

Towards Paraconsistent Neuroscience: a Review Paper on Some Applications of PANN

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Abstract: - In this expository work, we sketch some applications of a new theory of Artificial Neural Network - ANN, based on a paraconsistent annotated evidential logic $E\tau$. Such theory, called Paraconsistent Artificial Neural Network - PANN - has as characteristics the capability of manipulating uncertain, inconsistent and paracomplete concepts directly without trivialization. PANN differs from other usual ANNs which are based on classical logic or in some of its extensions. Some aspects such as the capability of adaptation, velocity processing, and other useful characteristics make the PANN a promising theory. Although there are some essential non-classical approaches for reasoning (v.g Fuzzy Set Theory) in this paper, we discuss how PANN can be a basis for a reasoning model for the human brain. As the logic $E\tau$ encompasses the classical logic and Fuzzy reasoning, we believe that PANN can be the basis for a new model for the computational scope of the Neuroscience.

Key-Words: - Paraconsistent Logic, Artificial Neural Network, Neurocomputation, Annotated Logic, Para-analyzer, Pattern Recognition, Biomedicine

1 Introduction

The Artificial Neural Network has been extensively studied in AI, so it has interesting applications. Nowadays a great deal of effort is focussed on the development of artificial neural networks for applications such as data compression, classification, pattern recognition, and optimization. For instance, it has turned out to be a useful tool for pattern recognition. Several theories of artificial neural networks have been proposed with different characteristics. In this paper, we discuss a new theory of artificial neural network based on a paraconsistent annotated logic $E\tau$.

The atomic formulas of the paraconsistent annotated logic $E\tau$ is composed by two components: we write as $p_{(\mu, \lambda)}$, where $(\mu, \lambda) \in [0, 1]^2$ ($[0, 1]$ is the real unitary interval and p denotes a propositional variable). An order relation is defined on $[0, 1]^2$: $(\mu_1, \lambda_1) \leq (\mu_2, \lambda_2) \Leftrightarrow \mu_1 \leq \mu_2$ and $\lambda_2 \leq \lambda_1$, constituting a lattice that will be symbolized by τ . A detailed account of annotated logics is to be found in [1, 4].

$p_{(\mu, \lambda)}$ can be intuitively read: “It is assumed that p ’s belief degree (or favorable evidence) is μ and disbelief degree (or contrary evidence) is λ .” Thus, $(1.0, 0.0)$ intuitively indicates total belief, $(0.0, 1.0)$ indicates total disbelief, $(1.0, 1.0)$ indicates total inconsistency, and $(0.0, 0.0)$ indicates total paracompleteness (absence of information). The operator $\sim : | \tau | \rightarrow | \tau |$ defined in the lattice $\sim [(\mu, \lambda)] = (\lambda, \mu)$ works as the “meaning” of the logical negation of $E\tau$.

The consideration of the values of the belief degree and disbelief degree is made, for example, by specialists who use heuristics knowledge, probability or statistics.

We can consider several important concepts (all considerations are taken with $0 \leq \mu, \lambda \leq 1$):

Segment DB - segment perfectly defined:

$$\mu + \lambda - 1 = 0$$

Segment AC - segment perfectly undefined: $\mu - \lambda = 0$

Uncertainty Degree: $G_{un}(\mu, \lambda) = \mu + \lambda - 1$;

Certainty Degree: $G_{ce}(\mu, \lambda) = \mu - \lambda$;

With the uncertainty and certainty degrees, we can get the following 12 regions of output: *extreme states* that are, False, True, Inconsistent and Paracomplete, and *non-extreme states*. All the states are represented in the lattice of the next figure: the usual Cartesian system can represent such lattice.

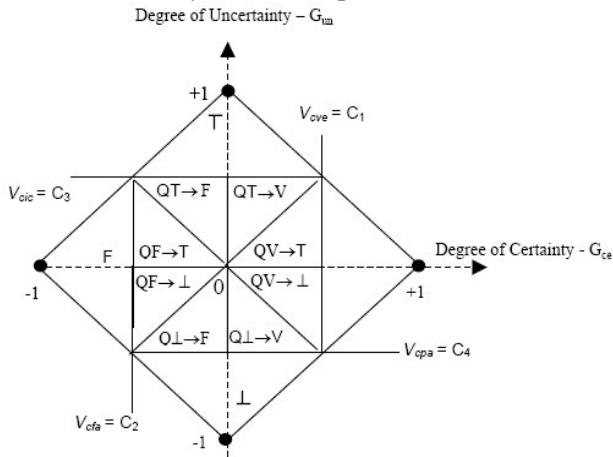


Fig. 1 - Representation of the certainty degrees and contradiction degrees

These states can be described with the values of the certainty degree and uncertainty degree using suitable equations. In this work, we have chosen the resolution 12 (number of the regions considered according to the Figure 1), but the resolution is entirely dependent on the precision of the analysis required in the output, and it can be externally adapted according to the applications.

