Professor Maria Viorica STEFANESCU
Department of Mathematics
The Bucharest Academy of Economic Studies
Cristian SURCEL, M.D.
Carmen SAVU, PhD
Center of Uronephrology and Renal Transplant
Fundeni Clinical Institute, Bucharest
Professor Massimiliano FERRARA, PhD
University of Reggio, Calabria

DATA ANALYSIS WITH APPLICATION IN MEDICINE

Abstract. *A classification algorithm and PCA are summarized. These are then used to analyze the impact of preexistent liver cirrhosis on perioperative mortality and morbidity of patients undergoing a urological intervention.*

Key words: *classification, PCA, liver cirrhosis, urological intervention*

JEL Classification C02, C61, C62.

Classification with Algorithm Based on an Ultrametric Distance

Proving that a total hierarchy determines and is determined by an ultrametric structure on X, S.C. Johnson ([3]) has firstly proposed a general scheme for constructing a classification based on ultrametric distance. Essentially, this scheme determines a chain of partitions which contains classes with growing diameters.

Let δ be an ultrametric distance on X.

STAGE 0:

Let $\mathbf{P}^0 = \{P_1^0, \dots, P_n^0\}$ be the discrete partition, with $P_i^0 = \{x^i,\ i = \overline{1,n}\}$.

Define $\delta(P_i^0, P_j^0) = \delta(x^i, x^j)$, $v_0 = 0$, $\mathbf{L}^0 = \{1,2,\dots, n\}$.

STAGE T (T ≥ 1):

1^0. Determine $v_t = \min\{\delta(P_i^{t-1}, P_j^{t-1}) \mid P_i^{t-1}, P_j^{t-1} \in \mathbf{P}^{t-1}\}$

2^0. $\mathbf{C}^t = \{(i,j) \mid i,j \in \mathbf{L}^{t-1},\ \delta(P_i^{t-1}, P_j^{t-1}) = v_t\}$,

$\mathbf{I}^t = \{i \in \mathbf{L}^{t-1} \mid \exists j, (i,j) \in \mathbf{C}^t\}$.

3^0. For each $i, j \in \mathbf{L}^{t-1}$, with $\{i \mid (i,j) \in \mathbf{C}^t\} \neq \emptyset$, put

$P_i^t = P_i^{t-1} \cup \{P_j^{t-1} \mid j \in \mathbf{L}^{t-1}, (i,j) \in \mathbf{C}^t\}$, $P_i^t = P_i^{t-1}$, if $i \in \mathbf{L}^{t-1} \setminus \mathbf{I}^t$.

4^0. $\mathbf{P}^t = \{P_i^t \mid$ distinct P_i^t obtained at $3^0\} \cup \{P_i^t \mid i \in \mathbf{L}^{t-1} \setminus \mathbf{I}^t$,
$\mathbf{I}^t$ = indices of elements of $\mathbf{P}^t\}$.

5^0. If $|\mathbf{P}^T| = 1$, write $\mathbf{L}^T = \{\mathbf{P}^0, \mathbf{P}^1, \ldots, \mathbf{P}^T\}$. STOP.
If $|\mathbf{P}^T| > 1$, go to 6^0.

6^0. Define $\delta(P_i^t, P_j^t) = \delta(P_i^{t-1}, P_j^{t-1})$, $i, j \in \mathbf{L}^t$.
Repeat the cycle for $t = t+1$.

Proposition 1. For every $i, j \in \mathbf{L}^t$ and $x, u \in P_i^t$, $y, v \in P_j^t$, it follows that $\delta(x, v) = \delta(u, v)$.

Proof. Inductively, in respect to t.

Let t = 1, $|P_i^1| \geq 2$ be.

According to 1^0 and 2^0, $\delta(x, u) = v_1 = \min\{\delta(a, b) \mid a, b \in X\}$.

Let $y \in P_j^1$ and assume that $\delta(x, y) > \delta(u, y)$.

But, $\delta(x, u) \leq \max\{\delta(x, u), \delta(u, y)\} = \delta(u, y)$, contradicting the previous inequality. Hence, $\delta(x, y) = \delta(u, y)$.

In the same way, it results δ(x, v) = δ(u, v). On the other hand, if y ≠ v, then δ (y, v) ≠ v_1. Interchanging the two pairs, we obtain another two inequalities, which complete the proof for t = 1.

