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OLD CHURCH PAINTINGS RESTORATION AND ARTIFICIAL INTELLIGENCE

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Abstract

For the restoration of churches and places of worship, with degraded, incomplete paintings, the correct identification of pigments used and original tint, proves to be mostly a hard, laborious process. Artificial Intelligence based on fuzzy logic, neuro-fuzzy networks, genetic algorithms, with usual techniques such as pattern recognition and classification, image processing and fuzzy clustering, can be successfully used for paintings restoration and also in recovering of the old texts, old manuscripts which suffered major damages over time.
In this paper we try to present the basics of fuzzy logic theory, the fuzzy reasoning and neuro-fuzzy network with some practical applications in image processing, pattern recognition and pigments identification, a set of very useful techniques in pictures restoration, because this invaluable heritage demands to be preserved and transmitted to future generations.

Keywords: artificial intelligence, fuzzy logic, neural network, image processing, pattern recognition, restoration

1. Introduction

AI - Artificial intelligence, namely the intelligence of machines. What makes a machine intelligent? If it can quickly solve difficult problems or complicated mathematical calculus? Or if it can mimic a human or use human language?

How can we determine if a machine can behave like a human? In 1950, Alan Mathison Turing, the British mathematician, philosopher, and logician proposed a general procedure to test the intelligence of an agent, now known as the Turing test, which allows almost all the major problems of artificial intelligence to be tested: if a machine could successfully mimic a human during an informal exchange of text messages, then, for most practical purposes, the

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computer might be considered intelligent [1]. However, even today, it is a very difficult challenge and at presents all agents fail.

But is this enough? Today modern computers can use natural language. Natural language understanding is the technology enabling computers to extract meaning from text. This is a real challenge even for the most sophisticated modern computers, something so easy and natural for humans, but notoriously difficult for machines. Natural language is a key component of software that can accept commands and queries from humans in their own language and produce answers whose meanings are automatically extracted from texts.

There is an inherent impreciseness present in our natural language when we describe phenomena that do not have sharply defined boundaries. Simple examples are '*Mihai is tall*', '*George is smart*', '*this apple is red*'. But '*how tall*', '*how smart*' and '*simple or hot red*'?

When we refer '*young*' there might be ages which lies in the range 0÷30 (the term '*young*' is vague). So, how young is Mihai who is 18 years old?

Fuzzy set theory provides mathematical tools for carrying out approximate reasoning processes when available information is uncertain, incomplete, imprecise, or vague.

While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric *linguistic variables* are often used to facilitate the expression of rules and facts.

Our understanding of most physical processes is based largely on imprecise human reasoning.

For many people the term 'fuzzy logic' sounds nonsensical and the term itself inspires certain scepticism. Where is the logic in a fuzzy set? In fact, fuzzy is absurdly simple and easier to understand. In fact the term 'fuzzy logic' does not refer to a lack of rigour in the method. Unlike the reasoning based on classical Boolean logic, fuzzy reasoning aims at the modelling of reasoning schemes based on uncertain or imprecise information, especially for systems for which a rigorous mathematical model is difficult to derive. The most visible applications are in the realms of consumer products, intelligent control and industrial systems. Less visible, but of growing importance, are applications relating to data processing, fault diagnosis, image processing, pattern recognition, expert and decision support systems.

However, there exists a general misconception of the term 'fuzzy' as imprecise and imperfect. Although fuzzy logic has evident advantages over traditional methods, they have also encountered some fierce opposition. Fuzzy logic is clearly much closer to human thinking and much easier to understand. Fuzzy control offers an alternative approach for many conventional systems, especially for nonlinear systems, with high degree of uncertainty [2].

Fuzzy set theory is a generalization of normal set theory and was introduced by Zadeh in 1965 [3]. He was the first who introduced the concept of 'linguistic variables' and 'fuzzy sets'. Fuzzy logic was specifically designed to mathematically represent uncertainty and vagueness and provide formalized tools for dealing with the imprecision intrinsic to many problems.

In normal set theory, an object is either a member (exclusively) of a set or not, and the set is often referred to as a crisp set. In classical theory a logic proposition can be either '*True*' of '*False*'.

If we define a set ***A*** in the universal set (of discourse) ***X*** with $A \subseteq X$, if an element is included in ***A***, the element is called a member of the set and we can use following notation $x \in A$. If the element is not included we can use the notation $x \notin A$.

For crisp set, we can use membership function (a characteristic function for representing whether an element is involved in a set A or not):

$$\mu_A(x) = \begin{cases} 1 & if \;\; x \in A \\ 0 & if \;\; x \notin A \end{cases} \tag{1}$$

We can say that the function $\mu_A(x)$ maps the elements in the universal set X to the set $\{0,1\}$:

$$\mu_A(x) : X \rightarrow [0,1] \tag{2}$$

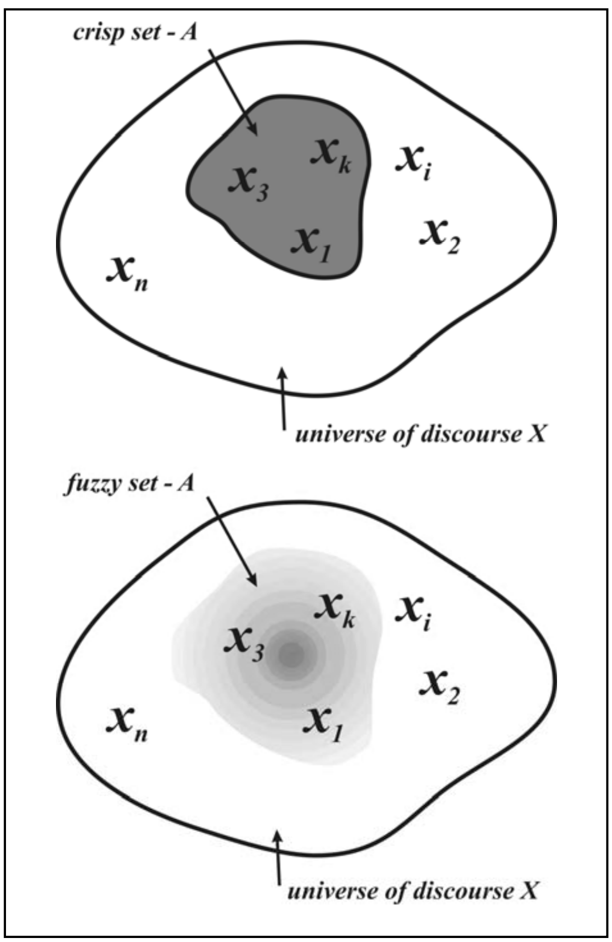

Figure 1. Crisp and fuzzy sets.

