CORE
Metadata, citation and similar papers at core.ac.uk
Provided by Nature Precedings

Laparoscopy Pneumoperitoneum Fuzzy Modeling

Otavio M. Becker Jr., Ernesto Araujo, Joao L. M. C. Azevedo

Otavio M. Becker Jr. - otaviobecker@hotmail.com

Jose Ernesto Araujo Jr. - ernesto.araujo.br@gmail.com

Joao Luiz Moreira Coutinho Azevedo - jozevedo.dcir@epm.br

(Corresponding Author)

Federal University of São Paulo, Brazil

R. Botucatu, 740 – CEP 04015-011, São Paulo, Brazil

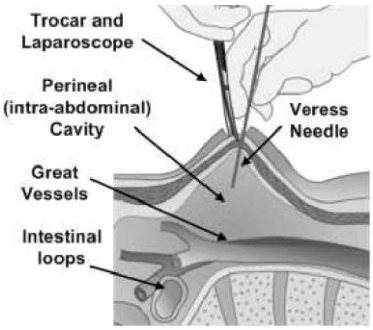


Fig. 1. Iatrogenic injuries to the great vessels or intestinal loops can occur when a Veress needle puncture is blindly inserted (Adapted from [5]).

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011

***Abstract*—Gas volume to intra-peritoneal pressure fuzzy modeling for evaluating pneumoperitoneum in videolaparoscopic surgery is proposed in this paper. The proposed approach innovates in using fuzzy logic and fuzzy set theory for evaluating the accuracy of the prognosis value in order to minimize or avoid iatrogenic injuries due to the blind needle puncture. In so doing, it demonstrates the feasibility of fuzzy analysis to contribute to medicine and health care. Fuzzy systems is employed here in synergy with artificial neural network based on backpropaga tion, multilayer perceptron architecture for building up numerical functions. Experimental data employed for analysis were col-lected in the accomplishment of the pneumoperitoneum in a random population of patients submitted to videolaparoscopic surgeries. Numerical results indicate that the proposed fuzzy mapping for describing the relation from the intra peritoneal pressure measures as function injected gas volumes succeeded in determnining a fuzzy model for this nonlinear system when compared to the statistical model.**

***Index Terms*—Fuzzy model, Pneumoperitoneum, Veress Nee-dle, Laparoscopic Surgery, Iatrogenic Injuries.**

I. Introduction

IN the last twenty years the minimaly invasive surgery has become the main access to a great number of surgeries. Also known as videolaparoscopic surgery, it presents diverse advantages upon the tradicional open surgery approach such as minor pain intensity, quicker recovery, reduced cost, only to mention few. The videolaparocopic surgery first requires a pneumoperitoneum that is an intra-abdominal space obtained through CO_2 gas insuflation. This procedure is achieved in two steps: the access to the perineal cavity and the gas insuflation.

The most employed technique to gain access to the peritoneal cavity in order to produce pneumoperitoneum is by using Veress needle puncture [1]. Unfortunately, regardless the technique used to achieve this access, most of the surgical complications occurs at the moment of accomplishing the pneumoperitoneum [2]. Injuries to the great vessels or intesti-nal loops can occur when a Veress needle is blindly inserted by surgeons into the abdomen for peritoneal insufflation (Fig 1). Vascular and inadvertent visceral injuries are, thus, the most common cause of death in videolaparoscopic procedures, respectively, achieving 15-25% and 25% of mortality [3], [4].

In order to minimize or avoid iatrogenic injuries due to the blind needle puncture there are five tests to verify whether t he tip of the needle is in the peritoneal cavity [5]. Nevertheless, these procedures reffer only to the access moment of the needle insertion but not to the gas insuflation. Related to the second step procedure it requires a distinct method of evaluation in order to verify the correctness, or not, of the needle tip positioning. This evaluation can be verified, for instance, by measuring the intraperitoneal pressure in time as well as the volume of gas into the abdomen in time at different pre-established time-points [5] yielding two distinct functions (or tables). The direct relationship of the pressure and volume of the gas as a reliable parameter of safe gas insuflation is investigated by employing statistical analysis in [6].

The classical analysis procedure in life sciences has been both the descriptive and inferencial statistics, respectively, for data computing and extratification, and for probabilist ic analysis. So far, such an approach has been appropriate when in search of mathematical formulations that gives support to the cause-effect relationship between variables. This approach finds out adequate models when data reffers to objects under analysis corresponding to simple and homogeneous samples. In the medical field, however, when there are complex, heterogeneous samples, and/or a great number of variables, as occur in the majority of clinical trials, this approach is not always sufficient to accomodate the uncertainty, imprecisi on, and vagueness.

The proposed approach differ from statistical analysis by using a technique from the artificial/computational intell igence field, named fuzzy systems for working as an alternative to

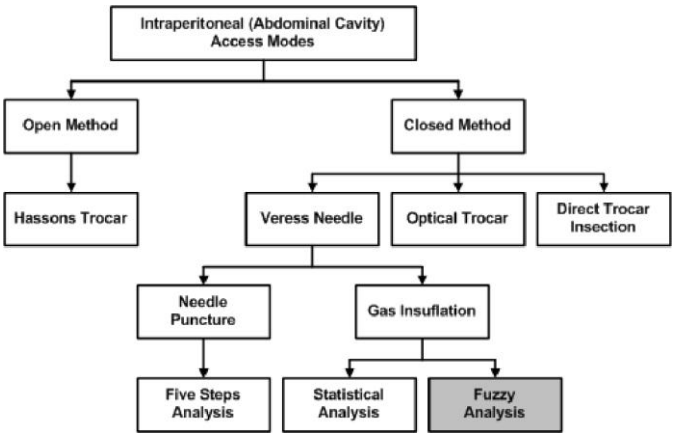


Fig. 2. Evaluation Mechanisms for Iatrogenic Vascular and Visceral Injuries.

deal with such a problem. Presented in a seminal paper in 1965 [7], fuzzy set theory and fuzzy logic may be understood, at first, as a way to reproduce knowledge by being able to linguistically interpret statements, modeling the common sense, and work as an interface between numbers and symbols, and later, as related to data-driven analysis able to build numer-ical functions (mappings) [8]. Further, since fuzzy set theory and fuzzy logic underlie fuzzy systems being an alternative to design intelligent systems [8], there is an increasing use in quantitative and, most important, qualitative indexes for decision-making in the biomedical and healthcare field [9].