So, such limit values called Control Values are:

- $V_{cic} = \text{maximum value of uncertainty control} = C_3$
- $V_{cve} = \text{maximum value of certainty control} = C_1$
- $V_{cfa} = \text{minimum value of uncertainty control} = C_2$
- $V_{cpa} = \text{minimum value of certainty control} = C_4$

For the discussion in the present paper we have used: $C_1 = C_3 = 1/2$ and $C_2 = C_4 = -1/2$.

Table 1. Extreme and Non-extreme states.

Extreme States	Symbol
True	V
False	F
Inconsistent	T
Paracomplete	⊥
Non-extreme states	Symbol
Quasi-true tending to Inconsistent	QV→T
Quasi-true tending to Paracomplete	QV→⊥
Quasi-false tending to Inconsistent	QF→T
Quasi-false tending to Paracomplete	QF→⊥
Quasi-inconsistent tending to True	QT→V
Quasi-inconsistent tending to False	QT→F

Quasi-paracomplete tending to True	$Q⊥→V$
Quasi-paracomplete tending to False	$Q⊥→F$

2 The Paraconsistent Artificial Neural Cells

In the paraconsistent analysis, the main aim is to know how to measure or to determine the certainty degree concerning a proposition if it is False or True [9]. Therefore, for this, we take into account only the certainty degree G_{ce} . The uncertainty degree G_{un} indicates the measure of the inconsistency or paracompleteness. If the certainty degree is low or the uncertainty degree is high, it generates a state that is called indefinición.

The resulting certainty degree G_{ce} is obtained as follows:

If: $V_{cfa} \leq G_{un} \leq V_{cve}$ or $V_{cic} \leq G_{un} \leq V_{cpa} \Rightarrow G_{ce} = \text{Indefinition}$

For: $V_{cpa} \leq G_{un} \leq V_{cic}$

If: $G_{un} \leq V_{cfa} \Rightarrow G_{ce} = \text{False}$ with degree G_{un}

$V_{cic} \leq G_{un} \Rightarrow G_{ce} = \text{True}$ with degree G_{un}

The algorithm that expresses a fundamental Paraconsistent Artificial Neural Cell - PANC - is:

* /Definition of the adjustable values * /

$V_{cve} = C_1$ * maximum value of certainty control * /

$V_{cfa} = C_2$ * / minimum value of certainty control * /

$V_{cic} = C_3$ * maximum value of uncertainty control * /

$V_{cpa} = C_4$ * minimum value of uncertainty control * /

* Input /Variables * /

μ, λ

* Output /Variables *

Digital output = S1

Analog output = S2a

Analog output = S2b

* /Mathematical expressions * /

begin:

$0 \leq \mu \leq 1$ e $0 \leq \lambda \leq 1$

$G_{un} = \mu + \lambda - 1$

$G_{ce} = \mu - \lambda$

* / determination of the extreme states * /

if $G_{ce} \geq C_1$ then $S_1 = V$

if $G_{ce} \geq C_2$ then $S_1 = F$

if $G_{un} \geq C_3$ then $S_1 = T$

if $G_{un} \leq C_4$ then $S_1 = \perp$

If not: $S_1 = I - \text{Indetermination}$
 $G_{un} = S_{2a}$
 $G_{ce} = S_{2b}$

A PANC is called *basic* PANC when given a pair (μ, λ) is used as input and resulting as output: G_{un} = resulting uncertainty degree, G_{ce} = resulting certainty degree, and X = constant of Indefinition, calculated by the equations $G_{un} = \mu + \lambda - 1$ and $G_{ce} = \mu - \lambda$

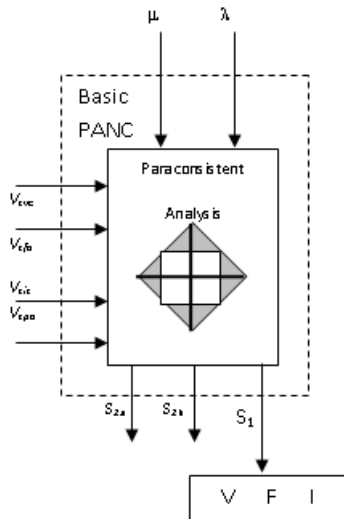


Fig. 2 - The Basic Paraconsistent Artificial Neural Cell

3 The Paraconsistent Artificial Neural Cell of Learning

A Paraconsistent Artificial Neural Cell of Learning – PANC-L is obtained from a basic PANC.

