Soft computing techniques for skills assessment of highly qualified personnel

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Abstract. This study applies Artificial Intelligence techniques to analyse the results obtained in different tests to assess the skills of high qualified personnel as engineers, pilots, doctors, dentists, etc. Several Exploratory Projection Pursuit techniques are successfully applied to a novel and real dataset for the assessment of personnel skills and to identify weaknesses to be improved in a later phase. These techniques reduce the complexity of the evaluation process and allow identifying the most relevant aspects in the personnel training in an intuitive way, enhancing the particular training process and thus, the human resources management as a whole and saving training costs.

Keywords: *EPP, PCA, MLHL, CMLHL, skills assessments, high qualified personnel.*

1 Introduction

Nowadays, in innovative sectors related to aviation, engineering, medicine, etc. where personnel with high aptitudes and skills are needed, the personnel training is especially important. In this way, the use of novel intelligent and intuitive tools, both for training, and assessment of the developed skills during the training period, is crucial to get high qualified personnel in the shortest possible time and with the lowest cost associated to the training process, to facilitate the skills development process, and to enhance the human resources management process in general [1].

The use of simulators represent a huge cost savings in many sectors [2-5], ensuring the maximum level of training. However, the evaluation of the final aptitudes and skills continues being made by human experts in most cases. It is then a great challenge when the number of variables to be considered is high. Therefore, having the adequate systems which facilitate these tasks and allow detecting in which parts of the training process actions are needed in an individual way, represents a vast advantage in obtaining the best training in the shortest time.

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Against this background, Artificial Intelligence (AI) and statistical models can resolve these issues, as they are able to work with a large amount of high-dimensional datasets, presenting this information to the user in a compressible way. Several Soft Computing techniques have been used previously in different areas [6, 7] for managing large amounts of high dimensional information.
Specifically, within the various existing AI techniques, “Exploratory Projection Pursuit” (EPP) algorithms [22-24], allow the visualization of high dimensional information in a compressible way for the user [8-10].

The novel study presented in this paper, applies several EPP techniques to a real dataset with the aim to comprehensively analyse high dimensional information for professionals in specific aspects for the assessment of highly qualified personnel.

The objective of this analysis is to determine the most relevant aspects of a personnel training process, and this accomplished in an objective way according to the individual needs of each person by stressing on those aspects of the training, which need to be improved during the training process.

In particular, three EPP algorithms were applied in this study: “Principal Components Analysis” (PCA) [20, 21], “Maximum Likelihood Hebbian Learning” (MLHL) [22] and “Cooperative Maximum Likelihood Hebbian Learning” (CMLHL) [24, 28]. These algorithms were employed to a novel and real dataset based on the assessments of university students’ skills referring to the field of odontology. These skills are related to the dental machining of great accuracy and finishing.

This paper is structured as follows: Section 2 presents the use of the EPP algorithms in this study; Section 3 illustrates the case study where the EPP algorithms were applied; Section 4 reflects the experiments developed and the results achieved; and finally, Section 5 shows the conclusions.

2 Exploratory Projection Pursuit

AI [11-13] is a set of several technologies aiming to solve inexact and complex problems [14, 15]. It investigates, simulates, and analyses very complex issues and phenomena in order to solve real-world problems [16, 17]. AI has been successfully applied to many different fields as, for example, feature selection [18, 19]. In this study, an extension of a neural PCA version [20, 21] and further EPP [22, 23] extensions are used to select the most relevant input features in the data set and to study their internal structure. Some projection methods such as PCA [20, 21], MLHL [22] and CMLHL [24-26] are applied to analyse the internal structure of the data and find out, which variables determine this internal structure and what they affect in this internal structure.

2.1 Principal Component Analysis

PCA originated in work by Pearson, and independently by Hotelling [20]. It refers to a statistical method describing multivariate dataset variation in term of uncorrelated variables, each of which is a linear combination of the original variables. Its main goal is to derive new variables, in decreasing order of importance, which are linear combinations of the original variables and are uncorrelated with each other. Using PCA, it is possible to find a smaller group of underlying variables that describe the data. PCA has been the most frequently reported linear operation involving unsupervised learning for data compression and feature selection [21].