The objetive of this paper is, thus, to investigate the feasibil-ity of design a fuzzy model to indicate the adequate needle tip positioning by employing the resulting intra-peritoneal pres-sure measure and the injected gas volume relationship. Results obtained with the proposed fuzzy modeling are compared to the traditional statistical analysis carried out in previous work [6].

II. Methods

A. Evaluation Mechanisms for Iatrogenic Vascular and Visceral Injuries

There are two main modes to access abdominal cavity in videolaparoscopic surgery. The first one is the open method that is carried out with Hasson's Trocar [10]. The second mode is the closed method which can be performed by (**i**) *Veress Needle Puncture*, (**ii**) *Optical Trocar Introduction*, and (**iii**) *Direct Trocar Introduction* [11], [12]. The evaluation mecha-nisms for iatrogenic vascular and visceral injuries when using the Veress needle puncture approach are employed both in the needle puncture insertion and the gas insuflation verificati on. While the first one is verified by performing the *Five Tests* [5], the insuflation can be accomplished by finding out a function that describes the intraperitoneal pressure behaviour according to the gas volume injected [6], for instance, when using statistical analysis. An alternative to statistical analysis, as previously mentioned, is to employ fuzzy analysis as proposed in this paper (Fig. 2).

Experimental data employed for analysis were collected in the accomplishment of the pneumoperitoneum in a random population of patients submitted to videolaparoscopic surg-eries.

B. Surgical Data Collection

Ninety-one consecutive patients with no exclusion criteria scheduled to undergo laparoscopic procedures were included in the present study. The laparoscopic surgeries took place at the General Surgery Department of the Hospital Jos´e de Carvalho Florence (HJCF) in S˜ao Jos´e dos Campos city, S˜ao Paulo state, Brazil. This group is composed of 69 women (75.8%) and 22 men (24.2%), i.e. a total of 92 patients, with a mean age of 47.92 years (standard deviation, **±15.06**, median, 46) for age ranging 16–86 years. The mean Body Mass Index (BMI) is 26.16 (standard deviation, **±4.97**, median, 25.71, range, 18.37–48.11). Forty patients (44%) belong to the healthy BMI group (**<**25), 34 (37.4%) to the overweight group (BMI 25–30), and 17 (18.7%) to the obese group (BMI **>**30). Sixty patients (65.9%) had previous abdominal surgery. In order to illustrate the dynamical behavior of the data collected for pressure and volume, with any lack of generality, a reduced number of patients are depicted in Fig. 3. This study was approved by the Research Ethics Committees of the University of Taubat´e, Brazil (no. 0039/07), and of the Federal University of S˜ao Paulo, Brazil (no. 1310/07). All patients included in this study gave written informed consent.

The patients were submitted to general anesthesia via orotracheal intubation and controlled mechanical ventilation. An orogastric tube was, then, introduced for aspiration of the stomach contents. Patients were placed in a 30 degrees proclive supine position. A 12-cm reusable Veress needle with a 2-mm external diameter was inserted into the abdominal wall through an incision in the left hypochondrium to create carbon dioxide pneumoperitoneum. After needle insertion, the five tests encompassing the (**i**) aspiration test (AT), (**ii**) injection test (IT), (**iii**) recovery test (RT), (**iv**) saline drop test (SDT), and (**v**) initial intraperitoneal pressure test (IIPT)

