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Artificial Neural Networks – An Alternative Method in the Selection of Human Origin Meant for the Varum Correcting Tibial Osteotomy

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Abstract: One of the most frequent diseases is the femuro-tibial arthrosis manifested through the extremely painful wearing away of the cartilage of the knee joint. A widely used method of treatment is the open osteotomy whose technique consists in the bone's sectioning followed by the straightening of the axle through the insertion of a bony graft. Starting with 1993 the TBF Laboratory, specialised in tissue engineering, produces Phoenix grafts for osteotomies. The Phoenix grafts are selected on the basis of clinical and biological tests carried out on the raw material - the femoral apophyses that are the result of the inserting of the coxo-femoral joint's prosthesis. One of the major problems of the open osteotomy is obtaining an in time-resistant consolidation, and this implies a resistance to compression of the bony graft superior to 60 MPa. In this respect, the present paper describes a method based on neural networks as a tool in classifying the mechanical resistance of the grafts and, also, a comparison with the classical multivariable statistical method. The goal is to select only those samples with a mechanical resistance superior to the value of 60 MPa and, for that, we are looking after a simple criterion that can be directly applied to them without destroying the grafts by testing. This is governed both: by financial reasons and limited resources.

1. Introduction

In the evolution of an internal or external femuro-tibial arthroses, the osteotomy - as a necessary surgical intervention - is considered of great importance [1] not for its capacity of modifying the arthrosis (regarded as process) which already exist but for its capacity of relieving the aches and stabilizing the arthroses (stopping the worsening of the joint's erodibility) [1]. The osteotomy can be realised in two ways – closing osteotomy and opening osteotomy – the last one supposing the adding of a graft – usually, a bony graft (Fig. 1).

Relating to this, in our study we tested the mechanical resistance of such bony grafts, obtained in the TBF Laboratory, and tried to discover a classifying criterion **without destroying the grafts** (Fig. 2).

In fact, this paper continues the studies that the research team from the TBF Laboratory already did in the direction mentioned above. The wish for a ***very good***

classifying criterion is issued from at least two reasons: one is that given by the all physical and psychic negative consequents for the patient that a bad graft implies and another is given by the effort (time and money) that all the preprocessing operations of making the raw material (the femural apophyses that are the result of the inserting of the coxo-femural joint's prosthesis) into a finished product (the grafts) suppose.

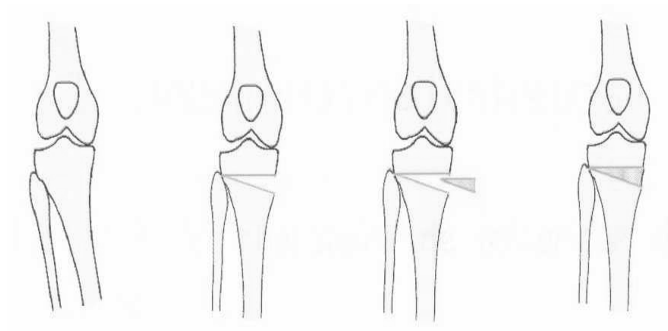

Fig. 1 – Opening osteotomy

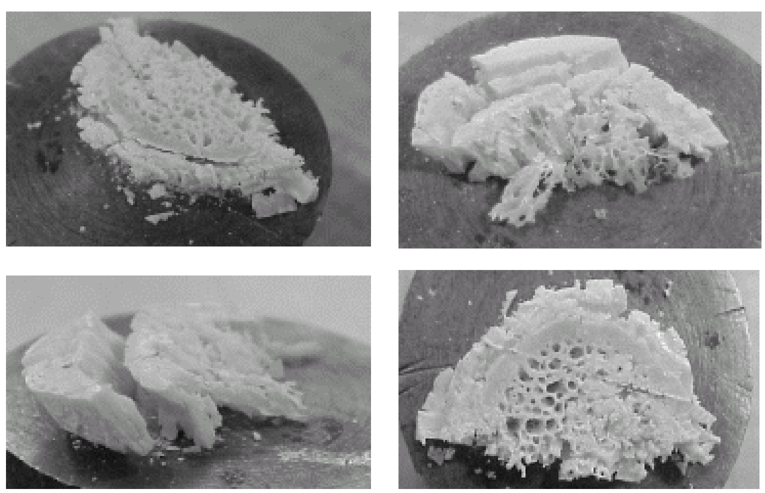

Fig. 2 – Destroyed bony grafts

That is why, in our paper we focused especially on this issue and, after a short presentation of the materials and the methods used for obtaining the grafts and their measurable characteristics, we present a better alternative to the classical multivariable statistical method proposed by the TBF's team: a method using the **neural networks** for the classifying problem.