2.2 A Neural Implementation of Exploratory Projection Pursuit

The standard statistical method of EPP [23, 24], provides a linear projection of a data set, but it projects the data onto a set of basic vectors which best reveal the interesting structure in the data. Interestingness is usually defined in terms of how far the distribution is from the Gaussian distribution [27]. One neural implementation of EPP is MLHL [22]. It identifies interestingness by maximizing the probability of the residuals under specific probability density functions that are non-Gaussian. An extended version of this model is the CMLHL [24, 28] model. CMLHL is based on MLHL [22] adding lateral connections [24, 28], which have been derived from the Rectified Gaussian Distribution [27]. The resultant net can find the independent factors of a data set but does so in a way that captures some type of global ordering in the data set.

Considering a N-dimensional input vector (x), and a M-dimensional output vector (y), with W_{ij} being the weight (linking input j to output i), then CMLHL can be expressed [28] as:

Feed-forward step:

$$y_i = \sum_{i=1}^{N} W_{ij} x_j, \forall i \tag{1}$$

Lateral activation passing:

$$y_i(t+1) = \left[y_i(t) + \tau (b - Ay) \right]^+ \tag{2}$$

Feedback step:

$$e_j = x_j - \sum_{i=1}^{M} W_{ij}, \forall j \tag{3}$$

Weight change:

$$\Delta W_{ij} = \eta y_i sign(e_j) \left| e_j \right|^{p-1} \tag{4}$$

Where: η is the learning rate, $[\,]^+$ is a rectification necessary to ensure that the $y - values$ remain within the positive quadrant, τ is the "strength" of the lateral connections, b is the bias parameter, p is a parameter related to the energy function [22, 24] and A is the symmetric matrix used to modify the response to the data [24]. The effect of this matrix is based on the relation between the distances separating the output neurons.

3 The Real Case Study

The real case study analysed in this paper, focuses on facilitating the identification of divergent or non-desirable situations in a training process. The aim of this study is to classify the psychomotor skills of odontology students using two training scenarios.

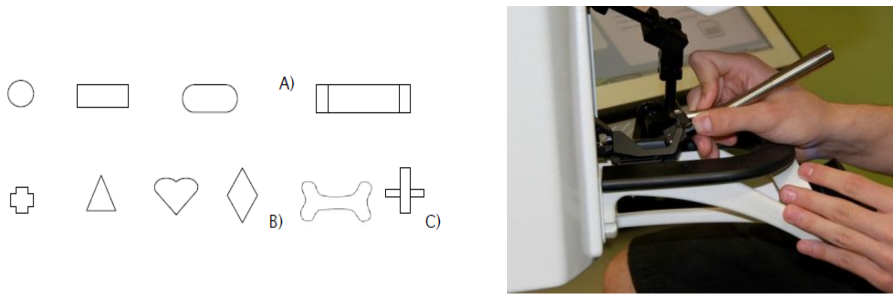
The first scenario refers to creating methacrylate figures during a Dental Aptitude Test, which consists of carving ten methacrylate figures by using rotatory systems and applying two different speeds (V1 and V2). V1 (low speed) rotates at a speed of 10.000-60.000 revolutions per minute (rpm), while V2 (turbine or high speed) rotates at a speed of 250.000 rpm. Seven of the figures made by the students can be easily created, while the remainders, which have several planes, involve a higher level of difficultly.

The second training scenario is based on a simulator (SIMODONT [29]), with unique advantages over conventional training as the experience is much more realistic and it uses true size 3D images. The students' performance can be measured in large detail, and the system allows for objectives comparison of the students' individual results.

3.1 Training Scenario 1 Description

Every student works on a methacrylate sheet at two different speeds, low speed and high speed. The low speed (10.000-60.000 rpm) is used to carve the first set of ten figures (see Figure 1a). After completing this part of the practical work, the students start carving the second part, which is basically a second round of the same figures, but this time using the high speed (150.000-250.000 rpm). The second part involves a higher level of difficulty as the bur is spinning faster, and better psychomotor skills are the pre-requisite for effectively completing this task.

Both parts of the practical work have to be completed during 90 minutes and the results have to be submitted to the supervisors.



a) b)

Fig. 1. Figures to be carved by the students (a), and simulator (b).

3.2 Training Scenario 2 Description

To help the dental student to obtain these skills in a virtual way, it is critical that the training system generates the precise sense of touch in a simulator [6, 46]. In some ways, it is a similar problem to training a pilot to control a plane using a simulator that provides a training experience so real that it counts as training hours.