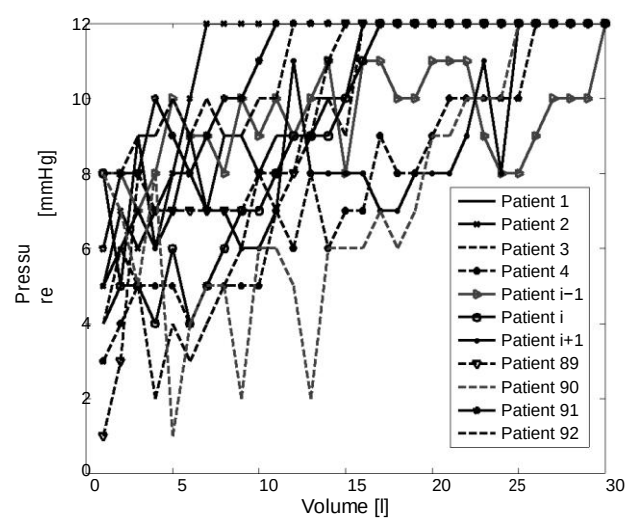
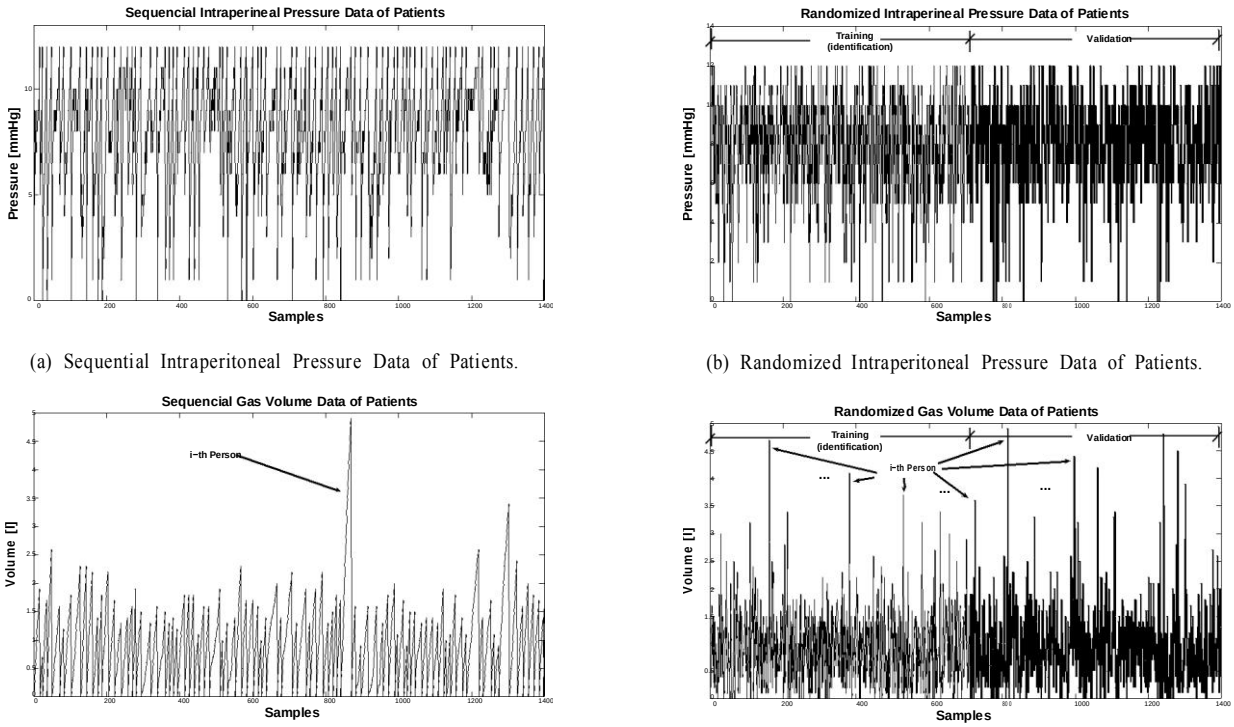


Fig. 3. Individual pressure-volume insuflation profile for a reduced number of patients.

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011



(a) Sequential Intraperitoneal Pressure Data of Patients.

(b) Randomized Intraperitoneal Pressure Data of Patients.

(c) Sequential Gas Volume Data of Patients.

(d) Randomized Gas Volume Data of Patients.

Fig. 4. Input experimental data for *Pressure*: sequential data per patient and randomized data for ANFIS' training and validation.

were performed [1], [12]. Details for such tests may be found in [5]. The IT, RT and SDT were performed and recorded according to a pre-established protocol, one after the other, regardless of the results (positive or negative).

The insufflator was set to a flow rate of 1.2 L/min and a maximum pressure of 12 mmHg. After connecting the insufflator to the Veress needle, if the IIPT was higher than 8 mmHb, the procedure was considered as a failure, the Veress needle was removed and the entire procedure started again. When the IIPT was lower than 8 mmHg the insufflation was kept on until the intraperitoneal pressure achieved 12 mmHg. Effective creation of pneumoperitoneum, visually confirme d by inserting a laparoscope into the peritoneal cavity, indicated that the needle was correctly positioned. Inability to effectively insufflate carbon dioxide into the peritoneal cavity confirm ed that the needle was incorrectly positioned.

The data collected for sequential intraperitoneal pressure data and the sequential gas volume data of patients, respec-tively, are shown in Fig. 4(a) and 4(c). The volume data for the **i**–th patient is represented by an monotonically increasing d ata sequence representing the $\mathbf{CO_2}$ gas insuflation. Differences in amplitude reflect the inherent, distinct physiological cha rac-teristics for a random population chosen in this study. This intensional random population is due to the interest in findi ng out a universal, more general model mainly when compared to results obtained for a limited, homogeneous physiological characteristic of uniforme population in [5]. Higher amplitude refers to patients with great wall complacency (elasticity), for instance, in recent pregnant women as well as multiple pregnancies in contrast to patients with previous abdominal surgeries that mostly present reduced amplitude. Although pressure volume carries this sort of changes they are not that easily perceptible. The correlation between intraperitoneal pressure and volume of gas insufflated into the peritoneal cavity was analyzed, with a 95% confidence interval being adopted.

C. Statistical Analysis

First, the direct relationship of the intra-perineal pressure, $\mathbf{P}$, and the injected gas volume, $\mathbf{V}$, into the abdominal cavity as a reliable parameter of safe gas insuflation is investigat ed by employing statistical analysis. The polynomial regression model for $\mathbf{1^{st}}$, $\mathbf{2^{nd}}$, and $\mathbf{3^{rd}}$ order were computed and the better result was determined by residual analysis and the explanation coeficient, $\mathbf{R^2}$. The statistical model is given as:

$$\mathbf{P = 4.83 + 5.72V - 1.85V^2 + 0.18V^3} \quad (1)$$

The resulting response is depicted in Fig. 5 [6].

D. Gas Volume to Intra-peritoneal Pressure Fuzzy Modeling in Videolaparoscopic Surgery

A fuzzy system is a formal and mathematical mechanisms for nonlinear input-output mapping usually applied in mod-eling, control system, and decision support systems when dealing with uncertainty, imprecision, vagueness, and partial truth. While fuzzy set theory allows in dealing with the inherent imperfection and subjectivity of clinical facts, fuzzy logic permit to aggregate simultaneously diverse variables in the same system as well as to build up a fuzzy mapping based both on experience of specilists and on data-driven analysis.