Neural and adaptive systems represent a unique and **growing interdisciplinary research field** that considers *adaptive, distributed, and mostly nonlinear systems* - three of the ingredients found in biology.

With neural networks the coefficients of the clustering function decomposition are automatically obtained from the input-output data pairs and the specified topology using systematic procedures called the learning rules. So ***there is no need for tedious calculations*** to obtain the parameters of the approximation *analytically*.

Once trained, the neural network becomes not only a parametric description of the function but also its implementation. Neural networks can be implemented in computers or analog hardware and *trained on-line*. This means that it is no need any more of specialists to use specialised programs in order to solve the classification problem. Now, with this solution, the work can be done by anyone who simply has all the input data (in our case: some measured geometric parameters).

2. Material and Method

A set of bony grafts were taken from the femural apophyses of the patients after a surgical intervention (coxo-femural joint's protheses). The grafts were obtained by using a special device which realises constant angles (β) of cutting. There were considered four sets of data, each of them corresponding to a specific angle of cutting (6, 8, 10, 12). For the compression tests, the grafts were cut at 1 cm from their bases (fig. 4.a).

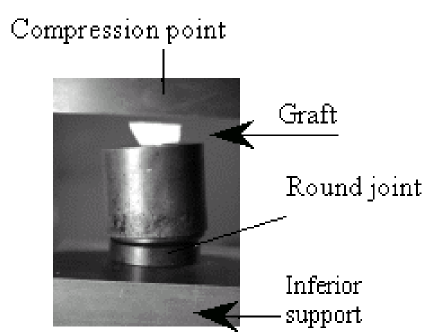

Fig. 3 – Compression device

The tests of the bone's resistance at compression were made on a Schenck RSA 250 traction device (Fig. 3) commanded by a computer. Each bony graft was placed on a turning around support in order to allow the angle β to be maintained. The effort of compression is applied progressively with a 0.5 mm/min speed. The maximum recorded effort permits us to calculate the maximum admitted tension using the following relation: $\sigma_{\max} = F_{\max} / S_{tot}$, where F_{max} is the maximum effort and S_{tot} is the total bony surface (cortical and spongy bone) measured by scanning the both faces of the bony grafts and using their average.

There were also measured other geometric parameters of the grafts such as: thickness of the cortical (*a, b, d*), the length of the sample (*E*), the width of the sample (*F*) (Fig. 4.b).

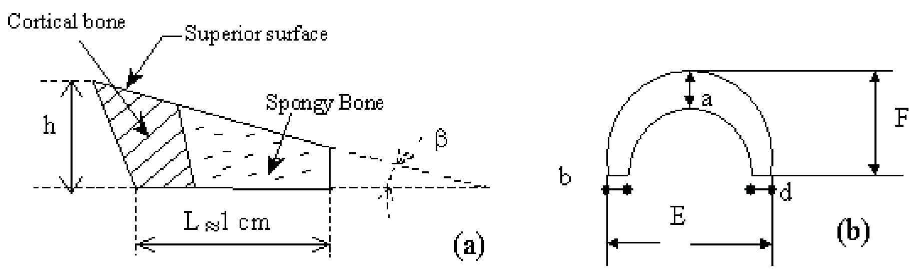

Fig. 4 – (a) Bony graft – transversal section (b) Scheme of the geometric

3. Statistical Data Processing

There were 14 variables we took into consideration: the age and the sex of the patient who's "unprocessed" bone (raw material) is, the directly measurable geometric parameters (*a, b, d, E, F, h*), the inclining angle of the graft, the computed geometric parameters (cortical and total surface) and the mechanical parameters of resistance (maximum effort, maximum total and cortical admissible tension).

The statistic method proposed by the TBF Laboratory used, as a preliminary step, the PCA (Principal Components Analysis) – analyse made with the programme UNISTAT® - in order to extract from the 14 variables only those with the great influence in the global behaviour of the studied set of the grafts. Thus, only two groups of variables were retained: one containing the mechanical variables of resistance and the other containing only the geometric parameters [2].

The best combination of them, proper for the classification problem, seemed to be the following new composed variables: a/F, $(b+d)/E$, $E(a+b+d)/3$.

Using as method – the Average Between Groups – and as measure – the Euclidian distance - the TBF Laboratory's team made a Hierarchical Cluster Analysis (with the same UNISTAT® programme) and obtained 3 different groups of grafts.

The classic statistical analyse of these three groups revealed that we have an exceptional group, weakly represented (3 grafts) with geometric characteristics and great resistance, another group with small resistance and a last group (the major one) with a resistance greater then 60 MPa.