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Fuzzy sets, on the other hand, have degrees of membership to that set. Thus, it is possible for an object to have partial membership in a set. A (graphical) comparison of a crisp set and a fuzzy set is shown in Figure 1 (note hat the boundary of the crisp set A is rigid and sharp and the fuzzy set have 'vague' boundaries).

Zadeh introduced fuzzy sets as an extension and generalization of the basic concepts of crisp sets. He extends the notion of binary membership to the real continuous interval $[0,1]$, where the limit points ***0*** and ***1*** correspond to no membership and full membership [4].

A type-1 fuzzy set ***A*** in the universe of discourse ***X*** is defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x)), x \in X\} \text{ or}$$

$$A = \mu_1 / x_1 + \mu_2 / x_2 + ... + \mu_n / x_n = \sum_{i=1}^{n} \mu_A(x_i) / x_i \tag{3}$$

where $\mu_A(x)$ is the membership function of ***A***, which indicates the degree, that x belongs to ***A***, (in fuzzy logic membership function can have any value between ***0*** and ***1***).

However, if the value of the membership function $\mu_A(x)$ is restricted to either 0 or 1, then A is reduced to a classical set and $\mu_A(x)$ is the characteristic function of ***A***.

There are different membership functions that can be used; triangular shape is the most common (Figure 2), but trapezoidal, bell, Gaussian, Cauchy, exponential shapes (to mention only a few of them) are also used. More complex functions are also possible but they require greater computing overhead to implement.

The membership function for a triangular fuzzy member is given by:

$$\mu_A(x) = \begin{cases} 0 & if \;\; x < a \\ \dfrac{x-a}{m-a} & if \;\; x \in [a, m] \\ \dfrac{b-x}{b-m} & if \;\; x \in [m, b] \\ 0 & if \;\; x > b \end{cases} \tag{4}$$

Almost every mathematical concept from classic sets can be generalized to fuzzy sets using the extension principle, a very important tool for fuzzy theory. It offers a facility for any function that maps an n-tuple $(x_1, x_2, ...x_n)$ in the crisp set ***A*** to crisp set ***B*** to be generalized to mapping a fuzzy subset in ***A*** to a fuzzy subset in ***B***, and furthermore any mathematical relationship between non-fuzzy elements can be extended to cover fuzzy entities.

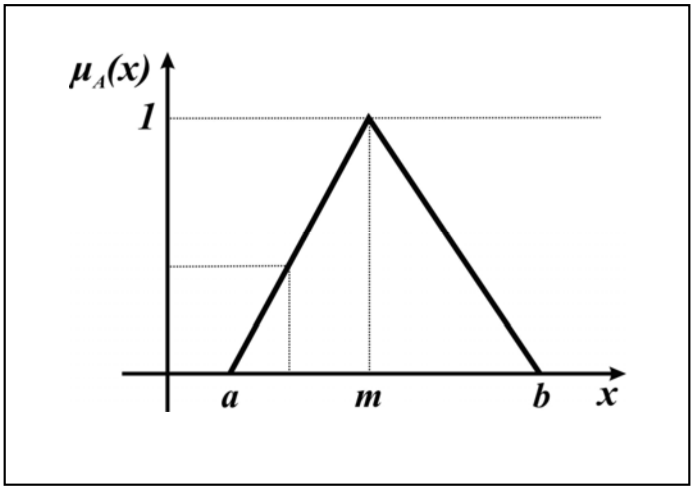

Figure 2. Triangular membership function.

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2. Fuzzy systems, linguistic variables, fuzzy reasoning

Fuzzy logic incorporates a simple, rule-based '***IF X AND Y THEN Z***' approach to a solving control problem rather than attempting to model a system mathematically [5]. The fuzzy logic model is empirically-based, relying on an operator's experience rather than their technical understanding of the system. The used terms are imprecise and yet very descriptive of what must actually happen.

Word like red, blue, white or young, tall are "fuzzy" and may have many values. They are just human opinions, not based on precise measurement and so they are fuzzy variables.

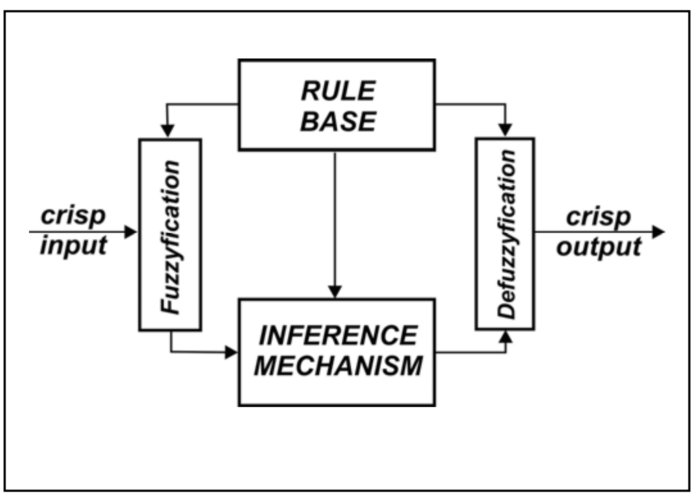

Figure 3. Fuzzy system – block diagram.

A fuzzy system is a static nonlinear mapping between its inputs and outputs. A fuzzy system is composed of the following four elements (Figure 3):

- A fuzzification mechanism, which convert crisp inputs to into fuzzy sets;
- A set of If-Then rules (fuzzy rule base - a linguistic description of experts knowledge);
- An inference mechanism (fuzzy inference engine) which emulates the expert's decision making;
- A defuzzification interface which convert the fuzzy results from inference mechanism to crisp outputs for the process.