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011

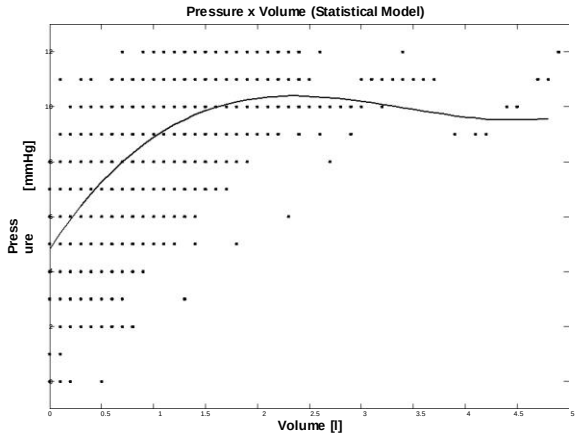


Fig. 5. Statistical Model, $P = 4.83 + 5.72V - 1.85V^2 + 0.18V^3$, for Intraperineal Pressure and Gas Volume Relationship [6].

The most known categories of fuzzy system are (**i**) linguistic and (**ii**) interpolative, model-based fuzzy system. The most employed linguistic approach is the Mamdani fuzzy system while the model-based approach is associate to the Takagi-Sugeno (T-S) fuzzy system. The T-S model [13] representation often provides efficient and computationally attractive so lu-tions to a wide range of modeling problems introducing a pow-erful multiple model structure that is capable to approximate nonlinear dynamics, multiple operating modes and significa nt parameter and structure variations [].

The T-S fuzzy model is employed in this paper. This technique assumes an important role when attempting to find out models from data. A fuzzy system represents a *nonlinear mapping* from input space vectors, X_n, to a scalar output space, Y, in the form, $f : X_n \rightarrow Y$, such that X_n and Y are universe of discourses that define the input-output spac e, $X_n \times Y$, and an associated fuzzy inference mechanism.

The essential idea is the partitioning of the input space into fuzzy areas and the approximation of each area through a linear model in such a way that a global nonlinear model is computed. In so doing, it is characterized as a set of **h**IF-THEN**O** rules where the consequent part are linear sub-models describing the dynamical behavior meanwhile the antecedent part is in charge of interpolating these sub-systems:

$$R_j : \text{IF } hx_1 \text{ is } M_{j1}\,O \text{ AND} \ldots \text{AND } hx_m \text{ is } M_{jm}\,O \text{ THEN } y_j = a_{j0} + a_{j1}\,\delta_{j1} + \ldots + a_{jq}\,\delta_{jq} \quad . \tag{2}$$

The **h**IF statements**O** defines the premise part that is featured as linguistic terms in the proposition form, hx_i is $M_{ji}\,O$, while the **h**THEN functions**O** constitutes the consequent part of the **j**-th rule of the fuzzy system that is characterized, but not limited to, as a linear polynomial, $y_j = a_{j0} + a_{j1}\,\delta_{j1} + \ldots + a_{jq}\,\delta_{jq}$. The vector $x = [x_1, \ldots, x_i]$ represents the **i**-th input vector of the premise, $\forall\, i = 1, \ldots, m$, and so, the dimensionality of the premise space. In general, the variable $\delta_i(\cdot)$ and the input variable are assigned to be the same, $\delta_i = x_i$ such that the linear output polinomial becomes $y_i = a_{i0} + a_{i1}\,x_{i1} + \ldots + a_{iq}\,x_{iq}$ introducing an additional nonlinearity performance to the T-S fuzzy system.

The premise of the Takagi-Sugeno fuzzy model corresponds to gas volume inserted into the abdominal cavity mapped into the consequent that is the intraperineal pressure measures. The input universe of discourses are parted into 3, 4, 5 and 6 membership functions and each linguistic label, M_{ji}, is here associated to a Gaussian, Bell, Trapezoidal, Triangular mem-bership functions to select the best for modeling the relation between the intra-perineal pressure and the gas volume. The final fuzzy mappings are compared to statistical approach.

The firing strength of the **j**-th rule, R_j, represents its acti-vation level and may, for instance, be chosen as the algebraic product:

$$\mu_j(x) = \mu_{M_{J1}}(x_1)\,\mu_{M_{J2}}(z_2) \ldots \mu_{M_{JM}}(x_m) \quad . \tag{3}$$

not only because it is more employed than the minimum operation but it so is due to the fact that the multiplicative weight yield a smooth response [13].

The fuzzy sets pertaining to a rule form a fuzzy region (cluster) within the premise space, $M_{ji} \times \ldots \times M_{jm}$, with a membership distribution described in eq. (3). Given the input vectors x, and a_{ij}, such as $j = 1, \ldots n$, where n denotes the number of rules the final output of the fuzzy system is inferre d by taking the weighted average of the local outputs $y_j(x_j, a_j)$ that is given by:

$$y = \frac{\sum_{j=1}^{M} \mu_j(x)\, y_j(x_j, a_j)}{\sum_{j=1}^{M} \mu_j(x)} \quad . \tag{4}$$

Its equivalent arquitecture is depicted in Fig. 6

In this paper fuzzy systems is employed in synergy with ar-tificial neural network by presenting learning capacity thr ough input-output examples [15]. Artificial neural network, for short Neural Network (NN), is one of the most prominent approaches for pattern classification, clustering/catego rization, function approximation, prediction/forecasting, optimization, content-addressable memory and control, as well [**?**]. Likewise fuzzy systems, neural network is a mathematical technique that maps input-output data sets by means of a nonlinear transfer function. Biologically inspired, this technique encompasses a large number of interconnected neuron-based processing elements in a massively parallel structure. Connecting each

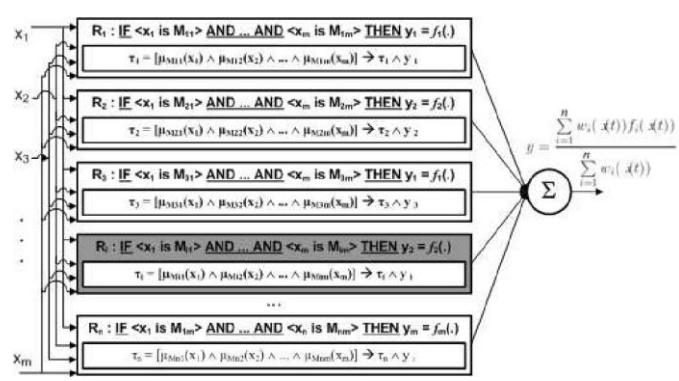


Fig. 6. Arquicteture of Takagi-Sugeno Fuzzy System.