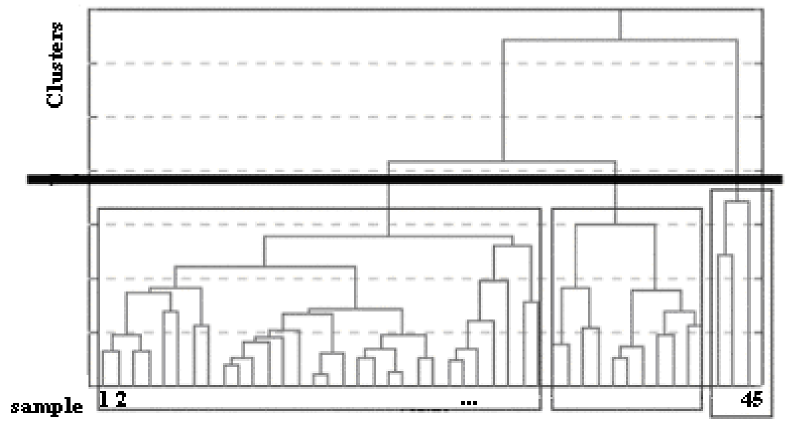

Fig. 5 – Hierarchical Cluster Analysis

Finally, this type of clustering led them to the following criterion that should remove the group of the grafts with a weakly resistance. This criterion supposes the following conditions to be simultaneously achieved in order to get grafts with good mechanical resistance:

$$\begin{cases} a / F > 0.26 \\ (b+d) / E > 0.142 \\ E(a+b+d)/3 > 44.84 \end{cases} \tag{1}$$

After the criterion was established, there were made validations on a test set of grafts. The results were good but susceptible to be improved.

4. Theoretical Consideration

The method (*artificial neural networks, ANN*) that we present in this paper assume that there is little information available to help us make principled decisions regarding the parameter values of the *discriminant functions* (each scaled likelihood can be thought of as a discriminant function, that is, a function that assigns a "score" to every point in the input space; the *decision surface* is define by the intersect of the discriminant functions). Therefore, *the parameters must be estimated from the available data.* One must first collect sufficient data that covers all the possible cases of interest, then use this data to select the parameters that *produce the smallest possible error*, using for that a error criterion already known. This is called training the classifier, and what we gain is *classifiers that are insensitive to the assumption on the probability density function of the data clusters (**nonparametric training**)* [3].

Assumptions about the data distribution are never needed in nonparametric training. Very frequently, nonparametric training utilizes **iterative algorithms** to find the best position of the discriminant functions. *However, the designer still has to directly address the two -fundamental issues of parametric classifier design, that is, the functional form of discriminant functions and their placement in pattern space.*

Thus, the ANN topology determines the number and shape of the discriminant functions and because the shapes of the discriminant functions change with the topology, ANNs are considered semiparametric classifiers. One of the central advantages of ANNs is that they are sufficiently powerful to create arbitrary discriminant functions so ANNs can achieve optimal classification.

In our case, we worked with two types of neural networks: *multiperceptron* (**MLP**) and, respectively, *radial basis function* (**RBF**).

In both cases we picked out the networks with *a single hidden layer* instead of those with more then one (Fig. 6). That is because the resulting maps for the last one, although they are sometimes very flexible and powerful, they are also hard to analyse.

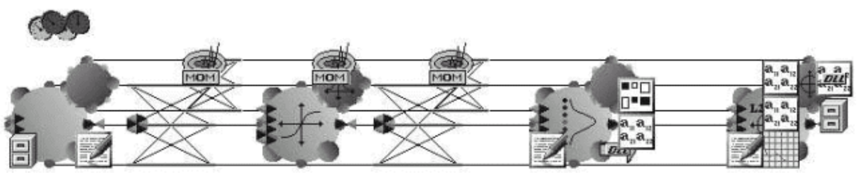

Fig.6 - MLP for the classification problem

We used 9 neurons on the input layer (corresponding to the 9 analised parameters: age, sex, porosite, cortical and total surface and their rapport, a/F, $(b+d)/E$, $E(a+b+d)/3$, 15 neurons and, respectively, 25 neurons for the hidden layer for MLP, respectively, RBF, and 2 neurons (corresponding to the 2 classes) for the output layer. The **SoftMaxAxon** used at the output of the network is the component used to interpret the output of the neural net as a probability. Its activation function is:

$$f(x_i, w_i) = \frac{\exp[x_i^{lin}]}{\sum_j \exp[x_i^{lin}]} \tag{2}$$

where $x_i^{lin} = \beta x_i$ is the scaled and offset input activity.