In this learning Cell, sometimes we need the action of the operator Not in the training process. Its function is to do the logical negation in the resulting output sign. For a training process, we consider a PANC of Analytic Connection the one not undergoing any learning process.

According to the paraconsistent analysis, a cell in these conditions has two inputs with an Indefinite value $\frac{1}{2}$.

So, the basic structural equation yields the same value $\frac{1}{2}$ as output. As a result, we get an indefiniton. For a detailed account see [9].

4 The Learning of a Panc-L

The learning cells can be used in the PANN as memory units and pattern sensors in primary layers. For instance, a PANC-L can be trained to learn a pattern by using an algorithm. For the training of a cell, we can use as a pattern, real values between 0

and 1. The cells can also be trained to recognize values between 0 and 1.

The learning of the cells with extreme values 0 or 1 composes the primary sensorial cells. Thus, the primary sensorial cells consider as a pattern a binary digit where the value 1 is equivalent to the logical state True, and the value 0 is equivalent to the logical state False. The appearance of the input 0 repeated times means that the resulting belief degree is going to increase gradually in the output reaching the value 1. In these conditions, we say that the cell has learned the falsehood pattern.

The same procedure is adopted when the value 1 is applied to the input repeated times. When the resulting belief degree in the output reaches the value 1 we say that the cell has learned the truth pattern. Therefore a PANC can learn two types of patterns: the truth pattern or the falsity pattern. In the learning process of a PANC, a learning factor can be introduced (LF) that is externally adjusted. Depending on the value of LF, it gives the cell a faster or slower learning. In the learning process, given an initial belief degree $\mu_r(k)$, we use the following equation to reach $\mu_r(k) = 1$, for some k.

So, for truth pattern we have

$$\mu_r(k+1) = \frac{(\mu_r - \mu_r(k))LF + 1}{2} \quad (1)$$

where $\mu_r(k)_c = 1 - \mu_r(k)$, and $0 \leq LF \leq 1$. For falsity pattern, we have

$$\mu_r(k+1) = \frac{(\mu_{1c} - \mu_r(k)_c)LF + 1}{2} \quad (2)$$

where $\mu_r(k)_c = 1 - \mu_r(k)$, $\mu_{1c} = 1 - \mu_1$, and $0 \leq LF \leq 1$

So we can say that the cell is completely learned when $\mu_r(k+1) = 1$.

If $LF = 1$, we say that the cell has a natural capacity for learning. Such capacity decreases as LF approaches 0. When $LF = 0$, the cell loses the learning capacity, and the resulting belief degree will always have the indefiniton value $\frac{1}{2}$.

5 Unlearning of a Panc-L

Even after having a cell trained to recognize a particular pattern, if insisently the input receives a value entirely different, the high uncertainty makes the cell unlearn the pattern gradually.

The repetition of the new values implies in a decreasing of the resulting belief degree. Then, the analysis has reached an indefiniton. By repeating this value, the resulting belief degree reaches 0 meaning that the cell is giving the null belief degree

to the former proposition to be learned. This is equivalent to saying that the cell is giving the maximum value to the negation of the proposition, so the new pattern must be confirmed.

Algorithmically, this is shown when the certainty degree G_{ce} reaches the value -1 . In this condition, the negation of the proposition is confirmed. This fact is obtained by applying the operator Not to the cell. It inverts the resulting belief degree in the output.

From this moment on the PANC considers as a new pattern the new value that appeared repeatedly and unlearning the pattern learned previously. By examining two factors, LF – learning factor and UF – unlearning factor, the cell can learn or unlearn faster or slower according to the application.

These factors are relevant giving the PANN a more dynamic process.

6 Applying in Alzheimer Disease

Several studies on behavioral and cognitive neurology have been conducted to characterize dementias through biological and functional markers. For instance, the electroencephalographic (EEG) activity, aimed at understanding the evolution of Alzheimer disease (AD), by following its progression, allowing toward better diagnostic criteria for early detection of cognitive impairment [21]. As far as we know, it seems that there is no method able to determine a definitive diagnosis of dementia, where a combination of tests would be necessary to obtain a probable diagnosis [22].

The EEG activity is a record of brain's electrical activity, providing a space-time representation of synchronic postsynaptic potentials. The main generating sources of these electrical fields are most likely perpendicular to the cortical surface, such as in the cortical pyramidal neurons.