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011

neuron, there are weights that compose the knowledge associate to intelligence that emerges from the collective behavior of the whole neural system.

There are a myriad of NN architectures but one of the most expressive is the Multilayer Perceptron (MLP). The topology of a typical MLP with two hidden layers is depicted in Fig. 7. The MLP uses a pre-determined set of inputs and target outputs, (x_i , y), the NN gives an output value, y_o, from the new input in the activation phase, weights are computed in a training (learning, adjusting) phase from an error minimization algorithm for reducing the square error, $(y - y_o)^2$, at each iteration. First, the set of input information is supplied to the input layer and the neural network propagates it in a forward manner for achieving a neural activation level output:

$$y_j = f\left(\sum^{P} W_{ji}\, x_i - \theta_j\right) \quad (5)$$

where x_i are the inputs such that $i = 1, \ldots, N$ are the number of inputs; y_j is the activation level of the hidden and output layer; W_{ji} is the weight from the i–th input, x_i , to the j–th neuron, x_j ; θ is the node threshold. The desired output and the computed neural network output are compared to change the weights inside the network in an adaptive behavior by using a *supervised learning*.

The advantage of using MLP is due to its ability to form any arbitrary regions, given sufficient hidden layers and ne ural units, being able to deal with complex pattern recognition and classification and optimization. It can deal with comple x decision regions since each node in the first layer can create an hyperplane, each node in the second layer can achieve a convex decision region, and the third one can form a concave regions [**?**]. When associate to the fuzzy regions as consequence of the premise part in (2) allows to tune the T-S fuzzy system. Actually, the T-S fuzzy structure in Fig. 6 and the NN structure in Fig. 7 are twosome. When working in synergy, fuzzy systems and neural networks compose a hybrid system that takes advantage of their individual char-acteristics yielding a Neuro-Fuzzy system with capacities of learning, adaptation, optimization meanwhile is able to deal with uncertain, imprecise, vague information. In doing so,

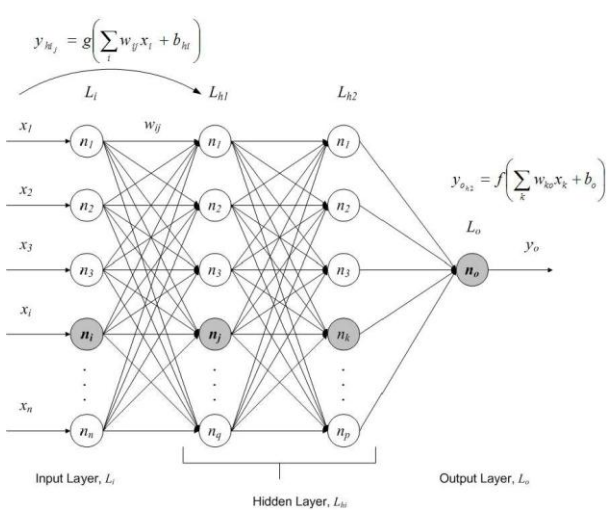


Fig. 7. The feedforward neural network architecture.

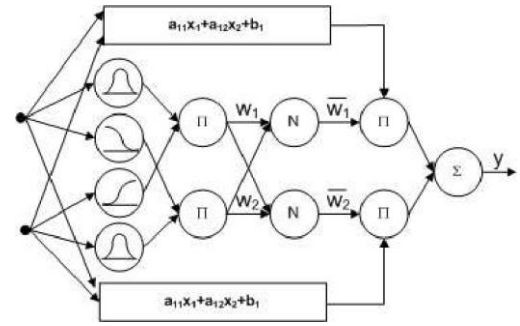


Fig. 8. ANFIS Structure.

the system is able to generalize when dealing with large amounts of numerical data and with imperfect knowledge representation through fuzzy rules [16]. The model used in this work is the well established hybrid system named Adaptive Neuro-Fuzzy Inference System (ANFIS) [17]. This neuro-fuzzy approach is effective in processing numerical data and presents distributed computational characteristic allowing that each node in the network to adjust its connections to obtain the best possible input-output mapping after learning from data. A neuro-fuzzy model equivalent to the Takagi-Sugeno system is depicted in Fig. 8. The parameters of membership functions are obtained by using the backpropagation algorithm achieving a supervised learning. This approach attempts to iteratively search a minimal error determined by the difference between the desired and actual measured outputs. The error signal is backward, then, of the output layer for each element of the previous intermediate layer that contributes directly to form the output in a feedforward manner. Nevertheless, each element of the intermediate layer just receives a portion of the signal of error total, proportional just to the relative contribution of each element in the formation of the original output. This process repeats, layer after layer, until each element of the network receives an error signal that describes its relative contribution to the total error. Based on this error, the weights of the connections are updated for each element allowing the neural network to converge all the patterns of the training group [18].

This example has two inputs x, y, one output f and two rules. The ANFIS structure is composed by the following elements:

1) *Input Layer*: Computes the degree of relevancy of the inputs x,y with relation of the subgroups fuzzy that form the partition of x and y, or either, the process of fuzzification.