A Fuzzy Inference System (FIS) simulate the human reasoning process, mapping an input space to an output space using a set of if-then rules like:

If *premis**e*** ***Then*** *consequent* (5)

The inference mechanism determines which rule is relevant to the current situation defined by the inputs and draws the conclusion using the inputs data and the information contained in the rules-base knowledge. For example, using the traditional modus ponens algorithm, according to which we can infer the truth of a proposition *B* from the truth of *A* and the implication $A \rightarrow B$, if *A* is identified with '*this apple is red*' and *B* with '*this apple is ripe*', if we have '*this apple is more or les red*' then we may infer '*this apple is more or less ripe*'.

In practice, the fuzzy rule sets usually have several antecedents that are combined using fuzzy operators, such as ***AND***, ***OR***, and ***NOT***, though again the definitions tend to vary: ***AND***, in one popular definition, simply uses the minimum weight of all the antecedents, while ***OR*** uses the maximum value.

There is also a ***NOT*** operator that subtracts a membership function from 1 to give the 'complementary' function. There are several different ways to define the result of a rule, but one of the most common and simplest is the '*max-min*' inference method, in which the output membership function is given the truth value generated by the premise.

Inputs to a fuzzy system can be an exact data ($Temp = 10^0C$) defined by a crisp values or a linguistic variable (*Temp = Low*) and a membership function attached. Similar, the outputs from a fuzzy system can be a fuzzy (linguistic) variable with attached membership function or exact, crisp data, when a single value is produced [5].

The most common inference techniques in practice are Mandami method, illustrated graphical in Figure 4, for a two-rule system where each rule comprise two antecedents and one consequent. The graphical inference is done for each rule and then the truncated membership of each rule is aggregated using min operator. There are many other proposed inference methods, Larsen, Takagi-Sugeno-Kang, Tsukamoto, to mention the most used of them, each method using different aggregation operators [6].

After inference mechanisms, the result (fuzzy data) need to be converted to crisp values, in practice being used five defuzzification strategy (all defuzzification methods are essentially empirically motivated): *COA - Centroid Of Area, BOA - Bisector Of Area, MOM - Mean Of Maximum, SOM - Smallest Of Maximum and LOM - Largest Of Maximum* (Figure 5).

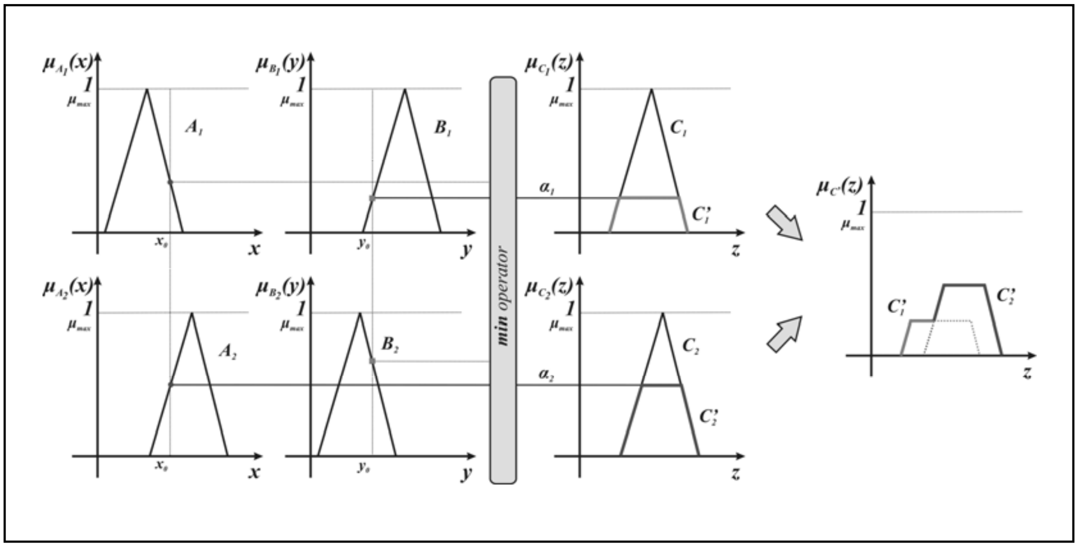

Figure 4. Graphical representation for Mandami inference method.

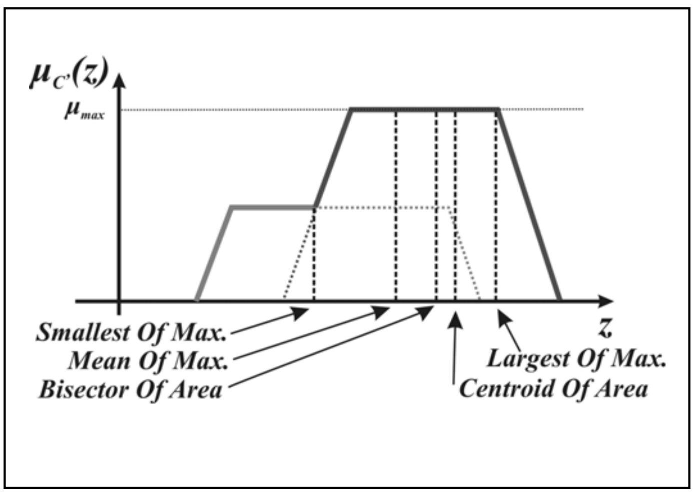

Figure 5. Various defuzzification methods.

3. Neural networks

From a simple point of view neural networks are computational networks which attempt to simulate the human nerve cell networks. Artificial neural networks are made up of interconnecting artificial neurons used for solving artificial intelligence problems without necessarily creating a model of a real biological system [7].

A single neuron may be connected to many other neurons and the total number of neurons and connections in a network may be extensive.

Artificial neural networks have been applied successfully to speech recognition, image analysis, pattern recognition and classification, system identification and adaptive control, in order to construct software agents or autonomous robots.

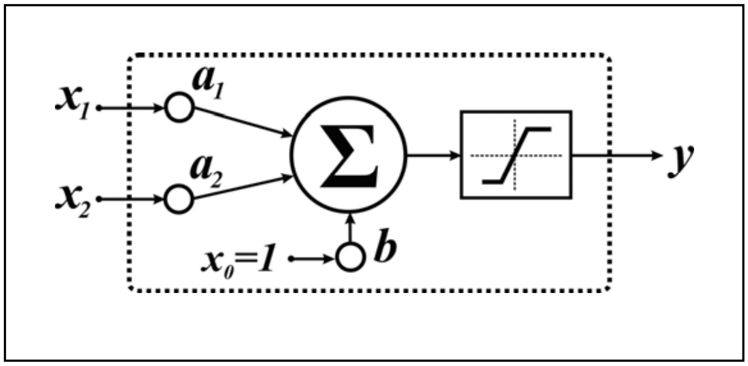

Figure 6. Functional block diagram of a neuron.

