computed Tomography MSCT. The paper emphasized the very high sensitivity of this new pyramidal neural nets application to small differences of medical image patterns. Using the easy of access information furnished now by Picture Archiving and Communication Systems PACS and a performant software as V+ and Adept Vision it is possible to apply PLN pyramidal nets as the medical imaging tool to forecast vascular lesions, especially for peripheral arteries.

Keywords: Neural Networks, Pattern Recognition, Artificial Intelligence, Medical Imaging

1. INTRODUCTION

Medical imaging problems typically use sensing methods with very different underlying physics: Magnetic Resonance Imaging MRI, X rays, and Computed Tomography CT. Medical imaging problems often deal with flexible, deformable, geometrically intricate objects, such as the surface of cortex or the bronchial structure of the lungs. Despite the apparent differences in underlying bases, developments over the past few decades in computer vision are beginning to revolutionize the use of medical images in surgery, diagnosis, and therapy evaluation.

Kaufman (1990) used neural models to assess healing in bone fractures. Today MRI technique is currently used as a standard diagnostic tool. The accurate and reproductible interpretation of an MRI, as performed by a highly trained physician, remains an extremely time-consuming and costly task. Ozkan (1990) used a three-layer backpropagation network with three units in the input layer and four units in the output layer as a supervised classifier to analyze MRI images.

Neural network models based on the Boundary Counter System BCS and on the Feature Counter System FCS have been used for medical imaging by Lehar (1990). Then Vannier (1991) used statistical classifiers such as the minimum distance, maximum likelihood, and parallelipiped to analyze MRI scans of the head. The classifiers were tested for their ability to discriminate six categories such as the gray and white matter of the brain, cerebrospinal fluid, edema, fat, and abnormal tissue (tumors and cysts).

Kulkarni (1995) used a fuzzy neural network to recognize six homogeneous areas, each of size 5 scans by 5 pixels. The areas represent training sets for the above six categories. The fuzzy neural network used consists of six layers. The model was trained with training-set data obtained by selecting regions of interest in the image [14].

2. MEDICAL IMAGING NONINVASIVE NEW TECHNIQUES AND TOOLS

The powerful noninvasive techniques Magnetic Resonance Imaging MRI, Computed Tomography Imaging CTI, and Multislice Spiral Computed Tomography MSCT can offer useful medical images with high accuracy. It can say now a new era in technological development for MRI, CTI and MSCT is under way, especially after the spectacular increasing of data storing, archiving, recovering and using based on Picture Archiving and Communication Systems PACS [2], [8], [9], [13], [15], [16].

The Magnetic Resonance Imaging MRI [8] has developed greately as Magnetic Resonance Angiography MRA [9] and now enjoy widespread applications in its newest form Contrast-Enhanced MR Angiography CEMRA [15].

The imaging modality that most closely resembles peripheral CEMRA is Computed Tomography Angiography CTA. Imaging of the complete outflow arteries is now feasible with multislice scanners used in Multislice Spiral Computed Tomography MSCT. Early spiral CT scanners were of limited use for vascular applications because of the conflicting demands of anatomical coverage and longitudinal spatial resolution. Single-slice spiral CT required compromises because thin slices provide high spatial resolution over a relatively small anatomical coverage, whereas thick slices cover a larger area but give only low spatial resolution [11].

Multislice Spiral Computed Tomography MSCT overcomes the fundamental limitations of the single-slice technique, allowing a larger anatomical volume to be scanned with thinner collimation and in a shorter time, while producing images with high spatial resolution [10], [16]. Images of variable thickness can be reconstructed, and they benefit from narrow collimation because partial volume artifacts are drastically suppressed. Repeated scanning is no longer required, minimizing exposure to x-rays. The contrast dose can also be reduced as a result of the shorter acquisition time. Other advantages of MSCT include the ability to examine during optimal contrast-enhancement and to perform multiphase organ studies. Postprocessing results such as angiographic reconstruction are also improved, and 3D isotropic resolution is feasible for improved volume rendering.

Postprocessing of medical images increased in quality and performances after the Picture Archiving and Communications System PACS have been installed in hospitals since 1990, mainly due to improvements in hardware and software [13], [17].

PACS is principally a digital tool to facilitate certain parts of the work of diagnostics. Its implementation requires a new vision of diagnostic radiology as a whole, including new aspects of radiation protection and heightened expectations among patients and healthcare professionals. New concepts in diagnostic reasoning are based on the understanding that radiology is shifting from a discipline for image generation and interpretation to an extensive real-time process-oriented information service.