2) *Membership Layer*: Computes the degree of activation of each rule, with that degree the consequence of the rule is being taken care of. The function for this layer is a *T-norm* that uses the probabilistic form. In this, the outputs of the neurons given by Eq. (6) are equivalent to (3):

$$w_1 = \mu_{A1}(x_1) \cdot \mu_{A2}(x_2) \cdot \mu_{A3}(x_3) \quad (6)$$

3) *Rule and Norm Layer*: Layer 3 is the degree of relevance of each rule, already normalized. Each point i calculates the reason for the firing strength of rule j for the sum of the firing strength of all the rules. The outputs of points this la yer

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011

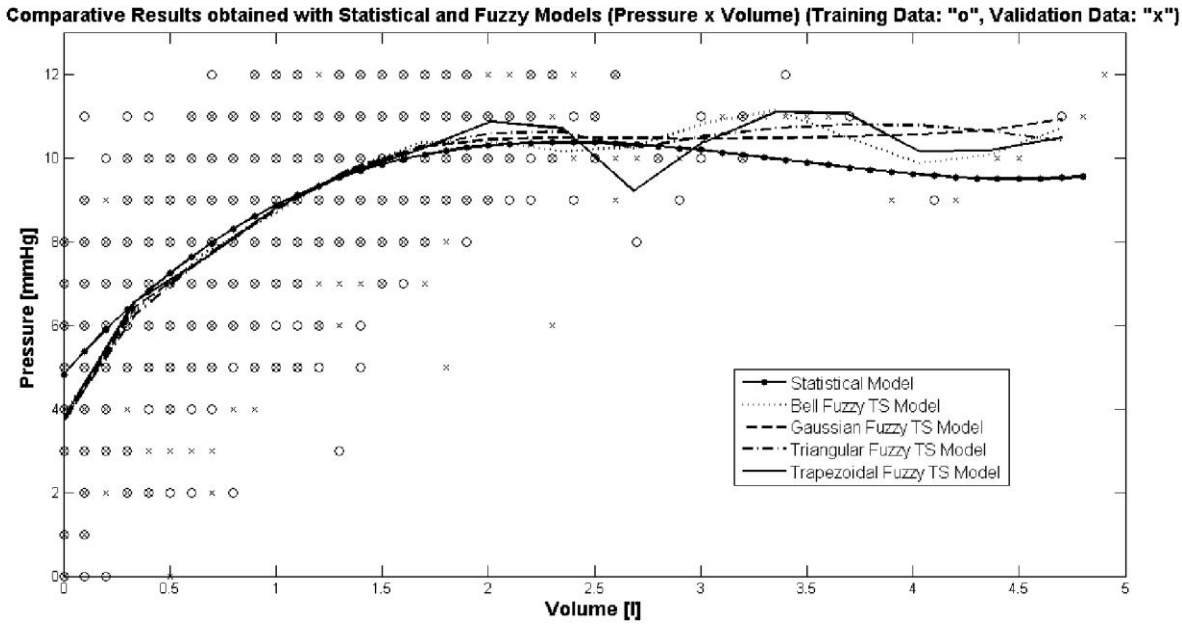


Fig. 9. Results.

referring to Fig. 8 are:

$$\bar{w}_1 = w_1 (w_1 + w_2 + w_3)$$
$$\bar{w}_2 = w_2 (w_1 + w_2 + w_3). \quad (7)$$

4) *Layer consequent*: Layer 4 contains the function of activation of the neurons, consequence part of the rules (C_i). It is calculated by the product of the normalized firing stren gth ($S_i \forall i = 1, 2, 3$) and the value of the consequence of the rule. The output values of each point of this layer are given by:

$$H_1 = \bar{w}_1 \cdot C_1$$
$$H_2 = \bar{w}_2 \cdot C_2 . \quad (8)$$

5) *Output layer*: It computes the necessary output of the network as:

$$F = H_1 + H_2 . \quad (9)$$

E. Fitness Index

Pearson multiple correlation coefficients , R^2, is chosen to evaluate the output during the optimization process. This co-efficient gives the rate between the variability of two measu res (variables) in which one is described by the variability of the other [19].

The performance evaluation of training phase is given by:

$$R^2_{training} = 1 - \frac{\sum_{k=1}^{0.5N_a} [y(k) - y(k)]^2}{\sum_{k=1}^{0.5N_a} [y(k) - \bar{y}]^2} \quad (10)$$

where N_a is the total number of samples evaluated, and $\bar{y}(k)$ is the system real output (Fig. 4(b) and 4(d)). When $R(.)^2$ is close to unit a sufficient accurate model for the measured dat a of the system is found.

The performance evaluation of validation phase of optimized T-S fuzzy system is achieved by:

$$R^2_{validation} = 1 - \frac{\sum_{k=0.5N_a+1}^{N_v} [y(k) - y(k)]^2}{\sum_{k=0.5N_a+1}^{N_v} [y(k) - \bar{y}]^2} . \quad (11)$$

where N_v is the total number of samples evaluated in validation phase (Fig. 4(b) and 4(d)).