Each neuron (using model proposed first time by McCulloch and Pits – Figure 6) has two or more inputs and each input has an associated weight *w*, which can be modified so as to model synaptic learning [8]. The unit computes some function *f* of the weighted sum of its inputs:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + \theta\right) \qquad (6)$$

where x_i represent the neuron inputs, w_i the associated weights, f the activation function and θ the bias.

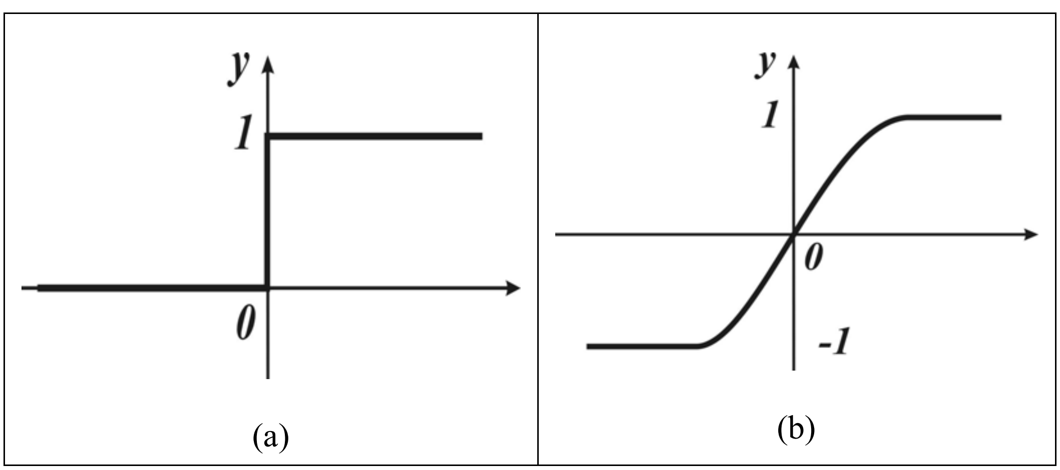

Figure 7. (a) Step threshold function; (b) s-threshold function.

The transfer function $f(x)$ (or threshold or activation function) may be a linear or a nonlinear function, particularly chosen to satisfy some specification of the real problem that the neuron (or neural network) is attempting to solve. In Figure 7a we can see the *step* or *hard-limiter* function, but in real world application we can choose any other continuous, limited function like *r* or *s-function* (Figure 7b):

$$y = \frac{1}{1+e^{-a}} \quad \text{where } \mathrm{a} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{a_i x_i} \tag{7}$$

For step function, the threshold relation for obtaining the output may be written:

$$y = f\left(\sum_{i=1}^{n} a_i x_i - b\right) = \begin{cases} 1 \; if \;\; a \geq b \\ 0 \; if \;\; a < b \end{cases} \quad \text{where } \mathrm{a} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{a_i x_i} \tag{8}$$

Since the perceptron (a single neuron structure) can solve only simple linear problems, for more complex problems different neural networks topologies (like feed-forward network showed in Figure 8) are used. A neural network has a layered structure, where each layer consists of units (neurons) which receive their inputs from a layer below and send their outputs in a layer above. In feed-forward neural networks the information propagates only forward as indicated by the direction of the arrows.

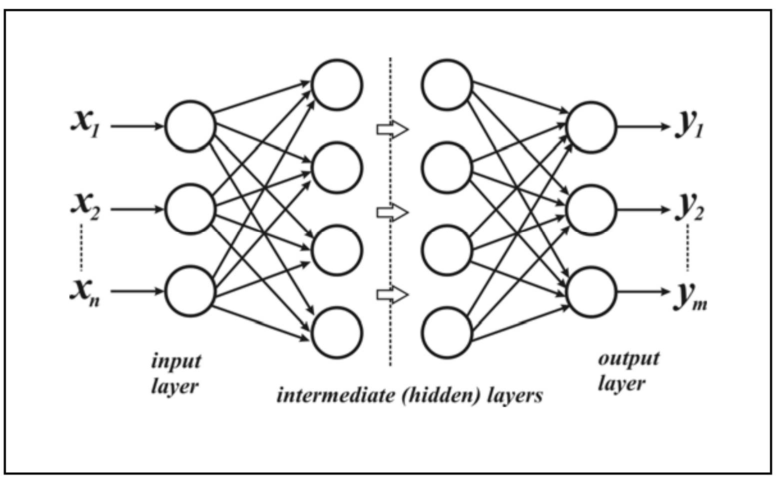

Figure 8. A feed-forward neural network structure.

Based on connection pattern artificial neural networks can be grouped into two categories: feed-forward networks and recurrent or feedback networks in which loops occur because of feedback connection.

An artificial neural network is a massively parallel distributed processor, inspired from biological neural networks, which can store experimental knowledge and makes it available for use. An artificial neural network consists of a finite number of neurons interconnected to each other. Among others similarities with the human brain, the artificial neural networks can acquire knowledge through learning process and store this knowledge in interneuron connectivity as synaptic weights [7].

Unlike computer systems that are programmed in advance to perform different tasks, neural networks need to be first trained from examples (supervised learning). Neural network must learn the connection weights from available training patterns; the neural networks ability to automatically learn from examples makes them very attractive for practical applications in various domains.

It should be clear that there is no prescribed methodology that predetermines a neural network architecture for a given problem or a general rule about how many neurons layers should be used.

There are many learning methods: supervised (an expert provide correct answer for each input pattern, the weights being modified to produce a answer as close as possible to correct answer), unsupervised (the network itself explores the underlying structure in data, and organizes patterns into categories from these correlations) and hybrid (a combination of supervised and unsupervised learning). A variant of supervised learning is the reinforcement learning in which the network is provided only with a critique of correctness of outputs, not with the correct answers themselves.