Further, let we presume that the proposition is verified until the stage t -1, (t ≥ 2) and let $P_i^t, P_j^t \in \mathbf{P}^t$. If $P_i^t, P_j^t \in \mathbf{P}^{t-1}$, the induction assumption ensures the truth of proposition.

1) Suppose that $P_i^t \notin \mathbf{P}^{t-1}$, $P_j^t \in \mathbf{P}^{t-1}$. Then there exist $i_1, i_2 \in \mathbf{L}^{t-1}$ such that $x, u \in P_i^{t-1} \cup P_{i_1}^{t-1} \cup P_{i_2}^{t-1}$, $u \in P_{i_2}^{t-1}$ and $\delta(P_i^{t-1}, P_{i_1}^{t-1}) =$
$= \delta(P_i^{t-1}, P_{i_2}^{t-1}) = v_t = \min\{\delta(P_k^{t-1}, P_l^{t-1}) \mid k, l \in \mathbf{L}^{t-1}, k \neq l\}$.

Consider three situations:

a) x, u belongs to the same set from the above union. Then, the desired equality results from induction assumption.

b) $x \in P_i^{t-1}$, $u \in P_{i_1}^{t-1}$. Then, $\delta(x, u) = \delta(P_i^{t-1}, P_{i_1}^{t-1}) = v_t =$ $\min\{\delta(a, b) \mid a \in P_k^t, b \in P_i^{t-1} \mid k, l \in \mathbf{L}^{t-1}, k \neq l\}$. As in the first step, we conclude that $\delta(x, y) = \delta(u, y)$ and $\delta(x, v) = \delta(u, v)$. But, from the induction assumption, $\delta(x, y) = \delta(x, v)$ and, hence, $\delta(x, y) = \delta(u, v)$.

c) $x \in P_{i_1}^{t-1}$, $u \in P_{i_2}^{t-1}$. It is sufficient to show that $\delta(x, u) = v_t$ and argue as in case *b)*.

Consider $z \in P_i^{t-1}$. Then we may write $\delta(x, u) \leq \max\{\delta(x, z), \delta(z, u)\} = v_t$.

In addition, if $\delta(x, u) = (P_{i_1}^{t-1}, P_{i_2}^{t-1})$, the inequality fails (otherwise one contradicts the choice of v_t).

2) $P_i^t, P_j^t \notin \mathbf{P}^{t-1}$. We may find $j_1, j_2 \in \mathbf{L}^t$ such that $y, v \in P_j^{t-1} \cup P_{j_1}^{t-1} \cup P_{j_2}^{t-1}$ and $\delta(P_j^{t-1}, P_{j_1}^{t-1}) = \delta(P_j^{t-1}, P_{j_2}^{t-1}) = v_t$.
From the first part of the proof it results that $\delta(x, y) = \delta(u, y)$ and $\delta(x, v) = \delta(u, v)$. Interchanging P_i^t and P_j^t we obtain again from 1) that $\delta(y, x) = \delta(v, x)$ and $\delta(y, u) = \delta(v, u)$.

Corollary. If $P_j^{t-1}, P_k^{t-1} \subseteq P_i^t$ for same $t \geq 1$ and $j, k \in \mathbf{L}^{t-1}$, then $\delta(P_k^{t-1}, P_i^{t-1}) = \delta(P_j^{t-1}, P_i^{t-1})$ for every $l \in \mathbf{L}^{t-1}$.

Proof. Indeed, the algorithm assures that $\delta(P_j^{t-1}, P_k^{t-1}) \leq v_t$. Then, we follow as in stage $t = 1$ of the previous proof.

Remarks. 1) Proposition 1 justifies the instructions of the algorithm. Since $\delta(P_j^t, P_j^t)$ is the same with the distance between any two points of the two sets, we can take $\delta(P_i^t, P_j^t) = \delta(P_i^{t-1}, P_j^{t-1})$ if, at the step t, P_i^t has been obtained as a union which includes P_i^{t-1}.

2) Moreover, the adopted notation has the usual signification:
$\delta(P_i^t, P_j^t) = \min_{x \in P_i^t,\ y \in P_j^t} \delta(x, y)$.