The software provides detailed feedback comparing the operator's performance with a pre-programmed acceptable "ideal" cavity preparation in its database at any point of the procedure.

3.3 Empirical Training Scenario 1 Evaluation

The real case scenario is empirically evaluated based on a survey of 38 dental students. The information analysed for each student is based on 128 variables, but we are measuring eighty variables in this part of the study.

The first eight most important variables are: Age of the student; Sex of the student; Mark obtained by the student in the university enrolment exam; Previous experience gained by the student (The students may have had professional experience as a nurse, dental technician, hygienist, dental technician and hygienist, or lack of previous work experience); Mark obtained by the student in the theoretical exam of the subject; Mark obtained by the students in the practical exam of the subject; Group class of the student; Number of figures carved by the student.

The following eighty variables (20 figures with four variables each) are the evaluations of the different parts of the figures (graded between 0 and 5). The way to interpret these variables is as follows: 'x' indicates the figure number and can range from 1 to 10, 'y' indicates the speed used to carve the figure by using Low Speed (1) or High speed (2), and 'z' indicates the evaluator who examines the test (1 or 2):Fx_Vy_Ez_WALL: quality of the walls; Fx_Vy_Ez_DEPTH: quality of the depth; Fx_Vy_Ez_EDGES: quality of the edges; Fx_Vy_Ez_FLOOR: evaluate the plain and irregularities presented on the floor.

3.4 Empirical Training Scenario 2 Evaluation

In this second evaluation, the SIMODONT simulator has been used to assess the skills of the students. As in the previous case scenario, a survey of 38 dental students has been analysed, but in this case only 48 variables have been measured for the analysis.

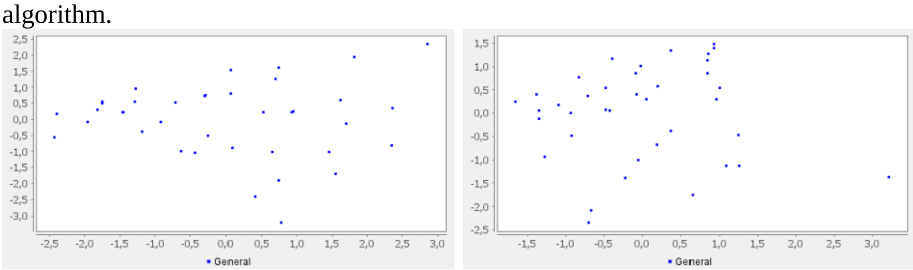
In this exercise, the goal of the student is to complete the target of each one of the three figures the exercise is based on, touching as less as possible the leeway bottom and sides and they should not erase any surface of the container (see Figure 1b).

Variables measured and evaluated in this exercise are: Target; Leeway Bottom (Amount of healthy tissue (not have to remove) removed from the cavity floor. % who do wrong); Leeway Sides (from the cavity sides %); Container Bottom (measure how much the student pass the limit of the virtual floor of the figure to carve, % respect of the total deep); Container Sides (% respect of the total figure surface); Time

Elapsed (used time to carve the figure, in seconds); Drill Time (total time the turbine (instrument) is active during the carve of the figure, in seconds); Moved with right (movements of the right hand, measure the indirect vision, in meters); Moved with left (movements of the left hand, measure the indirect vision, in meters).

4 Experiments and Results

Using both of the above-explained use cases, one dataset composed by 38 samples and 126 variables was created. A pre-process consisting of the normalization of the data was applied. Finally three algorithms were applied to the dataset (PCA, MLHL, and CMLHL). Figures 2a, 2b and 3 present the best projections of results for each algorithm.



a) b)

Fig. 2. PCA algorithm, projections 1-2 (a) and MLHL algorithm, projections 1-4, iters=100.000, lrate=0.001, m=5, p=2.2 (b)

Comparing the results of the three algorithms applied, the CMLHL offers a more clear separation of the clusters than the other two methods (PCA and MLHL), obtaining a clear internal structure of the data and defining two main axis of variation (see Figure 3). The following sub-section offers a more deep analysis of the CMLHL results.

4.1 CMLHL Results analysis

Figure 3, shows the projections obtained by the CMLHL algorithm.