4. Contrast enhancement and edge detection using Fuzzy logic

In pattern recognition and edge detection uncertainty can develop at any phase resulting in incomplete or imprecise data with huge impact in edge detection and pattern recognition.

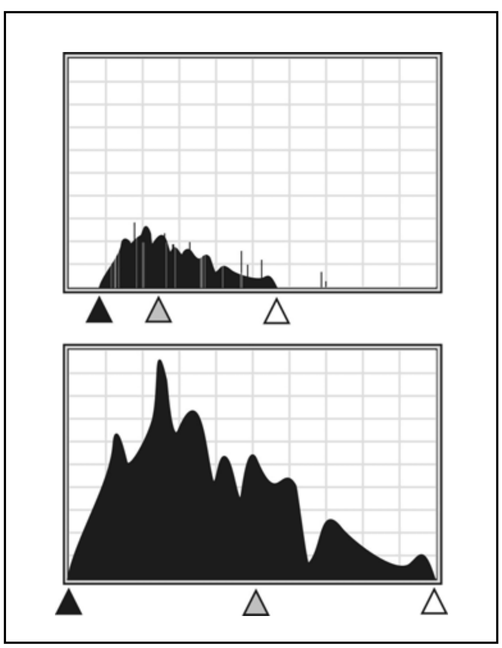

Figure 9. Picture histogram before and after contrast enhancement.

The incertitude in image (noise) may be explained in terms of greyness ambiguity and spatial ambiguity. Greyness ambiguity means incertitude in deciding a pixel as white or black and spatial ambiguity means incertitude in deciding if a pixel is or not a part of a defined shape.

An image X of size $X(MxN)$ can be represented as an array of fuzzy singletons:

$$X = \bigcup_{i=1}^{M} \bigcup_{j=1}^{N} \left(\mu_{ij}, x_{ij}\right) \tag{9}$$

where x_{ij} represent the pixel brightness/colour in RGB (HVS) colour space and μ_{ij} the associated membership function.

The most commonly used membership function for colour images besides Gaussian function is s-function defined as:

$$S\left(x_{mn}, a, b, c\right) = \begin{cases} 0 \ \mathit{if} \ \ 0 \le x_{mn} \le a \\ \dfrac{\left(x_{mn} - a\right)^2}{(b-a)\left(c-a\right)} \ \mathit{if} \ \ a \le x_{mn} \le b \\ 1 - \dfrac{\left(x_{mn} - c\right)^2}{\left(c-b\right)\left(c-a\right)} \ \mathit{if} \ \ b \le x_{mn} \le c \\ 1 \ \mathit{if} \ \ x_{mn} \ge c \end{cases} \tag{10}$$

The ambiguity of an image X can be measured by entropy of the fuzzy set:

$$H\left(X\right) = \frac{1}{M \cdot N} \sum_{i=1}^{M} \sum_{j=1}^{N} S_n\left(\mu_X\left(x_{ij}\right)\right) \tag{11}$$

where $S_n\left(\mu_X\left(x_{ij}\right)\right)$ represent the Shannon function:

$$S_n\left(\mu_X\left(x_{ij}\right)\right) = -\mu_X\left(x_{ij}\right)\log_2 \mu_X\left(x_{ij}\right) - \left(1 - \mu_X\left(x_{ij}\right)\right) \cdot \log_2\left(1 - \mu_X\left(x_{ij}\right)\right) \tag{12}$$

The contrast enhancement fuzzy procedure has seven steps, described as follows:

- first we must compute the membership value $\mu_{x_{ij}}$ for every pixel in digital image;
- after that we apply the Sobel operator to find edge value in fuzzy domain;
- step three, compute the mean edge value $E\mu_{x_{ij}}$ within a 5x5 pixel window centred on pixel (i, j) using the formula:

$$E\mu_{x_{ij}} = \sum_{m,n} \mu\left(x_{ij}\right)\delta\left(x_{ij}\right) / \sum_{m,n} \delta\left(x_{ij}\right) \tag{13}$$

- transform the contrast $C'\mu\left(x_{ij}\right)=\left(C\mu\left(x_{ij}\right)\right)^{\sigma_{ij}}$ where σ_{ij} is the amplification constant;
- calculate the modified membership value using transformed contrast $\mu'\left(x_{ij}\right)$;
- transform the modified membership value to grey level (defuzzifiation).

The two histograms, before and after contrast enhancement, are shown in Figure 9.

For edge detection the inputs to the fuzzy system are obtained by applying to the original image a high-pass filter, a first order edge detector filter (Sobel) and a low-pass filter [9]. During the image processing the Sobel operator are used to estimate the horizontal h_H and vertical h_V derivatives. Sobel operator's h_H and h_V are kernels with 3x3 elements given by:

$$h_H=\begin{bmatrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{bmatrix} \text{ and } h_V=\begin{bmatrix}1 & 2 & 1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{bmatrix} \tag{14}$$

and for high-pass filter we choose:

$$h_{HP}=\begin{bmatrix}-1/16 & -1/8 & -1/16\\ -1/8 & 3/4 & -1/8\\ -1/16 & -1/8 & -1/16\end{bmatrix} \tag{15}$$

The median filter h_{MF} was chosen to guarantee that the level of each pixel in output image is arithmetic mean of 5x5 window centred on that pixel. So the median filter is given by 5x5 matrixes:

$$h_{MF}=\begin{bmatrix}1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\\ 1 & 1 & 1 & 1 & 1\end{bmatrix} \tag{16}$$

Using the kernels associated with each filter, each pixel in filtered images can be calculated through a bidimensional convolution operation:

$$H=h_H * I,\ V=h_V * I,\ HP=h_{HP} * I,\ MF=h_{MF} * I \tag{17}$$

For system implementation we consider a 8-bit image quantization algorithm for each colour (R,G,B) and we use the Gaussian function for membership function, with linguistic variables '*high*', '*medium*' and '*low*'.

The fuzzy rules were defined like:

H are medium and HP are low $\rightarrow$ *Edges are high*

V are medium and HP are low $\rightarrow$ *Edges are high*

...

