Smart Structures and Systems, Vol. 7, No. 3 (2011) 229-240

DOI: http://dx.doi.org/10.12989/sss.2011.7.3.229

Bio-inspired neuro-symbolic approach to diagnostics of structures

Rahmat A. Shoureshi*, Tracy Schantz and Sun W. Lim

Intelligent Systems Lab, School of Engineering & Computer Science, University of Denver, Denver, Colorado, U.S.A

(Received November 22, 2010, Accepted November 26, 2010)

Abstract. Recent developments in Smart Structures with very large scale embedded sensors and actuators have introduced new challenges in terms of data processing and sensor fusion. These smart structures are dynamically classified as a large-scale system with thousands of sensors and actuators that form the musculoskeletal of the structure, analogous to human body. In order to develop structural health monitoring and diagnostics with data provided by thousands of sensors, new sensor informatics has to be developed. The focus of our on-going research is to develop techniques and algorithms that would utilize this musculoskeletal system effectively; thus creating the intelligence for such a large-scale autonomous structure. To achieve this level of intelligence, three major research tasks are being conducted: development of a Bio-Inspired data analysis and information extraction from thousands of sensors; development of an analytical technique for Optimal Sensory System using Structural Observability; and creation of a bio-inspired decision-making and control system. This paper is focused on the results of our effort on the first task, namely development of a Neuro-Morphic Engineering approach, using a neuro-symbolic data manipulation, inspired by the understanding of human information processing architecture, for sensor fusion and structural diagnostics.

Keywords: wireless sensors; bio-inspired data analysis; sensor data fusion; neuro-symbolic network; transmission and distribution infrastructure.

1. Introduction

New civil engineering construction is the largest industry in the world, accounting for more than 10% of the world's gross domestic product (GDP). Civil infrastructure systems are generally the most expensive investment and assets in any country. In the USA, this asset is estimated to be about $20 trillion. Over the last century, the United States has invested a significant amount of capital into developing and maintaining the nation's infrastructure in the form of roadways and bridges. However, this infrastructure is deteriorating at an alarming rate due to material or system deterioration caused by overuse, overloading, aging, damage or failure caused by external loads such as natural or man-made hazards (Lim, Tomizuka and Shoureshi 2003).

The National Bridge Inventory indicates that more than 104,000 bridges are rated as structurally deficient (Liu 1993) and even greater numbers have damage patterns that are yet undetected and pose a mounting risk to public safety (Small, Cooper 1998). With such a vast network of deteriorating infrastructure, there is a growing interest in continuous monitoring technologies. The importance of

*Corresponding Author, Professor, Dean, E-mail: rshoures@du.edu

understanding and predicting damage in civil structures is underscored by the economic losses incurred by recent seismic events: 2005 hurricane that devastated the Gulf Coast states of US, the destructions caused by the 2004 tsunami in South East Asia, the 2002 Bam, Iran earthquake with thousands of loss of life and millions of dollars of damage; the 1994 Northridge, California earthquake with over \$20B damage; and the 1995 Kobe, Japan earthquake with over \$100B damage. What is even more ambiguous is that presently, there are no effective techniques to assess the safety of an infrastructure after it has experienced seismic events, tornados, fire, etc.

Damage in structures can be defined as a decrease of the structural bearing capacity during their service period. This decrease is usually caused by degradation and deterioration of structural components and/or connections. Load-carrying structures such as buildings, bridges and offshore platforms continuously accumulate damage during their service life. Undetected damage may lead to structural failure and loss of human lives. It is, therefore, essential to detect damage within a structure and make appropriate repair as early as possible. The field of structural health monitoring (SHM) has experienced significant progress during the past decade (Shoureshi 2004, Straser and Kiremidjian 1996, Mal, Ricci and Gibson 2004, Casciati and Faravelli 2004, Kim, Kwon and Choi 2004, Kurata and Spencer 2004, Ou and Li 2004, Shinozuka, Fend and Chou 2004, Knoblauch, Noll and Müller 2003, Pickard, Knoblauch, Peters and Shen 2006, Shen, Hamlington, Pickard, Knoblauch and Peters 2006, Lynch 2004, Han 2004, Gheorghiu 2004, Rivera 2004, Husam 2002). Research on the monitoring of bridges have been actively conducted (Azarbayejani, El-Osery and Taha Reda 2009).