The amount of data produced in a clinical large radiology department per year is now in the range of several terabytes. Such enormous image libraries can only be archived in a digital form with a well-developed system architecture that offers optimal access to images. Internet or Intranet systems with their inherent logic of Hypertext Markup Language HTML are used with growing frequency [7]. Using JavaScript, examinations can be viewed with Web browsers. This capability, offered by many PACS companies, is emerging as a “de facto” standard for image viewing. This technical evolution merges the concepts of PACS, teleradiology and fuzzy-neural networks into global image management and communication systems [14].

3. COMPETITIVE PYRAMIDAL NEURAL NETWORKS OF PROBABILISTIC LOGIC NODES PLNs

Neural networks represent networks of adaptable nodes which, through a process of learning from task examples, store experiential knowledge and make it available for use. The process of storing experiential knowledge can be understand using the device called Probabilistic Logic Node PLN [1], [3], [12], [14], [18].

The Probabilistic Logic Node PLN can be defined as a RAM-neuron which, instead of storing just 0 and 1 for each pattern input j, stores P_j which is a string of bits that encode a number between 0 and 1 representing the probability of firing (producing a 1). The RAM memories that constitute the PLN structure store only three messages: 0 when the neuron always outputs 0, 1 when the neuron always output 1, and “x” when the neuron outputs 0 and 1 randomly with equal probability.

The piramidal neural network is a fully connected net for which each node is a pyramid of PLNs. Each pyramid as a network of cells is defined with three parameters: the width W, the depth D , and the number of inputs per cell N. These fundamental parameters respect the following relationship:

$$W = N^D; \quad D = \ln W / \ln N \qquad (1)$$

Each pyramid will contain hidden units. This means that an error is known only for the output of the entire pyramid rather than for each PLN, ant it is therefore necessary to find a way of training the intermediate layers. An untrained PLN pyramid will output 0 and 1 with equal probability in response to any input patterns as all the nodes containe only “x” values. This means too that it practically starts with 50 % errors.

For our application of pyramidal neural networks for medical imaging we used a training algorithm verified for a single pyramid. The training algorithm has the following 4 steps:

1. Identify the training set. This must consist first of a set marked Z0 of input patterns for which the response is to be 0, so Z0 = ($z0_1$, $z0_2$, … $z0_m$). Similarly we can define the set for which the pyramid must respond with a 1, that is Z1 = ($z1_1$, $z1_2$, … $z1_n$).

2. Select the training regime. This refers to any specific way in which the two sets defined above are to be presented to the net. The two sets can be applied in random order, interleaved, or one after the other. In general the fully learned solution may not depend on the selected regime, but in quoting experimental results it is always worth stating this training regime.

3. For the first training pattern applied to the input, if the the output is consistently right (e.g. remains at j for a pattern that belongs to Z_j) the state of the pyramid net remains unchanged. If the output is varying in time between 0 and 1, as soon as it becomes right, will be examined the current output for all nodes and store it. This means

that all the nodes whose input currently addresses a "x" will have the "x" replaced by their current output (which, as a result of the "x", has been arbitrarily selected). If the output is consistently wrong, all nodes that output a consistent output (i.e. do not have their "x" addressed) have the content of their stored location returned to "x".

4. Repeat applying the training pattern according to the regime until no errors are detected or the error rate reaches an irreductible minimum.

The above algorithm was applied in case of a two-layer pyramid of 3 input PLNs (first layer, PLN1, PLN2, PLN3) and 1 output PLN (second layer, PLN4), with, consequently nine inputs and one output. The nine inputs are arranged as a 3 x 3 matrix and the training set consist of set Z0 and set Z1 having their terms interleaved into a specific learned solution:

$$Z0 = (z0_1, z0_2, z0_3)$$
$$Z1 = (z1_1, z1_2, z1_3) \qquad (2)$$
$$\text{Training} = z1_1, z0_1, z1_2, z0_2, z1_3, z0_3$$

The training results of pyramide probabilistic logic nodes PLNs on inputs $z1_1$, $z0_1$ are presented in table 1, on inputs $z1_2$, $z0_2$ in table 2, and on inputs $z1_3$, $z0_3$ in table 3.