Regarding the activation function of the hidden layer the differences between the two networks consist in the fact that the *GaussianAxon* only responds significantly to a local area of the input space (where the peak of the Gaussian is located). It is therefore considered to be *a local function approximator*. The center of the Gaussian is controlled using the bias weight inherited from the BiasAxon, and its width using the β parameter inherited from the LinearAxon. Its activation function is:

$$f(x_i, w_i) = \exp(-\beta_i (x_i + w_i)^2) \tag{3}$$

The *TanhAxon* applies a bias and tanh function to each neuron in the layer. This will squash the range of each neuron in the layer to between -1 and 1. Such nonlinear elements provide a network with the ability to make soft decisions. Its activation function is:

$$F(x_i, w_i) = \tanh\left(x_i^{lin}\right) \tag{4}$$

where $x_i^{lin} = \beta\, x_i$ is the scaled and offset activity inherited from the LinearAxon.

The *network training* had been done using a set of 62 samples: 45 samples were used as *training set* (72.5%) and 17 samples as *cross-validation set* (27.5%).

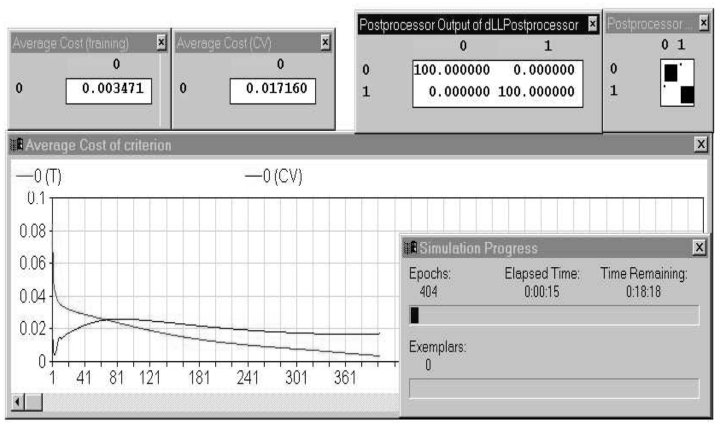

Fig. 7 – Results for MLP

5. Conclusions

The training results revealed that the MLP network is proper to this problem of classification and it is superior to RBF network not only from the point of view of the correct classification rate but even as time conssuming (Fig. 7, Fig.8).

The MLP succeeded to very well classify all the samples (100% right classifying rate for both classes) that is not the same for the RBF, which realised only a 94,12%, respectively, 96,00% correct classification. A deeply analyse showed that the RBF network had bad results only with the sample which had a very close value of the tension at compression (59,78 MPa) to the imposed threshold (60MPa) and with those samples being extremities for the frequency distributions of the investigated parameters.

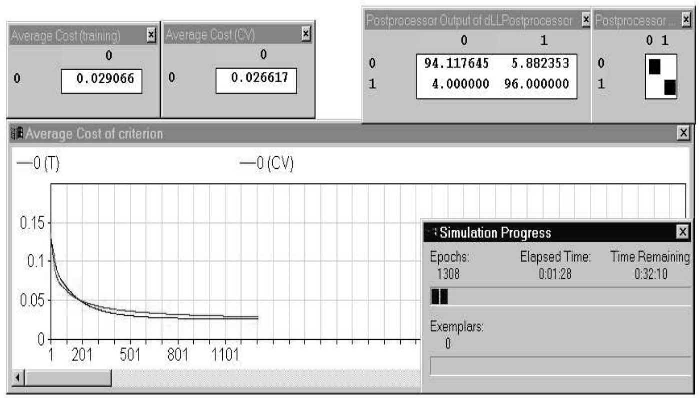

Fig. 8 – Results for RBF

A comparative study between the results of this paper and the previous researches made by the TBF Laboratory team reveals the followings:

- the neural network method gives a better solution then the classical statistical method which made wrong classifications for the samples: 15, 16, 34, 36, 37, 44, 57, 59;
- from the samples mentioned above two of them (the samples 5, 32) include the risk for the patient of being used a bad bony graft instead of a good one;
- the samples 34, 36, 37 are three of the four samples wrong classified by RBF which can be observed, too, as errors of the classification when using classical statistic method, what could suggest the existence of the data internal characteristics which explain this behaviours;
- TBF Laboratiory's team also eliminated the samples 2, 10 and 17 from their studies, considering them as having extreme geometric characteristics; in our case, the ANN succeeded to well solve the classification problem without eliminated the supposed "artefacts"; because we use all the grafts our system is close to "real world"
- because ANN are very suited for large amount of input data in our analyse we use 6 more parameters that give to us a larger quantity of useful information

that permits a better classification (porosity, age, sex, total surface, cortical surface, cortical surface/total surface); from a general point of view this information contains structures [4, 5] correlated with the bony grafts resistance; this position is confirmed by the practical results, too;

- moreover, the imposed limits from equation (1) are not at all objective.
- NeuroSolution (the simulation environment used in our paper) has the possibility to generate C++ code that can be inserted in a complex program. In this mode a technician or medical assistant staff without any knowledge into mathematics can manipulate the resulting software. This facility makes the neural method to be a very reliable one.

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