Visual inspection is the most common method for structural damage detection, which is unreliable for complex structures because certain critical damage may occur in inaccessible areas or may be covered by paint or skin. Visual inspection cannot provide a quantitative value for the remaining strength of the structure. Other non-destructive evaluation (NDE) methods includes: radiographic, fiber optics, X-ray, acoustic emission, and ultrasonic techniques. These traditional NDE methods, however, only give the effective deterioration state of local areas and tend to be impractical for large complicated structures. Finally, none of these approaches provide a quantitative assessment of the damage magnitude.

As the development of wireless sensors becomes more rapid and the price of this technology is decreasing, most of the structural health monitoring architecture is now geared toward the utilization of distributed, large scale wireless sensor. Lynch (2004) describes the concept of intelligent wireless sensors that can be further extended to include actuation capabilities. Lu and co-investigators (Lu, Loh, Yang, Lynch and Law 2008) further develop the wireless structural sensory system. Han (2004) has developed an infrastructure monitoring technique that addresses the specific issue of incorporating internet-technology into structural health monitoring. Han's approach has been applied to several case studies, including two bridges and a statue. Rao and co-worker (Rao and Anandakumar 2008) have developed a method for optimal sensor locations for structure monitoring. Glaser and co-investigators have developed acoustic sensors for structural monitoring (Grosse, Glaser, and Krüger 2010). Rice and colleague have investigated autonomous structural monitoring (Rice, Mechitov, Sim, Nagayama, Jang, Kim, Spencer, Agha, and Fujino 2010).

On the sensors side, applications of fiber optic and micro-electromechanical systems are the current state of the art for SHM. Gheorghiu (2004) has studied the application of fiber optic sensor (FOS) for SHM. FOS capability of reading various parameters is a promising candidate for life-long health monitoring of these structures. Rivera Rivera (2004) introduced the term Civionics, which involves the application of electronics to civil structures and aims to assist engineers in realizing the full benefits of structural health monitoring (SHM). MEMS (micro-electromechanical systems) research on inertial sensors has focused primarily on accelerometers and gyroscopes. The lightweight and miniature size of MEMS-based sensors has advantages in the power consumption, survivability, and cost reduction of a SHM system. Husam (2002) describes a SHM system consisted of a series of MEMS sensors: accelerometers and inclinometers – that are "wirelessly" connected to an on-site base station using the Bluetooth or IEEE 802.11b wireless protocols. Shoureshi (Shoureshi and Lim 2009) introduce the concept of a bio-inspired diagnostic approach for structures.

As new large scale and distributed sensor technologies are introduced and incorporated into structures, the need for informatics techniques that can provide effective sensor fusion and are able to transform large volume of data into useful information has significantly increased. Thus, we have initiated a basic research that attempts to understand sensor fusion and data processing capabilities of the human brain, and develop analogous engineered systems.

2. Brain sensor information processing

Human brain is a highly complex system, which is capable of performing a vast range of diverse tasks. One capability of the brain is to process information coming from thousands and thousands of sensory receptors and integrating this information into a unified perception of the environment. Up to now, technical systems used for machine perception are unable to compete with their biological archetype. Having an engineered system capable of perceiving objects, events, and situations in a similar and efficient manner as the brain does, would be very valuable for a wide range of applications. To perceive objects, events, and situations in an environment, sensors of various types are necessary. This introduces the challenge of fusing data and extracting information from a variety of sensors.