Theorem 1. The family $\mathbf{L}^k = \{\mathbf{P}^0, \mathbf{P}^1, \ldots, \mathbf{P}^T\}$ obtained with algorithm ($|\mathbf{P}^T| = 1$) is a complete chain of partitions of X. Moreover,
$v_{t-1} = \max_{P \in P^{t-1}} \rho(P) < \max_{P \in P^t} \rho(P) = v_t,\ t \geq 1.\ \left(\rho(P) = \max_{x, y \in P} \delta(x, y)\right)$.

Proof. The first part of theorem is easily verified by induction. For the second affirmation it is sufficient to verify that $v_t = \max_{P \in P^t} \rho(P)$ and $v_{t-1} < v_t$.

For $t = 1$ both properties are trivial. Suppose that they are true for t-1.
Assume that $P_i^t = P_i^{t-1} \cup P_j^{t-1}, P_i^{t-1}, P_j^{t-1} \in \mathbf{P}^{t-1}$. Then,
$\rho(P_i^t) = \max\left\{\rho(P_i^{t-1}), \rho(P_j^{t-1}), \delta(x, y) \,\middle|\, x \in P_i^{t-1}, y \in P_j^{t-1}\right\} = \max\left\{\rho(P_i^{t-1}), \rho(P_j^{t-1}), v_t\right\}$
Let $x, z \in P_i^{t-1}$, $y \in P_j^{t-1}$. Then,
$\delta(x, z) \leq \max\{\delta(x, y), \delta(y, z)\} = \delta(P_i^{t-1}, P_j^{t-1}) = v_t$. Hence, $\rho(P_i^{t-1}) \leq v_t$.
Consequently, $\rho(P_i^t) = v_t$ and $\max_{P \in P^t} \rho(P) = v_t$.

Finally, we notice that $v_{t-1} < v_t$. Indeed, in the case of equality the set P_i^t would be formed at the step t-1.

Theorem 2. The set A of distinct classes of partitions $\mathbf{P}^0, \mathbf{P}^1, \ldots, \mathbf{P}^T$ is a total hierarchy of X, indexed by the mapping $v: \mathbf{A} \to R^+$, $v(A) = v_\tau$, if $\tau = \min\{t \mid \mathbf{A} \in \mathbf{P}^t\}$.

Proof. Evidently, from the inequalities $v_0 < v_1 < \ldots < v_T$, above proved.

Corollary. The algorithm constructs a total ascending hierarchy.

Remark. The algorithm is well defined, that is, for each ultrametric distance constructs a unique total classification.

Principal Component Analysis

Principal Component Analysis (PCA) is one of the most common methods of factorial analysis of multidimensional data.

PCA analyzes quantitative numerical data in order to form homogeneous groups of statistical units and investigate interdependencies between variables. Being a descriptive method, it highlights fundamental properties of data, using numerical parameters and graphic plots.

The initial data is represented by different valued observations also known as variables, denoted by $X_1, \ldots, X_j, \ldots, X_p$ on a set of statistical units numbered from $i = 1$ to $i = n$. Frequently these data are presented as a table for which rows correspond to statistical units and columns represent the observed variables.

Statistical Units		***Variables***					
		X_1	X_2	...	X_j	...	X_p
	1	$x_1(1)$	$x_2(1)$	...	$x_j(1)$	...	$x_p(1)$
	2	$x_1(2)$	$x_2(2)$	...	$x_j(2)$	...	$x_p(2)$
	⋮	⋮	⋮	⋱	⋮	⋰	⋮
	i	$x_1(i)$	$x_2(i)$	...	$x_j(i)$	...	$x_p(i)$
	⋮	⋮	⋮	⋰	⋮	⋱	⋮
	n	$x_1(n)$	$x_2(n)$	...	$x_j(n)$	...	$x_p(n)$

The generic element of the table, situated at the crossing between row i and column j, $x_j(i)$, is the observation of variable X_j for the statistical unit i.

Data used for PCA must be quantitative, i.e. the notion of *average* must have meaning. PCA can be performed for data defined by a preference order between the p variables, but it is often recommended to apply Correspondence Analysis to this data.

Quantitative variables can be homogeneous (same units of measure, dispersion of same magnitude as the data) or heterogeneous. The variables can be discrete (can only take a finite number of values) or continuous (can take any value inside an interval). These do not affect the PCA method since the fundamental property of data is still that of being quantitative.

PCA will provide relevant results for sufficiently large data tables. The number of statistical units should be greater than 15 and the number of rows superior to 4. Obviously, this is only a suggestion, since often we can perform PCA on a smaller data set. Most commonly in practice, tables have hundreds of rows (statistical units) and tens of columns (variables).