About EEG visual analysis, several studies have shown that it is useful in aiding AD diagnosis, being indicated in some clinical protocols. It is well known that during the relaxed, awake state, normal EEG in adults is predominantly composed of the alpha band frequency, which is generated by interactions of the slum-cortical and thalamocortical systems. It is observed that in visual EEG analysis the most common finding is the slowing down of brain electrical activity compounds concerning delta and theta rhythms. Also, one notices the diminution or even the absence of the alpha rhythm. However, it is known that such findings are related to the moderate and advanced stages of AD [21].

In [14] 67 examinations were performed, and PANN has classified as follows:

Table 2 - Diagnosis – Normal individual x Probable AD patients

<i>Gold Standard</i>			
	A.D. Patient	Normal individual	Total
A.D. Patient	35.82%	14.93%	50.75%
Normal individual	8.96%	40.30%	49.25%
Total	44.78%	55.22%	100.00%
Sensitivity:	0.80		
Specificity:	0.73		
Index of coincidence (Kappa):	0.76		

7 Applying in Attention-Deficit/Hyperactivity Disorder (ADHD)

Previous researchers show that about 10% of the world population in school-age suffer from learning and/or behavioral disorders caused by neurological problems, such as ADHD, dyslexia, and dyscalculia, with foreseeable consequences in those students' insufficient performance in the school [10], [11], [12].

Concisely, a child without intellectual lowering is characterized as the bearer of Attention-deficit/hyperactivity disorder (ADHD) when it presents signs of:

Inattention: difficulty in maintaining attention in tasks or games; the child seems not to hear what is spoken; the problem in organizing tasks or activities; the child loses things; the child becomes distracted with any incentive, etc.

Hyperactivity: frequently the child leaves the classroom; the child is always inconveniencing friends; the child runs and climbs in trees, pieces of furniture, etc; the child speaks a lot, etc.

Impulsiveness: the child interrupts the activities of colleagues; the child does not wait his time; aggressiveness crises; etc.

Dyslexia: a specific reading difficulty affecting children for whom reading achievement was below that expected by a child's age and intelligence quotient (IQ);

Dyscalculia: when the child presents difficulties to recognize amounts or numbers and/or to figure out arithmetic calculations.

A child can present any combination of the disturbances above. All those disturbances have their origin in a cerebral dysfunction that can have multiple causes, many times showing a hereditary tendency.

Since from the first discoveries, those disturbances have been associated to diffuse cortical lesions and/or more specific, temporal-parietal areas lesions in the case of dyslexia and dyscalculia [10, 11, 21].

The disturbances of ADHD disorder seem to be associated to an alteration of the dopaminergic system, that is, it is involved with mechanisms of attention, and they seem to involve a frontal-lobe dysfunction and basal ganglia areas [11] [21].

Such disturbances and alterations EEG seem to be associated. Thus, some authors have proposed that there be an increase of the Delta activity in EEG in those tasks that demand more extensive attention to the internal processes.

Other authors [17] have described alterations of the Delta activity in Dyslexia and Dyscalculia children sufferers. [14] has proposed that a phase of the EEG component would be associated with the action of the memory work. More recently, [17] had shown Delta activity is reduced in occipitals areas, but not in frontals, when dyslexic's children were compared with normal ones.

Thus, the study of the Delta and Theta bands becomes vital in the context of the analysis of learning disturbances.

So, in this paper, we have studied two types of waves, specifically Delta and Theta waves band, where the size of frequency established clinically ranges from 1.0 Hz to 3.5 Hz and 4.0 Hz to 7.5 Hz respectively.

Seven exams of different EEG were analyzed, being two exams belonging to adults without any learning disturbance and five exams belonging to children with learning disturbances (exams and several diagnoses given by ENSCER - Teaching the Brain, EINA - Studies in Natural Intelligence and Artificial Ltda).

Each analysis was divided into three tests; each rehearsal consisted of 10 seconds of the analyzed, free from visual analysis of spikes and artifacts regarding the channels T3 and T4.

In the first battery, it was used as a filter for recognition of waves belonging to the Delta band.

In the second battery, it was used as a filter for recognition of waves belonging to the Theta band. In the third battery it was not used any filters for recognition, i.e., the system was free to recognize any wave type. The total number of exams is 180.

Table 3. Contingency table. PANN Analysis

	Visual Analysis					Total
	Delta	Theta	Alpha	Beta	Unrecognized	
Delta	31	3	0	0	0	34
Theta	15	88	1	1	0	105

Alpha	0	5	22	0	0	27
Beta	0	0	1	3	0	4
N/D	7	2	1	0	0	10
Total	53	98	25	4	0	180

Kappa Index = 0.80

Table 4. Statistical results - sensitivity and specificity: Delta waves.