The goals of sensor fusion are robustness, extended spatial and temporal coverage, increased confidence, reduced ambiguity and uncertainty, and improved resolution (Elmenreich 2002). The research field of sensor data fusion is relatively recent and dynamic. There have been several sensor fusion techniques developed. However, these techniques tend to be application dependent. Research in the neuro-science area has demonstrated that sensor fusion in the perceptual system of the human brain is of superior quality than all present engineered ones. Therefore, it seems to be particularly useful to study biological principles of sensor fusion. Fig. 1 presents an overview of the mechanisms and factors that form and influence human perception. These characteristics are derived from research

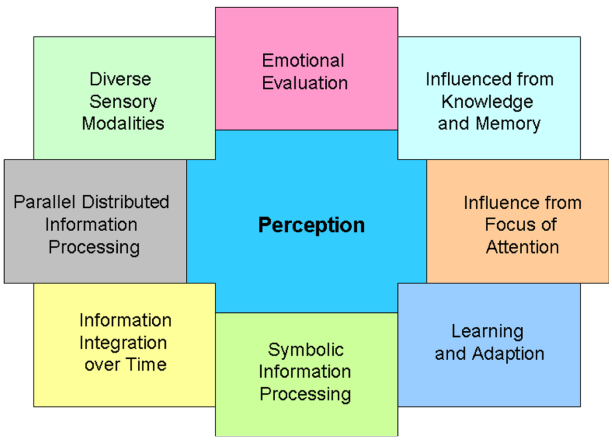

Fig. 1 Characteristics of human perception diverse sensory modalities (Velik *et al.* 2008)

results of neuroscience and neuropsychology about the perceptual system of the human brain (Luria 1973).

To perceive the external environment, our brain uses multiple sources of sensory information derived from several different modalities including vision, touch, and audition. The combination and integration of multiple sources of sensory information is the key to robust perception (Ernst and Bülthoff 2004).

2.1 Parallel distributed information processing

The perceptual system is no unitary central unit that processes all information in one step. Instead, sensory information is processed in parallel (Luria 1973).

2.2 Information integration over time

To perceive objects, events, and situations in an environment, single-moment snapshots of sensory information provided by different modalities is not always sufficient for unambiguous perception. The course and the succession of sensory signals over time are of importance (Roskies 1999).

2.3 Symbolic information processing

In the human brain, perceptual information from different modalities is processed by interacting neurons. However, humans do not think in terms of action potential and firing nerve cells, rather in terms of symbols. Mental processes are often considered as a process of symbol manipulation (French 1996).

2.4 Learning and adaptation

The perceptual system of the human brain is not fully developed at birth. Although certain patterns need to be predefined by the genetic code, many concepts and correlations concerning perception are learned and adapted during life of individuals (Luria 1973).

2.5 Influence from focus of attention

According to the hypothesis of focused attention, what we see is determined by what we attend to. At every moment, the environment presents far more perceptual information than can be effectively processed. Attention can be used to select relevant information and to ignore irrelevant or interfering information. Instead of trying to process all objects simultaneously, processing is limited to one object in a certain area of space at a time (Hommel and Milliken 2005).

2.6 Influence from knowledge and memory

Perception is facilitated by knowledge. Prior knowledge is often required for interpreting ambiguous sensory signals. Much of what we take for granted as the way the world is– as we perceive it – is in fact what we have learned about the world – as we remember it. Much of what we take for perception is in fact memory. We frequently see things that are not there, simply because we expect them to be there (Goldstein 2002).

2.7 Emotional evaluation

For perception, most often only the detection and the processing of stimuli from the external environment are considered. However, the perception of objects, events, and situations makes little sense if we do not know what influence they have on us. In the human brain, an evaluation of perceptual images is performed by emotions. The basic function of emotions in perception is to classify objects, events, and scenarios as good or bad. Emotions are necessary, to react adequately on perceived objects, events, and situations (Solms and Turnbull 2002).

3. Neuro-symbolic processing

Considering those unique aspects of the human brain perception, it is understood that humans do not think in terms of action potentials and firing nerve cells, rather they think in terms of symbols. According to the theory of symbolic systems, the mind is a symbol system and cognition is symbol manipulation. Examples for symbols are objects, characters, figures, sounds, or colors used to represent abstract ideas and concepts. Symbol manipulation offers the possibility to generate complex behavior (French 1996). In summary, neurons could be regarded as basic information processing unit on a physiological basis and symbols as information processing units on a more abstract level. There are neurons in the brain which respond exclusively to certain perceptual images. For example, there have been neurons found in the secondary visual cortex that respond exclusively to the perception of faces. This fact has inspired us to use neuro-symbols, which are used for perceptual images. Fig. 2 shows the concept of a neuro-symbol (Velik *et al*. 2008).