To make easier the interpretation of results, we can insert in the table *supplementary data*. Supplementary statistical units are those statistical units for which we have observations upon the variables, but we do not wish to take them into account when computing the statistical parameters. Similarly, we can also introduce *supplementary variables*.

Using the supplementary data we can characterize groups of statistical units on graphic plots, or highlight bonds between initial variables and various other variables.

In the beginning, we must define (by measuring) the *distance* or *similitude* between two statistical units. Two statistical units are similar if the observed variables take similar values.

Our objective is to quantify the distance between two statistical units, reflecting as much as possible reality – we must take into account all the variables (except supplementary ones) in order to define the function which expresses the distance between two statistical units. A first definition for the distance function would be the sum of the squares of the distances between the variable observations. This definition is not satisfactory because it would depend on the measurement units of the statistical units.

To stabilize the distance, we must *center* and *reduce* the data, obtaining the formula:

$$d^2(i,k) = \sum_{j=1}^{p} \left(x_j(i) - x_j(k)\right)^2 / \sigma_j^2$$

The distance no longer depends on the units of measure in which the variables are expressed. Using the formula above, we can calculate all distances between statistical units, that is $n(n-1)/2$ distances for n statistical units.

PCA best describes the data, providing a system of orthonormal axes conserving as good as possible the distances between data. The axes have additional properties: they are the straight lines that best fit the cloud of points corresponding to observations according to the least squares criterion and they are called the *factor axes*. Their directing vectors of the axes are called *eigenvectors* and are denoted by u_i.

Each eigenvector u_i has the components:

$$u_i = \left(u_i^1, u_i^2, \ldots, u_i^j, \ldots, u_i^p\right).$$

The axes origin characterizes the statistical unit defined by the average of the initial variables. This property has fundamental consequences in interpreting the results.

Next, the axes are taken in the descending order of closeness to the statistical units. The plane 1×2 will be the closest to the statistical units. On each projection plane the distances between points are inferior to the distances between the statistical units.

A *principal component* denoted by c_i is the list of coordinates of statistical units for the factor axis generated by u_i. Each principal component defines a new variable, because for each statistical unit there is a corresponding coordinate on the factor axis.

The principal components are centered and each pair is uncorrelated. They have great importance in interpreting the results as they explain the relationships between initial variables and justify the formation of homogeneous groups of statistical units. In doing this, we use correlation coefficient between principal components and initial variables.

The dispersion of a principal component is called the *eigenvalue* or *inertia* corresponding to factor axis of same rank. The eigenvalues λ_i are sorted in descending order and their number is equal to the number of initial variables, p. Each factor axis corresponds to an eigenvalue. We usually take into account only the first k nonzero eigenvalues.

The eigenvectors which generate the factor axes are the eigenvectors of the correlation matrix associated to the eigenvalues. These vectors

$u_i = (u_i^1, u_i^2, \dots, u_i^j, \dots, u_i^p)$ for $(\forall)\, i = 1, \dots, p$

are unitary (the sum of the squares of their components is equal to 1) and orthogonal (the sum of products of components of same rank for any pair of different vectors is null).

The coordinates $c_i(i)$ of the statistical units on the axis generated by u_i is given by

$$c_i(i) = \sum_{j=1}^{p} u_i^j x_j'(i).$$

The computation of coordinates of supplementary statistical units is performed using the same formula but without modifying the average and dispersion used in determining the reduced centered value of a variable. We use the formula for data reconstruction which expresses the reduced centered initial variables x' as a function of the principal components:

$$(\forall)\, i = 1, \dots, n \quad (\forall)\, j = 1, \dots, p \quad x_j'(i) = \sum_{i=1}^{k} u_i^j c_i(i).$$

Graphic representations are obtained using the above results.

The statistical units are in the planes whose axes are the factor axes, which are orthonormal. The coordinate of the statistical unit i on the axis i is equal to the $c_i(i)$ value of the principal component c_i referring to the statistical unit i. The origin of the axes characterizes the statistical unit whose values are equal to the averages of the initial variables. These planes are called *factor planes.*

Variables are represented using correlation circles: the coordinates of a variable are the correlation coefficients of this variable with respect to principal components which define the circle.