H are medium and M are low $\rightarrow$ Edges are low
V are medium and M are low$\rightarrow$ Edges are low

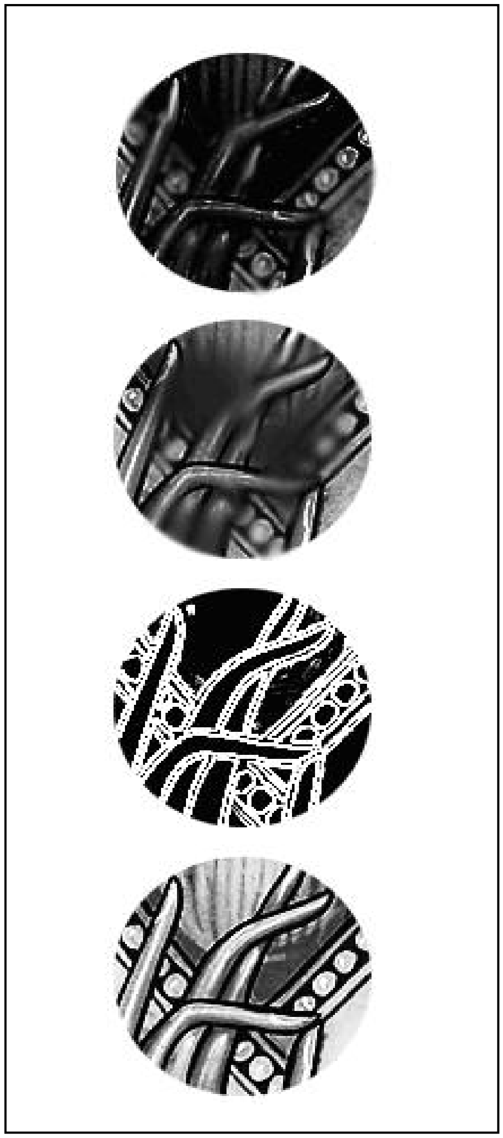

Figure 10. Contrast (plus level) enhancement and edge detection process.

The intermediate stages of reconstruction of the degraded image can be pursues in Figure 10 (the level and contrast enhancement stage, edge detection and final result).

5. Neural networks in image processing and pattern recognition

Object detection and pattern recognition is one of the most important research areas in robotics and computer vision. The major task is to locate and extract from real image regions (called regions of interest) that may contain objects, and to identify those objects using different techniques. Object detection and pattern recognition is not an easy task, the quality of detection and recognition being dependent on primary image quality, the kind of features extracted from the image, and also on algorithm and soft computing techniques used [10-13].

The features used to represent an object are the key to object detection and recognition. If useful features with good quality are unavailable to build an efficient representation of an object, good detection and recognition results cannot be achieved no matter what detection and recognition algorithms are used. However, in most real images, there is always some noise, making the extraction of features difficult.

For degraded painting restoration process, the neural networks can be used to trace the contour of the object and to extract the tint of pigments and used paints, all of the extracted data being extremely useful to restaurateurs (Figure11).

For each task (object recognition and classifier) we can build a simply recognition systems, trained first using some initial data and experts knowledge, the overall performance of hybrid neuro-fuzzy systems being remarkable.

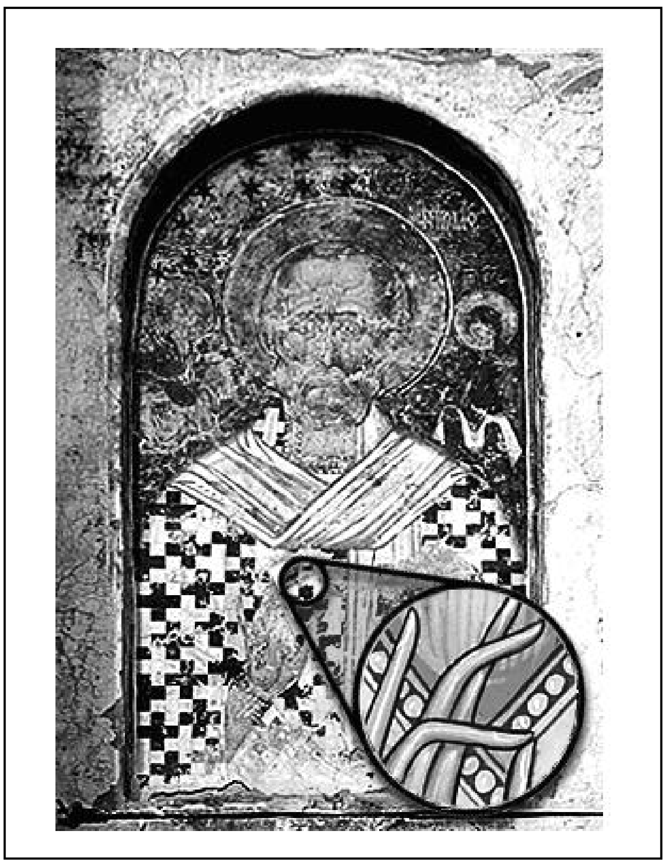

Figure 11. Degraded painting of Saint Nicolas, dated from the period of Petru Rareş (Bălineşti, Suceava).