3.1 Neuro-symbolic networks

Based on extensive research in the neuro-science area (Luria 1973), it has been proposed that the perceptual system of the brain has a cerebral organization as depicted in Fig. 3. Perception starts with information coming from sensory receptors, then this information is processed in three levels, which are referred to as primary cortex, secondary cortex, and tertiary cortex. Each sensory modality of human perception has its own primary and secondary cortex. This means that in the first two levels, information of different sensory modalities is processed separately and in parallel. In the tertiary cortex, information coming from all sensory modalities is merged.

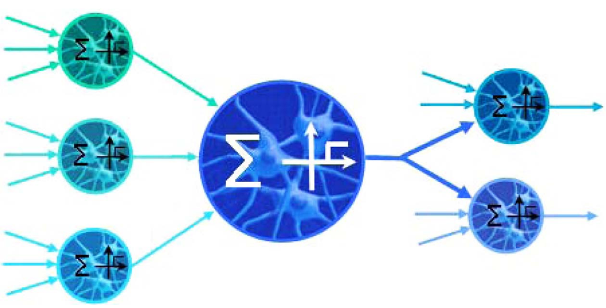

Fig. 2 Principal operation of a neuro-symbol

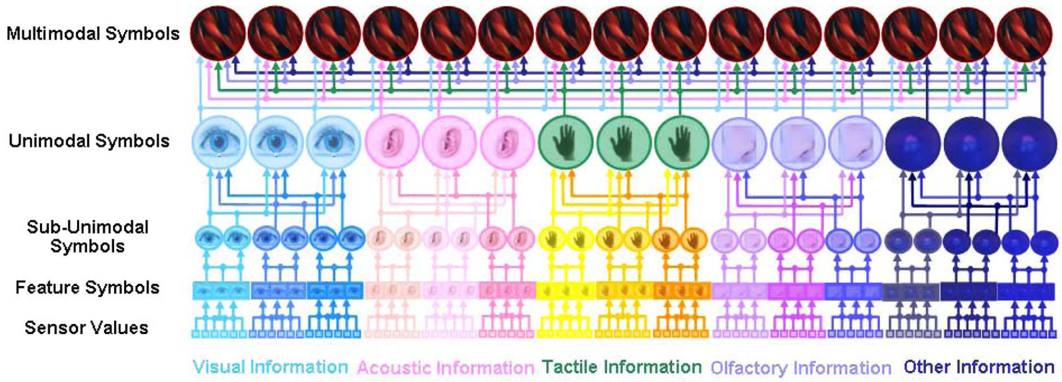

Fig. 3 Neuro-symbolic network of cortex (Velik *et al*. 2008)

This results in a unified multimodal perception. The tactile system of the brain comprises a whole group of sensory systems, including the cutaneous sensations, proprioception, and inesthesis. Therefore, this three level neuro-symbolic manipulation in the cortex forms a neuro-symbolic network, as shown in Fig. 3 (Velik *et al.* 2008).

4. Bio-inspired neuro-symbolic network

Based on the understanding that neuro-science researchers have provided, as described in the previous section, and considering our previous investigations in the development of Intelligent Control systems, we have proposed the following neuro-symbolic network which integrates artificial neural network with fuzzy logic. This neuro-fuzzy system is a new approach using combination of the neural networks and symbolic systems to obtain the advantages of both without suffering from their shortcomings. It is a hybrid neural system to model cognitive functions, using a supervised learning. Input and target data have to be presented in the learning process. The neural network portion provides robustness, the ability to learn from examples, it is fault tolerant, can handle incomplete information, is able to generalize to similar input, and it is a parallel distributed systems with the potential of providing increased speed of processing. However, neural network by itself is unable to provide an explanation for the underlying reasoning mechanisms. On the other hand, symbolic processing can explain its inference process, utilizes powerful declaration languages for knowledge representation, and allows explicit control, fast initial coding, dynamic variable binding, and knowledge abstraction. Therefore, symbolic processing would complement the artificial neural networks and together, they provide a powerful system that could represent some of the features of the human cortex.