Application in medicine of Data Analysis

We conducted a comparative study of patients that underwent urologic surgery during January 2006 – December 2009 in our department. The patients were identified through the informatics' medical registry based on ICD-9 (''International Classification of Diseases", 9th Revision Code). Diagnosis of cirrhosis was preconfirmed by clinical criteria (typical signs and symptoms, previous episodes of

hepatic encephalopathy or variceal bleeding), imaging (dysmorphic or atrophic liver, portal hypertension), endoscopic (esophageal varices), peroperative, and/or histological suggestive findings. Chronic renal failure under dialysis therapy and oral anticoagulants were considered exclusion criteria, such as insufficient data available to determine MELD and Child-Turcotte-Pugh scores. Poor outcome was considered death within 30 days p.o., hospitalization >21 days and ICU admittance >14 days. Survival rates were reported using Kaplan Meier curves.

Measurements:

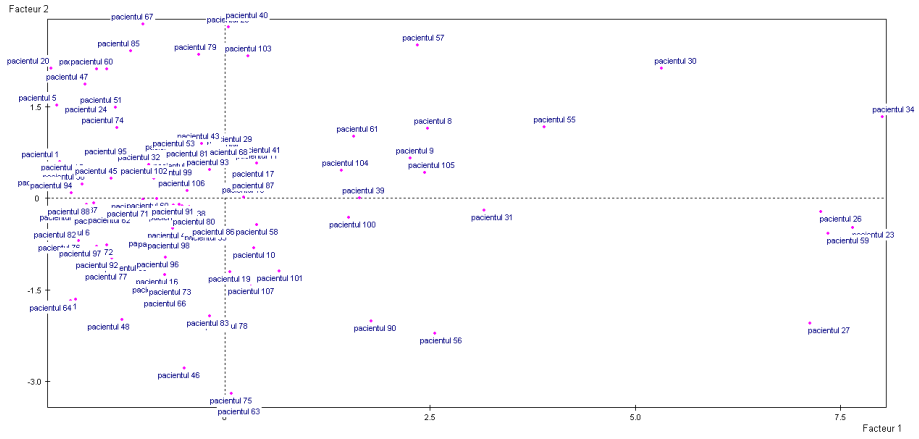
The study contains a review of clinical charts and results of laboratory variables at admittance. The variables studied included age, sex, associated diseases, etiology of liver disease, presence and grade of ascites and hepatic encephalopathy (definition based on West Haven criteria [9]), and laboratory values (bilirubinemia, albuminemia, creatininemia, prothrombinemia and INR). The type of urological procedure (peritoneal/retroperitoneal/endoscopic) and the type of anesthesia (general anesthesia vs other types) were recorded. Child-Turcotte-Pugh [10, 11, 12] classification was determined and Child-Turcotte-Pugh-modified scoring systems, described by Huo [16] were assessed using the following variables: severity of hepatic encephalopathy (grade 1-3), ascites (absent, mild, moderate), total bilirubin (mg/dL), serum albumin (gm/dL), and prothrombin time (seconds). MELD score was determined using the formula described by Freeman [10, 13]:

MELD score = 9.57*Ln creatininemia mg/dl + 3.78*Ln bilirubinemia mg/dl + 11.2*Ln ‘‘International Normalized Ratio’’ + 6.43.

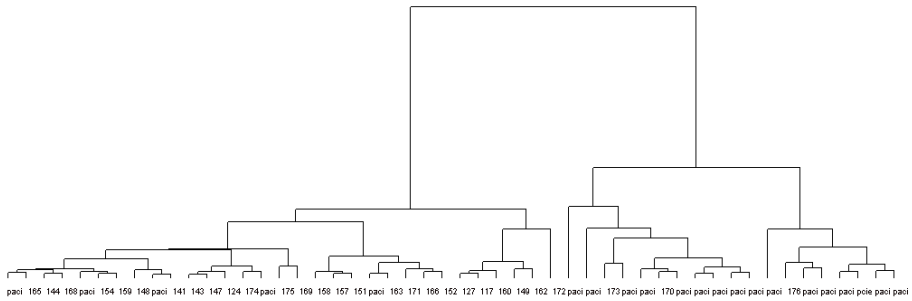
Minimal values were set to 1.0 and maximal serum creatinine level was considered 4.0 mg/dl

Our study contains 113 patients with prediagnosed liver cirrhosis which were divided in 3 groups according to the type of surgery perfomed: 28 peritoneal/30 retroperitoneal/55 endoscopic. For the univariate analysis the study group was compared to a control group of 107 patients without liver cirrhosis also divided in 3 groups: 25 peritoneal/29 retroperitoneal/54 endoscopic. The groups were homogenous and well balanced according to the age, sex, type of urological procedure.