Training of probabilistic logic nodes PLNs on inputs $z1_1$, $z0_1$ Table 1

INPUT Addresses			Probabilistic logic nodes PLN											
			Initial state				After training on $z1_1$			100 100 100	After training on $z0_1$			111 000 000
			PL N1	PL N2	PL N3	PL N4	PL N1	PL N2	PL N3	PL N4	PL N1	PL N2	PL N3	PL N4
0	0	0	X	X	X	X	X	X	X	X	X	0	1	X
0	0	1	X	X	X	X	X	X	X	X	X	X	X	X
0	1	0	X	X	X	X	X	X	X	X	X	X	X	X
0	1	1	X	X	X	X	X	X	X	1	X	X	X	1
1	0	0	X	X	X	X	0	1	1	X	0	1	1	X
1	0	1	X	X	X	X	X	X	X	X	X	X	X	0
1	1	0	X	X	X	X	X	X	X	X	X	X	X	X
1	1	1	X	X	X	X	X	X	X	X	1	X	X	X

Training of probabilistic logic nodes PLNs on inputs $z1_2$, $z0_2$ Table 2

INPUT Addresses			Probabilistic logic nodes PLN											
			Initial state				After training on $z1_2$			010 010 010	After training on $z0_2$			000 111 000
			PL N1	PL N2	PL N3	PL N4	PL N1	PL N2	PL N3	PL N4	PL N1	PL N2	PL N3	PL N4
0	0	0	X	X	X	X	X	0	1	X	1	0	1	X
0	0	1	X	X	X	X	X	X	X	X	X	X	X	X
0	1	0	X	X	X	X	1	1	0	X	1	1	0	X
0	1	1	X	X	X	X	X	X	X	1	X	X	X	1
1	0	0	X	X	X	X	0	1	1	X	0	1	1	X
1	0	1	X	X	X	X	X	X	X	0	X	X	X	0
1	1	0	X	X	X	X	X	X	X	1	X	X	X	1
1	1	1	X	X	X	X	1	X	X	X	1	1	X	0

Training of probabilistic logic nodes PLNs on inputs $z1_3$, $z0_3$ Table 3

INPUT Addresses			Probabilistic logic nodes PLN											
			Initial state				After training on $z1_3$			001 001 001	After training on $z0_3$			000 000 111
			PLN1	PLN2	PLN3	PLN4	PLN1	PLN2	PLN3	PLN4	PLN1	PLN2	PLN3	PLN4
0	0	0	X	X	X	X	1	0	1	1	1	0	1	1
0	0	1	X	X	X	X	0	0	0	X	0	0	0	X
0	1	0	X	X	X	X	1	1	0	X	1	1	0	X
0	1	1	X	X	X	X	X	X	X	1	X	X	X	1
1	0	0	X	X	X	X	0	1	1	X	0	1	1	0
1	0	1	X	X	X	X	X	X	X	0	X	X	X	0
1	1	0	X	X	X	X	X	X	X	1	X	X	X	1
1	1	1	X	X	X	X	1	1	X	0	1	1	0	0

The analysis of the tables shows that the output of the pyramid will produce a 1 with following response probability RP:

$$RP\ [\%] = 100\ [1 - (1/2)^D] \quad (3)$$

The number of locations per each node LPN having N inputs is:

$$LPN = 2^N \quad (4)$$

The number of total pyramid nodes T(N,D) is in line with the equation:

$$T(N,D) = (W - 1) / (N - 1) = (N^D - 1) / (N - 1) \quad (5)$$

The storage capacity C of the entirely competitive pyramidal neural network is:

$$C = (LPN) * T(N,D) = (2^N) * (N^D - 1) / (N - 1) \quad (6)$$

We made an analysis of the parameters above for the chosen piramidal neural networks of PLNs destinated for medical imaging applications, and the results are presented in table 4. The results show that for a fixed W, the higher the value of N, the smaller response probability RP will be. This emphasizes the particular characteristic of the pyramid net that distinguishes it strongly from other nets, that is the possibility to make the pyramid net very sensitive to small differences in patterns. This quality strongly recommends it as being very suited for medical imaging.

Analysis for medical imaging piramidal neural networks of PLNs Table 4

Width W	Inputs per cell N	Depth D	Response Probabil. RP [%]	Location per node LPN	Total nodes T(N,D)	Storage Capacity C
Equation	(1)	(1)	(3)	(4)	(5)	(6)
16	2	4	93.8	2^2	15	60
	4	2	75.9	2^4	5	80
	16	1	50.0	2^{16}	1	65,536
256	2	8	99.6	2^2	255	1020
	4	4	93.8	2^4	85	1360
	16	2	75.0	2^{16}	17	$17*2^{16}$

4. CONCLUSIONS

The paper analyses the applications of artificial intelligence represented by competitive pyramidal neural networks of probabilistic logic nodes PLN in Medical Imaging. The paper presents the training algorithm of PLN pyramidal nets with specific images of lesions obtained using the newest medical imaging noninvasive tools. The paper emphasizes among other qualities the very high sensitivity of this new pyramidal neural nets application to small differences of medical image patterns.

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