III. Results and Discussion

In order to verify the best tuning of the T-S fuzzy model for achieving the intra-peritoneal pressure measure and the injected gas volume relationship, several simulations are per-formed. In each simulation, the T-S fuzzy inference model with **2, 3, 4**, and **5** membership rules in the triangular, trapezoidal, bell, and Gaussian shapes achieved a good approximation in training and validation phases. Results are accomplished when using the adaptive neuro-fuzzy inference system, where the learning ability of the artificial neural network and the abi lity of dealing with imprecise, uncertain, vague information of T-S fuzzy system work in synergy. The best results for each of the independent runs carried out based on distinct initial trial solutions are presented in Table II. The intra-peritoneal pressure measure and the injected gas volume relationship obtained with the fuzzy analysis is depicted in Fig 9.Graphical

TABLE I
Liver Fibrosis Degree obtained by FAPRI

Experimental Data Input-output Modeling	Comparative Parameter (R^2)
Statistical Polynomial Regression	0.5567
Fuzzy Model (Triangular)	0.5865
Fuzzy Model (Trapezoidal)	0.5881
Fuzzy Model (Bell)	0.5873
Fuzzy Model (Gaussian)	0.5826

TABLE II
LIVER FIBROSIS DEGREE OBTAINED BY FAPRI

	R^2_{TRAIN}	R^2_{VAL}	$R^2_{HARMONIC}$	Mean Train. Error	Mean St. Deviation	Mean Val. Error	Mean St. Deviation
Tri-2mf	0.585628622	0.492355929	0.534957062	-0.000000041	1.756285801	0.000932671	1.746072194
Tri-3mf	0.586567744	0.488139865	0.532846511	-0.000000164	1.754294468	0.006319130	1.753296750
Tri-4mf	0.587748713	0.491034197	0.535056154	-0.000000431	1.751787106	0.014149815	1.748286713
Tri-5mf	0.583455035	0.481554809	0.527630011	0.000000496	1.760886078	0.018333997	1.764454842
Trap-2mf	0.578111309	0.480703487	0.524926783	0.000000002	1.772145015	0.012340653	1.765955207
Trap-3mf	0.588148164	0.484565419	0.531355743	-0.000000037	1.750938204	-0.006274939	1.759408191
Trap-4mf	0.577650899	0.477819394	0.523013873	-0.000000001	1.773111728	0.014845563	1.770833322
Trap-5mf	0.588009783	0.491880765	0.535666698	-0.000000021	1.751232333	-0.000625476	1.746889317
Gauss-2mf	0.583157245	0.483514013	0.528681536	-0.000000069	1.761515399	0.007553301	1.761196733
Gauss-3mf	0.582604876	0.484853846	0.529253655	-0.000000076	1.762682127	0.007161227	1.758912460
Gauss-4mf	0.587570303	0.492484426	0.535841771	0.000000003	1.752166127	-0.003765742	1.745847376
Gauss-5mf	0.587888446	0.490740802	0.534939782	-0.000000051	1.751490196	-0.005911147	1.748837897
Bell-2mf	0.583483098	0.488768879	0.531942838	0.000000014	1.760826761	0.008711129	1.752208838
Bell-3mf	0.587336309	0.493916751	0.536590836	-0.000000115	1.752663105	0.003356020	1.743382870
Bell-4mf	0.587944481	0.492374787	0.535932381	-0.000000197	1.751371119	-0.000753314	1.746039848
Bell-5mf	0.590606523	0.458928354	0.516507046	-0.000001161	1.745704675	-0.024122020	1.802482452

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011

results show that the T-S fuzzy system presents successful results when predicting nonlinear input-output mapping when compared to statistical input-output mapping.

The resulting T-S fuzzy system determined by using the artificial neural optimization approach is given as:

$$\begin{aligned} Rs_1 &: \text{IF } \mathbf{hvolume} \text{ is} \mathbf{O} \text{ THEN } \mathbf{P = 8.968V + 3.78} \\ Rs_2 &: \text{IF } \mathbf{hvolume} \text{ is} \mathbf{O} \text{ THEN } \mathbf{P = 4.446V - 2.87} \\ Rs_3 &: \text{IF } \mathbf{hvolume} \text{ is} \mathbf{O} \text{ THEN } \mathbf{P = 0.914V + 6.21} \end{aligned} \tag{12}$$

such that for finding the value of the resulting membership function, $\mu_j(x)$, by employing expression in (3). The membership functions in this paper are defined according to the gen-eral description as follows. Consider a membership function, $\mu_A : X \rightarrow [0, 1]$, defined upon an universe of discourse, X, to which is associated a set of terms $T = \{A^j_1, A^j_2, \}$; a linguistic term $A^j_i \in T$, where $c(A^j_i) = \{x_0 \in X_1 | \mu_{A^{ji}}(x_0) = 1\}$ and $s(A^j_i) = \{x_0 \in X_1 | \mu_{A^{ji}}(x_0) > 0\}$, respectively, denote the core and support of A^j_i. In this paper each term $A^j_i \in T$ is shaped as a Gaussian membership function and represented by the pair $A^j_i = hm, \sigma O$, according to a Gaussian function as shown in eq. (**??**) such that m is the mean value and σ is the standard deviation, where $c(A) = [m]$. Taken into account the first input, the core (center of the Gaussian function) and the standard deviation for the two membership functions may also be represented, respectively, $A^1_1 = h1.9587, 4.2321O$, $A^1_2 = h1.9601, 4.2321O$, $A^1_3 = h0.6503, 4.2321O$, $A^1_4 = h1.9606, 4.2321O$, $A^1_5 = h4.0531, 4.2321O$, while for the second input the membership functions are $A^2_1 = h0.4257, 3.1909O$, $A^2_2 = h1.1031, 3.1909O$, $A^2_3 = h0.8170, 3.1909O$, $A^2_4 = h0.9571, 3.1909O$, $A^2_5 = h0.9641, 3.1909O$.

The final, global output is computed as :

$$P = x.xxxV \quad , \tag{13}$$

by using expression in (4) such that the number of rules is $M = 5$, and .

IV. CONCLUSIONS

This paper innovates in using fuzzy logic and fuzzy set theory for evaluating the accuracy of the prognosis value of intra-peritoneal pressure measures as function of the injected gas volumes as a reliable parameter of safe gas insuflation. Being a mathematical and formal mechanism for describing natural phenomena, this approach is used to build up a fuzzy model to indicate and adequate needle tip positioning by employing the resulting intra-perineal pressure measure and the injected gas volume relationship.