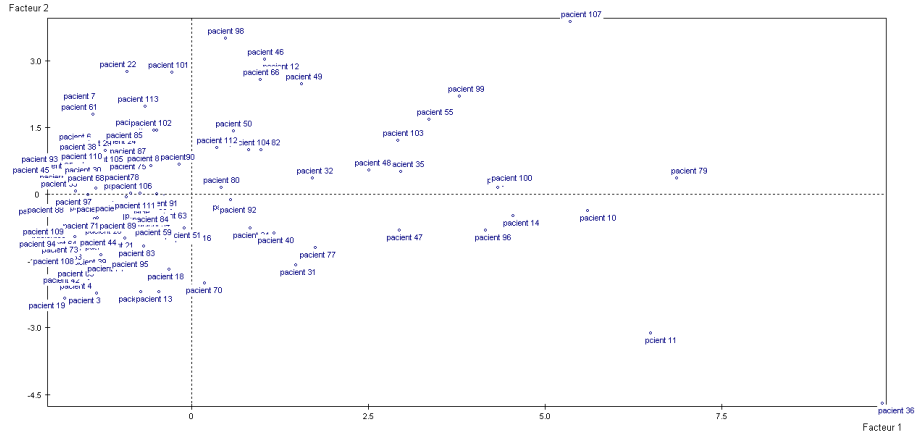
PCA and Classification for the study group and the control group prove that the groups were homogeneous.



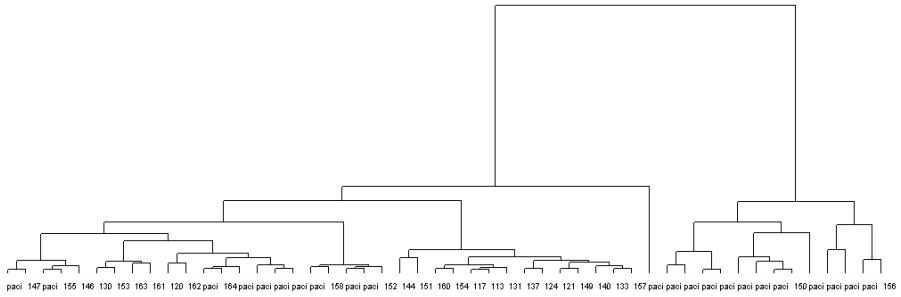
The first principal plane for study group.