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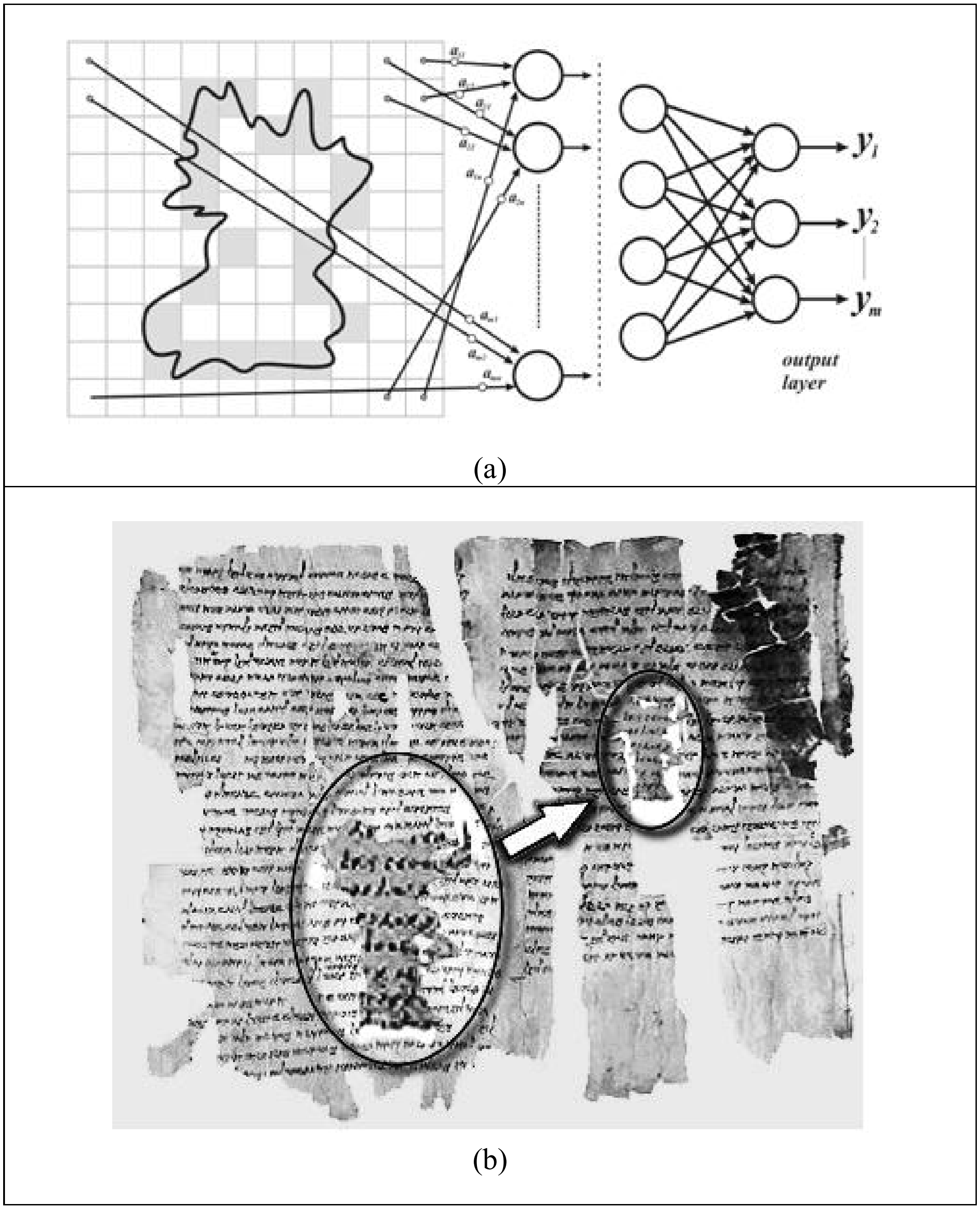
The first stage in any pattern recognition system (ex. for manuscript restoration) is data collection using some equipment like camera and scanners. The input data can be digitized using different schemes and pre-processing techniques using also some filtering method to reduce the eventually noise effect.



(a)

(b)

Figure 12. (a) Manuscript fragments classification using a multi-layer neural network; (b) Pattern (contour) recognition in old manuscript restoration.

After fragments digitization and contour tracing, a hybrid neuro-fuzzy system (which combines the advantages of the two paradigms) can be used to extract pattern from scanned images (Figure 12a), and to identify the place for all separated pieces (Figure 12b), the image of manuscript being virtually reconstructed.

Recognition is usually difficult by both a high degree of overlapping among fragment classes and a high variability within each classes; this is due partly to the quality of the scanned image, which comes from different type of manuscripts with greatly varying quality and partly to the pre-processing of substrate (degraded old paper or even animal skin for medieval manuscripts).

For paintings original pigment and tint analyse we can use Raman spectroscopy and a neuro-fuzzy network system for spectrum (and elemental pigment) identification.

Raman spectroscopy is commonly used in chemistry, since vibrational information is specific for the chemical bonds in molecules. It therefore provides a fingerprint by which the molecule can be identified, for any organic or inorganic pigment. For instance, the vibrational frequencies of Cr_2O_3 and Fe_2O_3 can be identified (using notch or edge filters for laser beam) and assigned on the basis of normal coordinate analyses using infrared and Raman spectra (Table 1) [14].

Table 1. Some common pigments band wavenumbers (Raman spectrum).

Pigment (colour)	Composition	Band wavenumbers[a] / cm^{-1} and relative intensities[b]	Excitation wavelength and power
Ivory black	carbon	961m; ~ 1325vs(br); ~ 1580vs(br)	632.8 nm 6 mW
Azurite (blue)	$2CuCO_3.Cu(OH)_2$	145w; 180w; 250m; 284w; 335w; 403vs; 545w; 746w(sh); 767m; 839m; 940w; 1098m; 1432m; 1459w; 1580m; 1623vw	514.5 nm 2 mW
Chromium oxide (green)	Cr_2O_3	221vw; 308w; 349w; 552vs; 611w	514.5 nm 4 mW
Iron oxide (orange)	Fe_2O_3	224vs; 291vs; 407m; 494w; 608m	632.8 nm 3 mW
Purpurin (red)	$C_{14}H_{18}O_5$	953m; 1019w; 1049m; 1091w; 1138w; 1160vw; 1229vs; 1312s; 1334s(sh); 1394s; 1452vs	632.8 nm 1.5 mW

a - ± 1 cm^{-1}.
b - s = strong, m = medium, w = weak, v = very, sh = shoulder, br = broad

In Figure 13 is shown the Raman spectrum of two elemental pigments, mixed together, obtained with green argon laser (514nm) spectrometer and the individual spectrum of both pigments [15].

The Raman instrument consist of the laser (in this case argon laser with excitation lines between 350nm and 700nm, usually 514nm and 60mW), optics, spectrometer, CCD or CMOS detector and computer. Laser beam is focused on the sample and the dispersed light is read and transmitted by the CCD/CMOS sensor to spectrometer for range detection.

