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

[1]JAIR M. ABE, [2]KAZUMI NAKAMATSU, [3]SEIKI AKAMA, [4]ARI AHARARI
[1]Graduate Program in Production Engineering
Paulista University
R. Dr. Bacelar 1212, CEP04026-002, São Paulo, SP – BRAZIL
[1]Institute for Advanced Studies – University of São Paulo – BRAZIL
[2]School of Human Science and Environment
University of Hyogo – JAPAN
[3]C-Republic, Tokyo – JAPAN
[4]Sojo University – JAPAN
jairabe@uol.com.br

*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 Eτ. 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 Eτ 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 Eτ 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.

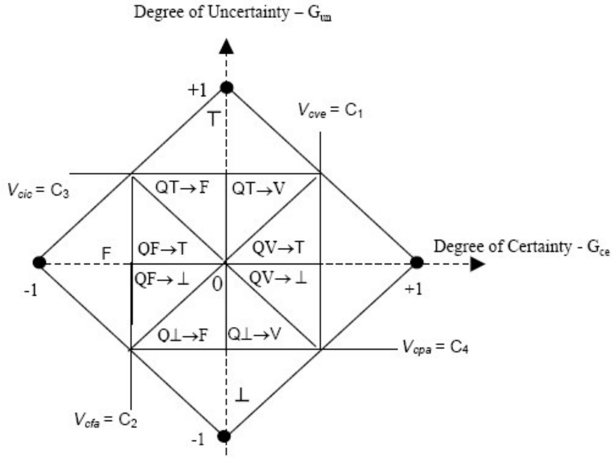


Fig. 1 - Representation of the certainty degrees and contradiction degrees

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:

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

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

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

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

For the discussion in the present paper we have used: $C_1 = C_3 = ½$ and $C_2 = C_4 = -½$.

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 indefinition.

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

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

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

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

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

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

```
* /Definition of the adjustable values * /
   Vcve = C1 * maximum value of certainty control * /
Vcfa =C2 * / minimum value of certainty control * /
   Vcic =C3 * maximum value of uncertainty control * /
   Vcpa =C4 * minimum value of uncertainty control* /
      * Input /Variables * /
    μ, λ
     * Output /Variables *
   Digital output = S1
   Analog output = S2a
   Analog output = S2b
* /Mathematical expressions * /
begin:
0≤ μ ≤ 1 e 0≤ λ≤ 1
Gun = μ + λ - 1
Gce = μ - λ
* / determination of the extreme states * /
if Gce ≥ C1 then S1 = V
if Gce ≥ C2 then S1 = F
if Gun ≥ C3 then S1 = T
if Gun ≤ C4 then S1 = ⊥
```

```
If not: S1 = I - Indetermination
    Gun = S2a
    Gce = S2b
```

A PANC is called *basic* PANC when given a pair ($\mu$, $\lambda$) 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 $G_{ce} = \mu - \lambda$

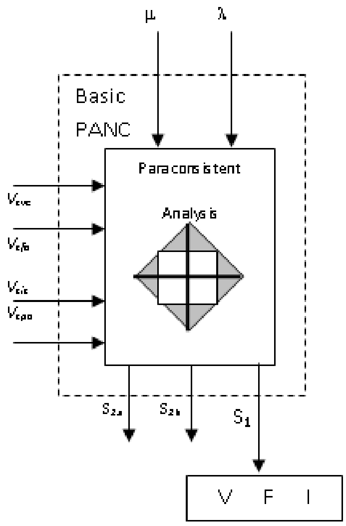


Fig. 2 - The Basic Paraconsistent Artificial Neural Cell

## 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 ½.

So, the basic structural equation yields the same value ½ as output. As a result, we get an indefinition. 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

$$\mu_r(k+1) = \frac{(\mu_1 - \mu_r(k)_c)LF + 1}{2} \quad (1)$$

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 indefinition value ½.

## 5 Unlearning of a Panc-L

Even after having a cell trained to recognize a particular pattern, if insistently 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 indefinition. 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

| | Gold Standard | | |
|---|---|---|---|
| | 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 | | | | | |
|---|---|---|---|---|---|---|
| | Delta | Theta | Alpha | Beta | Unrecognized | Total |
| 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 | | |
|---|---|---|---|---|
| | | Delta | Not Delta | Total |
| 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 | | |
|---|---|---|---|---|
| | | Theta | Not Theta | Total |
| 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 | | |
|---|---|---|---|---|
| | | Alpha | Not Alpha | Total |
| 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 | | |
|---|---|---|---|---|
| | | Beta | Not Beta | Total |
| 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 | | |
|---|---|---|---|---|
| | | Unrecognized | Recognized | Total |
| 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) 1,050 | Hits 91.14% | Errors 8.86% | Hits % |
| 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.

*References:*

[1] Abe, J.M., Foundations of Annotated Logics, Doctor thesis (in Portuguese) University of São Paulo, Brazil, 1992.

[2] Abe, J.M., Some Aspects of Paraconsistent Systems and Applications, Logique et Analyse, 157, 83-96, 1997.

[3] Abe, J.M., Paraconsistent Intelligent Based-Systems: New Trends in the Applications of Paraconsistency, editor, Book Series: "Intelligent Systems Reference Library," Springer-Verlag, Vol. 94, ISBN:978-3-319-19721-0, 306 pages, Germany, 2015.