Classification for study group



The first principal plane for control group



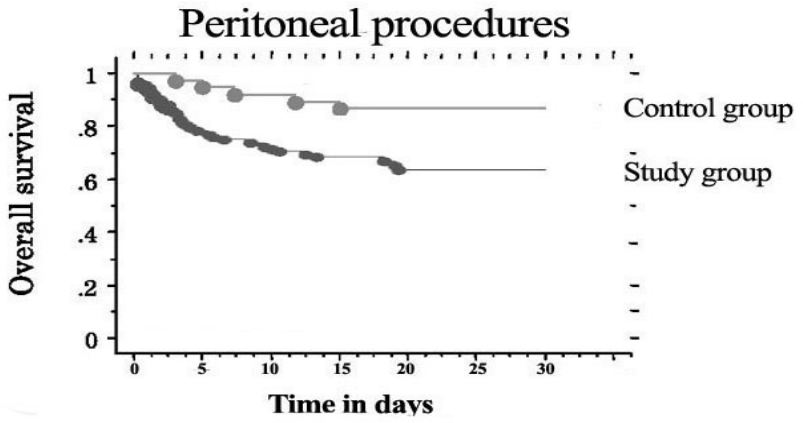
Classification for control group

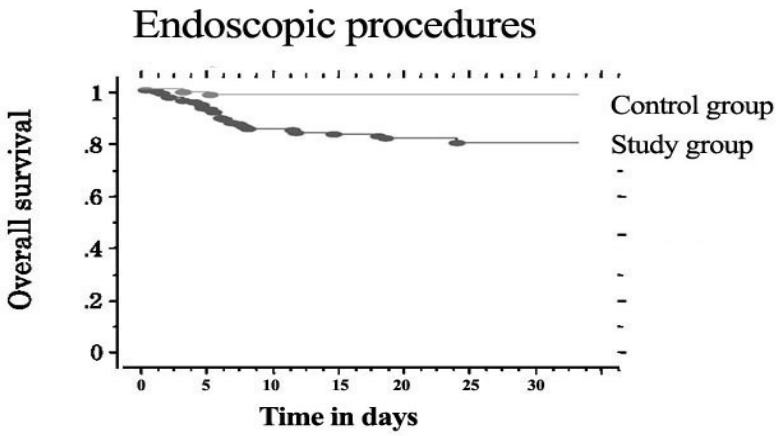
In our study group 62% were male and the mean age was 52.6 years. The etiology of cirrhosis was viral in 48.6% and alcoholic in 30% of the cases. Most of patients were included in Child-Turcotte-Pugh's B class (54%), and the mean value of MELD was 12 (Table 1).

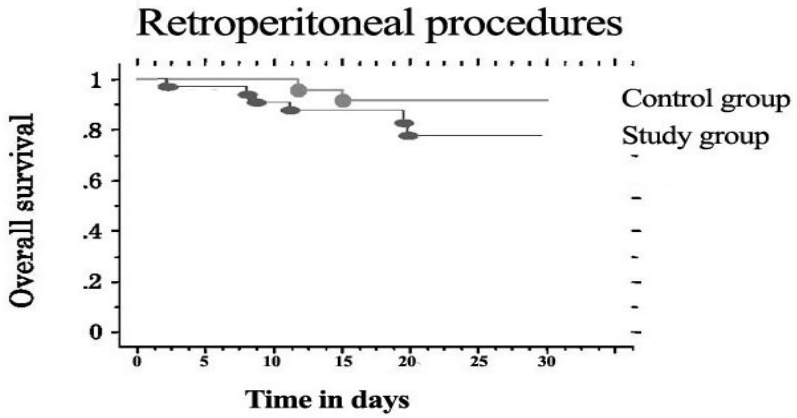
Variable	**No. (%) of Patients**
Age, mean (range)	52.6 (26-79)
Sex, male	70 (62)
History of smoking	26 (23)
Underlying liver disease	
Viral Hepatitis (B, B+D, C)	55 (48.6)
N/A	17 (15.3)
Alcohol	34 (30)
PSC or PBC	7 (6.1)
Ascites	47 (41.6)
Hepatic encephalopathy	5 (4.42)
CKD stage III	16 (18)
Total bilirubin level, mg/dL, mean (range)	1.7 (0.5-5.1)
INR, mean (range)	1.5 (0.8-9.3)
Child-Turcotte-Pugh class	
A	47 (41.6)
B	61 (54)
C	5 (4.4)
MELD score	
<10	33 (29.2)
10 --18	55 (48.6)
>18	25 (22.12)
Hemoglobin level, g/dL, mean (range)	8.8 (5.2-12.4)

Table 1: Baseline Characteristics of patients from study group *Abbreviations:* CKD, Cronic Kindney disease; INR, international normalized ratio; MELD, model *for end-stage liver disease; N/A, not available; PBC, primary biliary cirrhosis; PSC, primary sclerosing cholangitis.*

Overall, postoperative mortality was 13% in patients with liver cirrhosis group (1.2% endoscopic / 4.8% retroperitoneal / transperitoneal 7%) compared to 4.5% (0.73% endoscopic / 1.25% retroperitoneal / 2.52% transperitoneal) in the control group (p = 0.003). Major complications that increased ICU addmitance or hospitalization time (bleeding, postoperative hemodialysis, severe sepsis, respiratory failure) occurred in 23.24% of cases, respectively 5.03% (p = 0.002). The most important factors involved in the development of early postoperative complications were the presence of ascites and sepsis preoperatively, rapid development of postoperative hepatorenal syndrome which required hemodialysis.







Discussions:

The potential interest of MELD as a predictive factor of postoperative outcome for patients with cirrhosis has been confirmed by several authors in a wide variety of surgical operations [13-15]. Northup et al. reported, in a retrospective series of 130 patients undergoing general, orthopedic, cardiovascular and urologic procedures, published in 2005, that operative mortality risk increased 1% for each additional point for MELD scores between 5 and 20 and 2% for values >20 (c = 0.72) [14, 16]. Finally, there are several limitations of this study: retrospective design, potential selection bias (e.g., unknown number of patients with indication for surgery who were not operated on because of high surgical risk), low dimension of the sample, heterogeneity of the surgical procedures and limited number of analyzed variables.