		Visual analysis		Total
		Delta	Not Delta	
PANN Analysis	True	31	124	155
	False	22	3	25
	Total	53	127	180

Sensitivity = 58%; Specificity = 97%

Table 5. Statistical results - sensitivity and specificity: Theta waves.

		Visual analysis		Total
		Theta	Not Theta	
PANN Analysis	True	88	65	153
	False	10	17	27
	Total	98	82	180

Sensitivity = 89%; Specificity = 79%

Table 6. Statistical results - sensitivity and specificity: Alpha waves.

		Visual analysis		Total
		Alpha	Not Alpha	
PANN Analysis	True	22	150	172
	False	3	5	8
	Total	25	155	180

Sensitivity = 88%; Specificity = 96%

Table 7. Statistical results - sensitivity and specificity: Beta waves.

		Visual analysis		Total
		Beta	Not Beta	
PANN Analysis	True	3	175	178
	False	1	1	2
	Total	4	176	180

Sensitivity = 75%; Specificity = 99%

Table 8. Statistical results - sensitivity and specificity: Unrecognized waves.

		Visual analysis		Total
		Unrecognized	Recognized	
PANN Analysis	True	0	180	180
	False	0	0	0
	Total	0	180	180

Sensitivity = 100%; Specificity = 100%

8 Applying in Handwritten Numerical Character Recognition

The system performance was evaluated with real data by using Brazilian checks batches and considering all characteristics available in the

extracting characteristics step, "Histogram: External Border," "Histogram: Diagonal Internal (right to left) Border" and "Histogram: Diagonal Internal (left to right) Border."

The best tests performed by the system to Magnetic Ink Character Recognition presented good results with 97.72 percent of hits.

For these tests, we have used a sample with 1,930 elements with thirteen types of different characters being nine distinct digits and three special characters.

The best tests performed by the system with Magnetic Ink Character Recognition Numerical Characters are presented for each type of character on Table 9. For these tests used a sample with 1,354 characters.

The hits percentage for each type of character is presented in Table 10 [24, 25].

Table 9. Results obtained for the test with Magnetic Ink Character Recognition

Character	Sample	Errors	Hits	Hits %
0	436	1	435	99.77
1	264	3	261	98.86
2	122	2	120	98.36
3	153	1	152	99.35
4	152	1	151	99.34
5	190	17	173	91.05
6	111	2	109	98.20
7	98	1	97	98.98
8	146	1	145	99.31
9	102	4	98	96.08
{	78	9	69	88.46
}	39	0	39	100.00
[39	1	38	97.44
Total	1,930	2.23%	97.77%	

Table 10. Results obtained for the test with Magnetic Ink Character Recognition – sensibility, specificity, efficiency, accuracy

Character	sensibility	specificity	efficiency	accuracy
0	0.998	0.994	0.996	0.995
1	0.989	1.000	0.994	0.998
2	0.984	1.000	0.992	0.999
3	0.993	0.998	0.996	0.998
4	0.993	1.000	0.997	0.999
5	0.911	1.000	0.955	0.991
6	0.982	0.993	0.988	0.993
7	0.989	1.000	0.995	0.999
8	0.993	0.999	0.996	0.999
9	0.961	0.996	0.978	0.994
{	0.885	1.000	0.942	0.995
}	1.000	0.994	0.997	0.994
[0.974	1.000	0.987	0.999

The best tests performed by the system with Handwritten Numerical Characters are presented for each type of character on Table 2. For these tests used a sample with 1,050 characters.

Table 11. Results for tests with Handwritten Numerical Character

	Selected features for the test: "Histogram: External Border", "Histogram: Diagonal Internal (right to left) Border" and "Histogram: Diagonal Internal (left to right) Border"			
	Sample (size)	Hits	Errors	Hits %
	1,050	91.14%	8.86%	
0	109	109	0	100.00
1	92	62	30	67.39
2	121	117	4	96.69
3	134	121	13	90.30
4	85	76	9	89.41
5	103	79	24	76.70
6	104	103	1	99.04
7	88	87	1	98.86
8	116	109	7	93.97
9	98	94	4	95.92

9 Conclusions

The appearance of non-classical logical systems notably in the past and present century is one of the landmarks in the History of Logic. Till decades ago, the Boolean thinking (classical logic) was identical to rationality.

However, with these new logical systems, they face us some philosophical issues: are non-classical logics new logics? If so, there are in consequence distinct rationalities? Do logicity and rationality coincide? All these questions occupy philosophers, logicians, and scientists in general.

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