[4] Abe, J.M., S. Akama, K. Nakamatsu, Introduction to Annotated Logics - Foundations for Paracomplete and Paraconsistent Reasoning, Intelligent Systems

Reference Library, Volume 88, Springer International Publishing, Copyright Holder Springer, ISBN 978-3-319-17911-7, Edition Number 1, 190 pages, 2015.

[5] Abe, J.M., H.F.S. Lopes, & R. Anghinah, Paraconsistent Artificial Neural Network and Alzheimer Disease: A Preliminary Study, Dementia & Neuropsychologia, Vol 3., 241-247, 2007.

[6] Akama, S., Towards Paraconsistent Engineering, Intelligent Systems Reference Library, Volume 110, 234 pages, 2016, ISBN: 978-3-319-40417-2 (Print) 978-3-319-40418-9 (Online), Series ISSN 1868-4394, Springer, DOI: 10.1007/978-3-319-40418-9

[7] Anghinah, R., Estudo da densidade espectral e da coerência do eletrencefalograma em indivíduos adultos normais e com doença de Alzheimer provável, PhD thesis (in Portuguese), Faculty of Medicine, University of São Paulo, São Paulo, 2003.

[8] Blonds, T.A., Attention-Deficit Disorders and Hyperactivity. In Developmental Disabilities in Infancy and Ramus, F., Developmental dyslexia: specific phonological deficit or general sensorimotor dysfunction? Current Opinion in Neurobiology, 13:1-7, 2003.

[9] Da Silva Filho, J.I., G.L Torres & J.M. Abe, Uncertainty Treatment Using Paraconsistent Logic - Introducing Paraconsistent Artificial Neural Networks, IOS Press, Holanda, Vol. 211, ISBN 978-1-60750-557-0, doi: 10.3233/978-1-60750-558-7-I, 328pp., 2010.

[10] Gallarburda, A.M., G.F. Sherman, G.G. Rosen, F. Aboitiz & N. Genschiwind, Developmental dyslexia: four consecutive patients with cortical anomalies. Ann. Neurology, 18:2122-2333, 1985.

[11] Hynd, G.W., R. Hooper & T. Takahashi, Dyslexia and Language-Based disabilities. In Text Book of Pediatric Neuropsychiatry, Coffeyand Brumbak (eds), American Psychiatric Press, 691-718, 1985.

[12] Lindsay, R.L., Dyscalculia. In Developmental Disabilities in Infancy and Childhood, Capute and Accardo (eds.);Paul Brookes Publishing Co, Baltimore, 405-415, 1996.

[13] Lopes, H.F.S., J.M. Abe, P.A.M. Kanda, S. Machado, B. Velasques, P. Ribeiro, L.F.H. Basile, R. Nitrini, R. Anghinah, Improved Application of Paraconsistent Artificial Neural Networks in Diagnosis of Alzheimer's Disease, American Journal of Neuroscience 2 (1): Science Publications, ISSN 1948-9900, 54-64, 2011.

[14] Mario M.C., Modelo de análise de variáveis craniométricas através das Redes Neurais Artificiais Paraconsistentes, Ph. D. Thesis (in Portuguse), University of São Paulo, 2006.

[15] Mario M.C., Abe, J.M., Ortega, N., Del Santo Jr., M., Paraconsistent Artificial Neural Network as Auxiliary in Cephalometric Diagnosis, Artificial Organs, Wiley Interscience, ISSN: 0160-564X, v.34, i.7, 215-221, 2010.

[16] Temple, E., Brain mechanisms in normal and dyslexic readers. Current Opinion in Neurobiology, 12:178-183, 2002.

[17] Voeller, K.K.S., Attention-Deficit / Hyperactivity: Neurobiological and clinical aspects of attention and disorders of attention. In Text Book of Pediatric Neuropsychiatry, Coffey and Brumbak (eds), American Psychiatric Press, 691-718, 1998.

[18] Berger L, Morris JC. Diagnosis of Alzheimer Disease. Terry RD, Katzman R, Bick KL, eds.: New York: Reaven Press, Ltd., 9-25, 1994.

[19] Fratiglioni L, Viitanen M, von Strauss E, Tontodonai V, Herlitz A, Wimblad. Very old women at highest risk of demencia and AD: Incidence data from Kungsholmen project, Stockhom. Neurology 1997; 48:132-138.

[20] Dayle DD, Pedley TA. Current Practice of Clinical Eletroencephalography. 2nd ed., Raven Press, New York. 1990; 107-137..

[21] Abdleazeem, S., El-Sherif E.: Arabic handwritten digit recognition. International Journal of Document Analysis and Recognition (IJDAR), vol. 11(3), pp. 127-141, Springer-Verlag, 2008.

[22] Souza, S., J.M. Abe, Handwritten Numerical Characters Recognition based on Paraconsistent Artificial Neural Networks, Recent Developments in Computational Collective Intelligence, A. Bdic et al. (eds.), Studies in Computational Intelligence 513, DOI: 10.1007/978-3-319-01787-7_9, © Springer International Publishing Switzerland, 93-102, ISSN: 1860-949X, 2014

[23] Souza, S., Jair Minoro Abe, Paraconsistent Artificial Neural Networks and Aspects of Pattern Recognition, a chapter of the book Paraconsistent Intelligent Based-Systems - New Trends in the Applications of Paraconsistency, Ed. (J.M. Abe) - Book Series: “Intelligent Systems Reference Library”, Springer-Verlag, Vol. 94, ISBN:978-3-319-19721-0, Germany, 207-231, 2015