Conclusions

Reduction of postoperative morbidity and mortality is still a great challenge in cirrhotic patients. Today, an improvement in perioperative outcome of cirrhotic patients undergoing urologic surgery has been achieved as a result of a continuous advance in preoperative imagining, surgical technique, anesthesia and critical care unit management. However, probably the most important factor for better outcome in cirrhotic patients is based on a careful and accurate patient selection. Preoperative patients' selection must be performed by multidisciplinary teams with special focus in hepatic diseases working in referral high-volume center

REFERENCES

[1] **Jardine, N., Sibson, R. (1968),** ***The Construction of Hierarchic Classifications***, *Computer Journal*, 11, 177-184;

[2] **Ştefănescu, M.V, Ferrara, M., Dedu, S. (2008),** ***Algorithms for Hierarchical Classification with Applications in Portfolio Management***. *Economic Computation and Economic Cybernetics Studies and Research*, 3-4, 42, 109-122;

[3] **Saporta, G. (2006),** ***Probabilités, Analyse des Données et Statistique***; *Editions Techip, Paris;*

[4] **Saporta, G., Ştefanescu , M.V. (1996),** ***Analiza Datelor şi Informatică***; *Economică Publishing*, Bucharest;
[5] **Ştefanescu, M.V. (1985)** , ***Fundamental Algorithms for Hierarchical Classification .*** *Economic Computation and Economic Cybernetics Studies and Research*, 20, 55-60, 37-48;
[6**] Ştefanescu, M.V. (1984*), The Scatter Function and Hierarchical Classification ;*** *Proceedings of the Fifth Symposium "Cybernetic Modelling of Production Processes"*, 336-340;
[7] **Ştefanescu , M.V. (1984),** ***Mathematical Basis of Total Hierarchical Clustering;*** *Economic Computation and Economic Cybernetics Studies and Research*, 19, 55-6;
[8] **Thierry F. (1997),** ***L'analyse des données, mode d'employ***; *Press Universitaires de Rennes;*
[9] **Ferenci, P., Lockwood, A., Mullen, K. et al. (2002),** ***Hepatic Encephalopathy: Definition, Nomenclature, Diagnosis and Quantification: Final Report of the Working paper at the 11th world congress of gastroenterology***, Vienna, 1998. *Hepatology* 35:716–721;
[10] **Farzan, F., Sacha, P., Parwis, B., D. Schiano T. (2007),** ***Early and Late Outcome of Cardiac Surgery in Patients with Liver Cirrhosis,*** *Liver transplantation* 13:990-995;
[11] **Befeler, A., Palmer, D., Hoffman M., Longo, W. (2005*) The Safety of Intra-abdominal Surgery in Patients with Cirrhosis,*** *Arch Surg* ;140:650-654;
[12] **Pugh, R.N., Murray-Lyon, I.M., Dawson, J.L. et al. (1973),** ***Transection of the Oesophagus for Bleeding Oesophageal Varices***. *Br. J. Surg* 60:646–649;
[13] **Freeman, R.B. (2005),** ***MELD: the Holy Grail of Organ Allocation*****?** *J. Hepatol* 42:16–20;
[14] **Northup, P.G, Wanomaker R.C., Lee, V.D., et al (2005),** ***Model for End-Stage Liver Disease (MELD) Predicts Non-transplant Surgical Mortality in Patients with Cirrhosis.*** *Ann. Surg.* 242:244–251;
[15] **The, S.H., Sheppard, B.C., Schwartz, J. et al. (2008)** ***Model for End-stage Liver Disease Score Fails to Predict Perioperative Outcome after Hepatic Resection for Hepatocellular Carcinoma in Patients without Cirrhosis***. *Am J. Surg.* 195:697–701;
[16] **Huo, T.I., Lin, H.C., Wu, J.C. et al. (2006),** ***Proposal of a Modified Child-Turcotte-Pugh Scoring System and Comparison with the Model for End-stage Liver Disease for Outcome Prediction in Patients with Cirrhosis***. *Liver Transplant* 12:65–71.