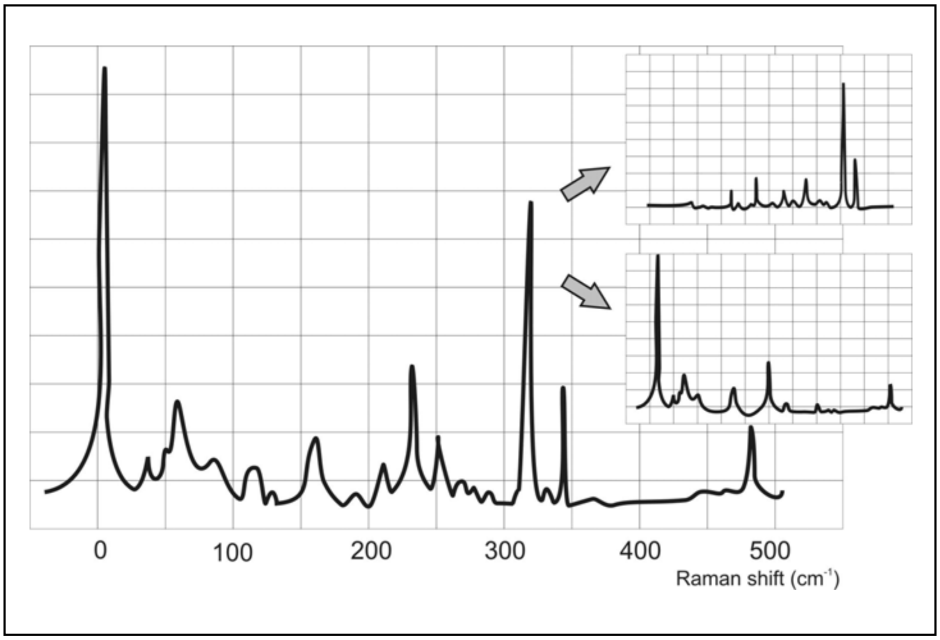


Figure 13. Raman spectrum of two pigments mixture.

The Raman spectra identification of an unknown substance is based on the comparison between an unknown experimental spectrum, and pattern spectra. Frequently the comparison is made by the spectroscopist by visual inspection, but this is slow and imprecise and moreover the Raman spectrum is inevitably affected by noise (background, flicker, readout etc.) which introduces ambiguity into the correlation values.

First, using the resulting spectrum from a sample taken from the surfaces of degraded painting, we need to locate the wavenumber position of the Raman bands, automatically or even by hand (local maximum detection). After that, the identification of the unknown spectrum is done by searching the coincidence of the Raman bands of the reference spectra using fuzzy logic.

The experimental Raman spectrum is read as a vector of N points where $e(i)$ corresponds to the intensity for the defined wavenumber. Because the Raman bands depend on instrumental conditions (spot of the laser, wavelength, time of exposure), which can change for different measurement, even with the same spectrometer, we first need to normalize the obtained data.

In practical situations we can try to identify a complex substance, a mixture of two or more elemental chemical substances. In that case the measured Raman spectrum can contains a mixture of two or more individual spectrum, corresponding to elementary substances, and the value of membership function for output fuzzy variable is clearly between 0 and 1, so for calculation of the degree of similarity, between experimental and library spectrum, and correctly identify the chemical substances based on Raman spectrum we use the centroid method.

6. Conclusions

Fuzzy systems and neural networks are very useful wherever there is a need to bridge the communication gap between humans and machines. The strength of neural networks is their capability to learn from patterns, useful in applications where the complexity of the data or task makes the design of such a function by hand impractical.

Although the neural networks are far from human intelligence they have been employed for many interesting practical application like function approximation, physical system modelling, clustering, data classification, prediction, system identification, optimization, character and pattern recognition, signal processing and many more.

Pattern recognition using fuzzy, neural, or hybrid neuro-fuzzy approaches, has gained popularity partly because of intelligent decision processes involved in some of the above techniques, thus providing better classification and partly because of simplicity in computation required by these methods as opposed to traditional statistical approaches for complex data structures.

Automated pattern recognition can provide a valuable support with consistent performance. These techniques permitted the development of methods and algorithms that can perform tasks normally associated with intelligent human behaviour. For instance, the primary advantage of fuzzy pattern recognition compared to the classical methods are the ability of a system to classify patterns in a non-dichotomous way, as humans do, and to handle vague information.

Despite the impressive result and high speed of recognition, the methodology needs to be extended so that it can be easily generalized in other domains of interest.

References

[1] T. Munakata, *Fundamentals of the New Artificial Intelligence,* 2nd edn., Springer, London, 2008, 1.

[2] F.M. Mcneill, *Fuzzy Logic, A Practical Approach,* Academic Press, London, 1994, 2.

[3] L.A. Zadeh, Fuzzy Set. Syst., **8** (1965) 338.

[4] L.A. Zadeh, IEEE Software, **11(6)** (1994) 48.

[5] W. Siler and J.J. Buckley, *Fuzzy Expert Systems and Fuzzy Reasonin,* Wiley, Hoboken, New Jersey, 2005, 40, 49, 119.
[6] P. Melin and O. Castillo, *Hybrid Intelligent Systems for Pattern Recognition Using Soft Computing,* Springer, Berlin, 2005, 19, 33.
[7] J.-S.R. Jang, C.-T. Sun and E. Mizutani, *Neuro-Fuzzy and Soft Computing,* Prentice Hall, Upper Saddle River, 1997, 199.
[8] O. Omidvar and J. Dayhoff, *Neural Networks and Pattern Recognition*, Academic Press, San Diego, 1998, 2.
[9] C.J. Miosso and A. Bauchspiess, *Fuzzy Inference System Applied to Edge Detection in Digital Image,* Congresso Brasileiro de Redes Neurais, PUC, Rio de Janeiro, 2001, 481–486.
[10] C.T. Leondes, *Image Processing and Pattern Recognition*, Vol.5, Academic Press, San Diego, 1998, 40.
[11] D. Dubois and H. Prade, *Fuzzy Models and Algoritms for Patten Recognision and Image Processing*, Springer, New York, 2005, 1, 550, 624.
[12] D. Gillies, *Artificial Intelligence and Scientific Method,* Oxford Press, Oxford, 2003, 19.
[13] R.A. Dunne, *A Statistical Approach to Neural Networks for Pattern Recognition,* Wiley, Hoboken, New Jersey, 2007, 121.
[14] I.M. Beel, R.J.H. Clark and P.J. Gibbs, *Raman Spectroscopic Library of Natural and Synthetic Pigments*, available at www.chem.ucl.ac.uk/resources/raman/index.html
[15] J.R.Ferraro, K.Nakamoto and C.W. Brown, *Introductory Raman Spectroscopy,* 2nd edn., Elsevier, San Diego, 2003, 54.