The use of fuzzy set theory and fuzzy logic in building up input-output nonlinear mapping as in intelligent decision support system, modeling and controle seems to be adequate for the field of life sciences being an alternative or a complemen t to be used in conjunction with inferencial statistic analysis.

Nesta etapa, as fibras musculares da parede abdominal alongam-se, criando o espao de trabalho, sempre que a presso decorrente do volume insuflado iguala ou supera a tenso da parede. Os grficos de cada paciente para o comportamento 77

da presso durante a insuflao mostraram que a presso atinge um determinado valor para um momento determinado ou volume insuflado e na mensurao seguinte, a mesma diminui, e assim sucessivamente at atingir o valor pressrico final pr-determinado. Este comportamento corresponde distenso progressiva da parede, em que a musculatura, apesar da cu-rarizao, no atinge seu ponto mximo de estiramento, cujo limite determinado pelo envoltrio conjuntivo. Ocorre o alongamento paulatino, mas no gradual, das fibras musculares at o limite dado pelo envoltrio conjuntivo. comum na prtica clnica, no decurso de um procedimento por via laparoscpica, que o sbito aumento da presso intra-abdominal e a diminuio do espao de trabalho, correspondam ao fim do efeito curarizante36 da droga utilizada, e a retomada do tnus normal da musculatura da parede abdominal.

The proposed approach demonstrates the feasibility of fuzzy analysis for finding out a gas-volume to intraperitone al-pressure mapping. Further, results demonstrated the effica cy of fuzzy system modeling mainly when compared to statistical inference.

assim uma alternativa para lidar com comportamentos dinmicos que no podem ser descritos pelos mtodos de mode-lagem convencional devido falta de um conhecimento preciso

e formal sobre o sistema, seja devido ao comportamento no-linear, devido complexidade do sistema pelo alto grau de incerteza na informao, ou ainda devido s caractersticas variantes no tempo31.

Uma das principais razes para o sucesso de sistemas nebulosos (fuzzy) a vantajosa relao custo-benefcio para soluo de grande nmero de problemas reais.

REFERENCES

[1] D. Molloy, P. D. Kaloo, M. Cooper, and T. V. Nguyen, "Lapar oscopic entry: a literature review and analysis of techniques and complications of primary port entry," *Australian New Zealand Journal of Obstetrics and Gynaecology*. vol. 42, pp. 246–253, 2002.

[2] M. Catarci, M. Carlini, P. Gentileschi, and E. Santoro, " Major and minor injuries during the creation of pneumoperitoneum," *Surgical Endoscopy*, vol. 15, pp. 566–569, 2001.

[3] D. Anaise, *Vascular and bowel injuries during laparoscopy*.

[4] J. Wind and J. Cremers, "Medical liability insurance cla ims on entry-related complications in laparoscopy," *Surgical Endoscopy*, vol. 21, pp. 2094–2099, 2007.

[5] O. C. Azevedo, J. Azevedo, A. Sorbello, G. Miguel, R. Guindalini, A. Godoy, J. Wilson, and L. Jorge, "Evaluation of tests perfo rmed to confirm the position of the veress needle for creation of pneu moperitoneum in selected patients: a prospective clinical trial," *Acta Cir´urgica Brasileira*, vol. 21, pp. 385–391, 2006.

[6] O. M. Becker, "Veress needle left hypochondrium punctur e efficiency and accuracy by fuzzy inference method," S˜ao Jos´e dos Camp os, p. 196, 2006.

[7] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, pp. 338–353, 1965.

[8] E. Araujo, "Fuzzy logic, fuzzy set theory, and approxima te reasoning teaching experience in medical and healthcare education," *Artificial Intelligence in Medicine*, p. Submitted, 2009.

[9] I. Virant-Klun and J. Virant, "Fuzzy logic alternative f or analysis in the biomedical sciences," *Computers Biomedical Research*, vol. 32, pp. 305–321, 2006.

[10] H. M. Hasson, "A modified instrument and method for lapar oscopy," *Amer J Obstet Gynec* , vol. 110, pp. 887–???, 1971.

[11] A. Hasan, O. Banli, and B. Kavlakoglu, "Comparison betw een direct trocar and veress needle insertion in laparoscopic cholecystectomy," *J Laparoendosc & Adv Tech.*, vol. 17, pp. 709–712, 2007.

[12] P. G. aes, "Pneumoperitoneum, punctures and trocars," in *Brazilian Con-sensus in Ginecological Videoendoscoscopy*, N. Donadio and L. C. A. Neto, Eds. Artes M´edicas, 2001, pp. 27–32, in Portuguese.

[13] T. Takagi and M. Sugeno, "Fuzzy identification of system s and its applications to modeling and control," *IEEE Trans. on Systems, Man and Cybernetics*, vol. 15, no. 1, pp. 116–132, 1985.

[15] C.-T. Lin and C. S. G. Lee, *Neural fuzzy systems: A neuro-fuzzy synergism to intelligent systems*. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1996.

[16] B. J.C., "Guest editorial," *IEEE Trans. On Neural Networks*, vol. 3, no. 1, p. 641, 1992.

[17] J.-S. R. Jang, "Anfis: Adaptive-network-based fuzzy in ference system," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.

[18] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, *Parallel distributed processing*, ser. Foundations. Cambridge, Massachusetts: Ed. MIT Press, 1987, vol. 1, d. E. Rumelhart, J. L. McClelland and the PDP group.

[19] B. Schiweizer, H. Xie, and Y. Lee, "Fuzzy logic models fo r ranking process effects," *IEEE Trans. on Fuzzy Systems*, vol. 5, pp. 545–55, 1997.

Nature Precedings : doi:10.1038/npre.2011.6060.1 : Posted 24 Jun 2011