Fig. 4 represents our neuro-symbolic network. This network is a combination of a fuzzy inference system (intelligent reasoning capability based on the linguistic "if/then" rule statements) and an adaptive neural network (adaptive learning capability). It uses Tsukamoto-type fuzzy reasoning for both fuzzification and defuzzification processes; namely, its membership functions are half bell-shape functions, called monotonic nonlinear functions. It is applicable to multi-input/multi-output (MIMO) systems which employs associated hybrid learning algorithm to tune the parameters of membership functions. It utilizes Least Square Estimation in its forward processing, and Gradient Descent method in its

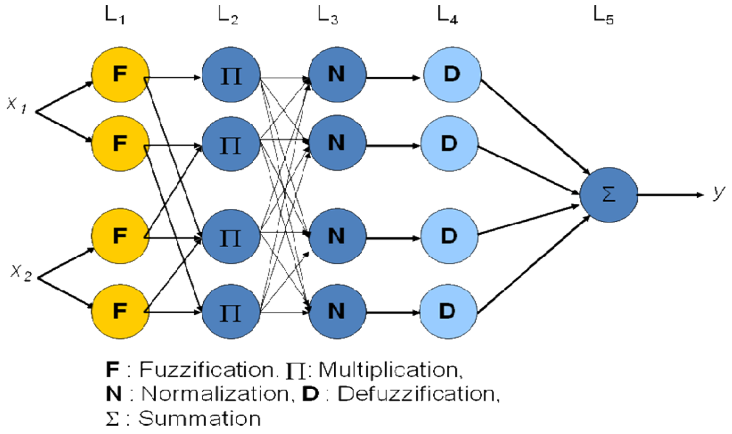

Fig. 4 Architecture of proposed neuro-symbolic network

backward processing. It updates and determines an optimal learning rate based on the changes of the error function versus the step size.

4.1 Network information processing architecture

Following describes operations at each level of this network and their outputs (Shoureshi and Lim 2009).

Layer 1 (Fuzzification layer): Each node generates a membership degree of a linguistic value. The k^{th} node in this layer performs the following operation

$$O_k^1 = \mu_{A_{ij}}(x_i) = \frac{1}{1 + \left(\frac{x_i - a_{ij}}{b_{ij}}\right)^2} \tag{1}$$

Layer 2 (Multiplication Layer): Each node calculates the firing strength of each rule by using multiplication operation.

$$O_k^2 = \prod_i O_{ij}^1(x_i) \quad (1 \le k \le 4) \tag{2}$$

Layer 3 (Normalization layer): The number of nodes in this layer is the same as the first layer, where the output of layer two is determined according to

$$O_k^3 = \frac{O_k^2}{\sum_k O_k^2} \; (1 \le k \le 4) \tag{3}$$

Layer 4 (Defuzzification layer): The number of nodes in this layer is equal to the number of nodes in layer one times the number of outputs. The defuzzified value for the k^{th} node is

$$y_k = \left\{ \begin{array}{l} c_k - d_k\sqrt{\dfrac{1}{O_k^3} - 1} \ \text{ if } k = odd \\ c_k + d_k\sqrt{\dfrac{1}{O_k^3} - 1} \ \text{ if } k = even \end{array} \right\} (1 \le k \le 4) \tag{4}$$

where $\{c_k, d_k\}$ are consequent parameters and are used to adjust the shape of the membership function of the consequent part. Then, the output of this layer becomes

$$O_k^4 = O_k^3 \cdot y_k = \left\{ \begin{array}{l} O_k^3 \cdot \left(c_k - d_k\sqrt{\dfrac{1}{O_k^3} - 1} \right) \ \text{ if } k = odd \\ O_k^3 \cdot \left(c_k + d_k\sqrt{\dfrac{1}{O_k^3} - 1} \right) \ \text{ if } k = even \end{array} \right\} (1 \le k \le 4) \tag{5}$$

Layer 5 (Summation layer): In this layer the number of nodes is equal to the number of outputs. There is only one connection between each node in layer four and a node in the output layer, and we have

$$O^5 = \sum_k O_k^4 \ (1 \le k \le 4)$$

In the training process, it tries to find the minimizing error function between target value and the network output. For a given training data set with P entries, the error function is defined as

$$E = \sum_{p=1}^{P} E_p = \frac{1}{2}\sum_{p=1}^{P} (T_p - O_p^5)^2, (1 \le p \le P) \tag{7}$$

Where O_p^5 is the pth output of the network and T_p is the pth desired target. The premise parameters $\{a_{ij}, b_{ij}\}$ are updated according to a gradient descent and the consequent parameters $\{c_k, d_k\}$ are updated using a LMS algorithm.

5. Case study and its experimental results

In order to demonstrate the ability of this network for diagnostics of structures, we consider the predicting corrosion levels on angle stubs of the portion of transmission towers below the ground (Stranovsky *et al.* 2011). The US transmission and distribution (T&D) infrastructure of the electric grid is deteriorating at an alarming rate. This infrastructure is subjected to significant environmental forces that can have a detrimental impact on its service life. Present inspection techniques have many short-comings, especially their inability to provide accurate and reliable information about the state of the structure below the ground without going through a costly excavation. Visual and auditory inspection and soil measurement techniques are not accurate and cannot predict the present state of the T&D infrastructure, namely tower legs, angle stubs, anchor rods, steel poles, and the

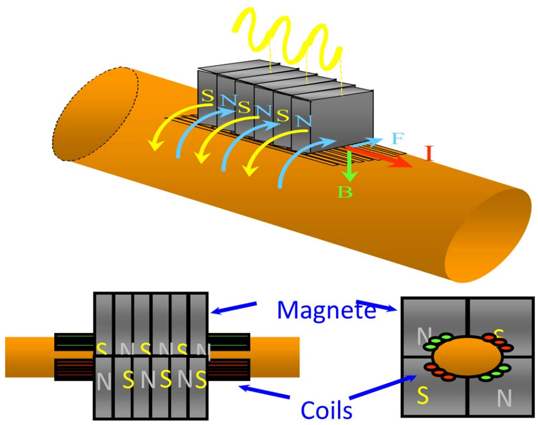

Fig. 5 Structure's electromagnetic sensing

conductor itself, especially for those sections below the ground, or covered by suspension assembly, shoes, or armor rods. Therefore, there is a real need for an effective, accurate, and proven non-destructive evaluation (NDE) technology that can detect and diagnose corrosion levels and the degree of damage in these structures below the ground.

Through a joint effort of the University of Denver (DU), New York Power Authority (NYPA), and Osmose Utilities Services Company, an NDE transmission tower leg inspection project was initiated. The DU NDE technology was applied to a set of NYPA towers, to inspect below the ground condition of tower legs. Osmose conducted soil tests, excavated these legs, and verified the inspection results and diagnostic predictions. In this study, we have used two sensing modality: structural modal characteristic measurement using an on line electromagnetic sensing; and soil tests including pH measurement and soil resistivity. Fig. 5 shows the principal operation of the DU NDE technology.

By a direct electromagnetic coupling between the inspection system and the structure, vibration modes of these T&D structures are excited by using our broadband excitation power electronic system. Through its receiving element, these inspection systems create vibration signatures of the T&D structure. This uniquely designed transducer applies Lorentz force on the T&D structure by the coupling of the alternated magnets and coils. This force twists the surface of the structure about its longitudinal or torsinal axis. This results in excitation of the modes of these structures. Therefore, our transducer can control the vibration mode to be excited on the T&D structure, by driving a specific vibration frequency matching to the structural modal characteristics. As corrosion develops and penetrates into the structure, its modal characteristics would change, thus the signature obtained by our transducer would be able to provide information about the corrosion level of the structure. Fig. 6 shows this NDE system during the actual inspection. Also shown are the actual excavation and verification of corrosion on these structures. Based on the second sensing modality, namely, soil tests, measurements presented in Figs. 7 and 8 have been obtained.

Sensing results from these two modalities were given to our neuro-symbolic network. Table 1 shows the result of this network analysis and its predictions about the structural corrosion. This table also shows results of the actual corrosion measurements, obtained from the excavation of these towers. As shown, our neuro-symbolic network has produced very accurate results and decisions about the corrosion levels of these towers.

Fig. 6 NDE system during inspection of transmission line stub angle (left) and acutal excavation and inspection (right)

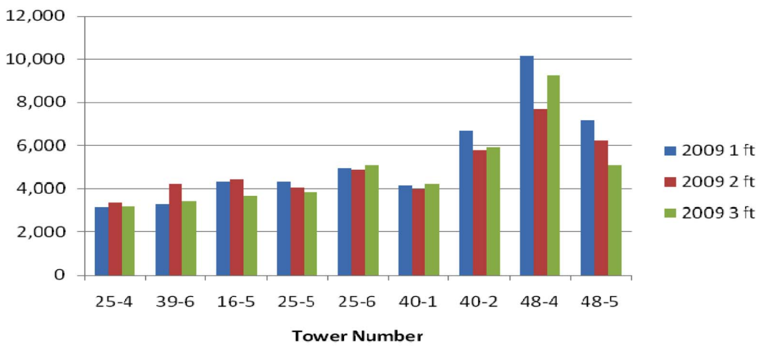

Fig. 7 Soil resistivity measurements at different locations of various towers

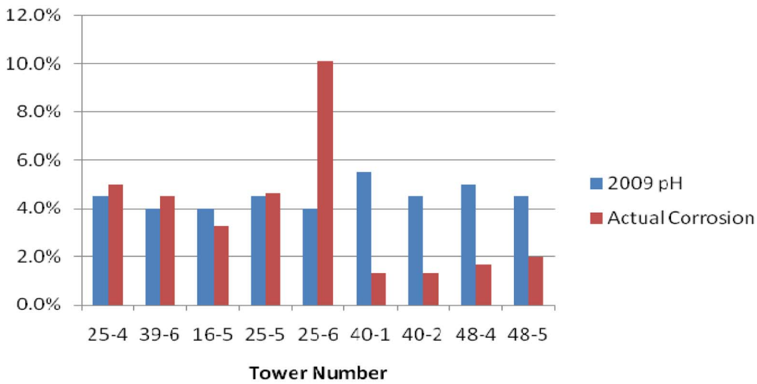

Fig. 8 Soil pH measurements of different towers and actual corrosion levels

6. Conclusions

This paper presented some of the results of our on-going research related to structural heath monitoring and diagnostics, using bio-inspired data processing and decision-making. Based on developing some understanding of the operation of data within the human brain, using results of the neuroscience research community, we have developed a neuro-symbolic network. This network

Table 1 Corrosion level decision results of neuro-symbolic network

Tower number	% of corrosion after excavation	Soil measurement results	Neuro-symbolic network corrosion level decision
25-4	5.0%	moderate	<8%
39-6	4.5%	severe	<10%
16-5	3.3%	moderate	<7%
25-5	4.6%	mild	<10%
25-6	10.1%	mild	<15%
40-1	1.3%	moderate	<8%
40-2	1.3%	mild	<8%
48-4	1.7%	mild	<5%
48-5	2.0%	mild	<8%

integrates key features of artificial neural networks and fuzzy logic to create an inference engine. Through a unique joint project with a utility (NYPA) and a utility service company (Osmose) we were able to implement this research results on the assessment of corrosion levels of the surface of tower legs of transmission lines which are embedded below the ground. Two sensor modalities were used. One based on measurements related to the modal characteristics of the structure, the other based on soil measurements. These different sensory data were presented to our network. From this neuro-symbolic network we obtained prediction of corrosion levels with excellent accuracy, as verified by the actual excavation of these towers.

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