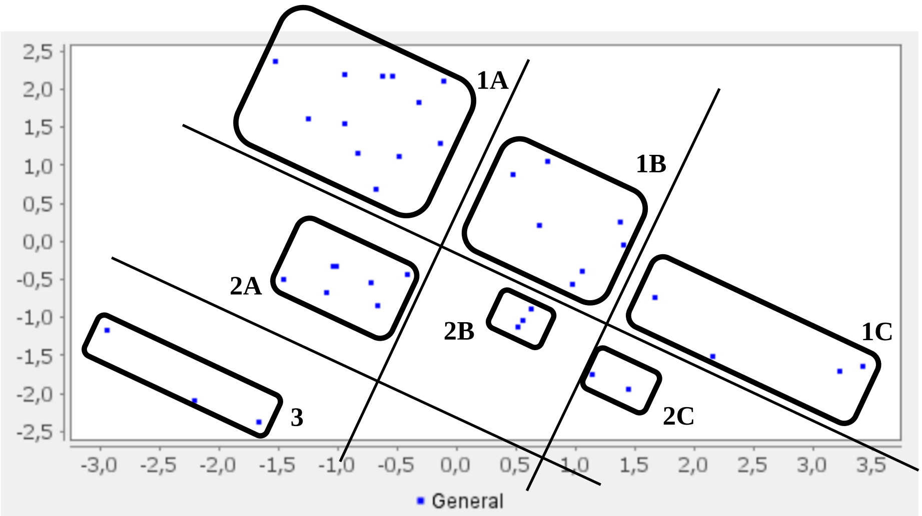
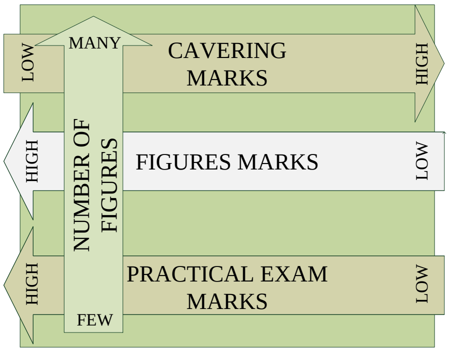


Fig. 3. Clusters for projections 2-4 of CMLHL, iters=100.000, lrate=0.01, m=6, p=1.6, τ=0.25

The identified clusters are presented in Figure 4a in a schematic way, where a descriptive name was given to each one, based on their most relevant characteristics. Based on the most relevant characteristics, which define the internal structure of the data, the diagram in Figure 4b was created, were the variation of each variable is represented by an arrow.

CLUSTER 1A **EXCELENT** **Many figures** **High quality**	CLUSTER 1B **HARD WORKER** **Many figures** **Medium quality**	CLUSTER 1C **CARELESS** **Many figures** **Low quality**
CLUSTER 2A **SKILLFUL** **Average figures** **High quality**	CLUSTER 2B **WITHIN HALF** **Average figures** **Medium quality**	CLUSTER 2C **UNSKILLFUL** **Average figures** **Low quality**
CLUSTER 3 **VAGUE** **Few figures** **High quality**		

a)



b)

Fig. 4. Schematic diagram (a) and diagram about parameters variation (b)

Cluster 1A: The best students belong to this cluster, because they make the highest number of figures, and most of these figures are made with high quality. The "drill time" and the "elapsed time" employed in the simulations are the highest, getting the lowest error in the simulations. All figures are made with great care, trying to achieve the best result.

The quality of students belonging to this cluster is reflected in the theoretical exam marks (the highest), but the practical exam marks are not as high as expected, being close to the marks of other clusters (1B, 2A, 2B), and in some cases even lower.

Cluster 1B: In this group, the students are hard workers, performing a high number of figures with a normal quality. This effort to improve their skills performing a high number of figures is reflected in the theoretical/practical exam with high marks, similar to the cluster 1A students.

Cluster 1C: Students of this cluster perform a high number of figures but with a low quality. These students do not have interest in the subject and this is reflected in the final marks, getting low marks in the practical exam in spite of performing a high number of figures (high experience).

Cluster 2A: Skilled students. They perform a normal/low number of figures with a high quality. Their marks in the practical exam are variable, some achieve good marks and other - bad marks. This indicates the need of developing a higher number of figures.

Cluster 2B: Students with normal skills. They make an average number of figures with a medium quality. The students' marks in this cluster are similar to cluster 1B, the main difference between both clusters is the number of figures created.

Cluster 2C: Students with low skills. They perform a medium number of figures but with low quality. They must perform a higher number of figures to improve their skills. It is reflected in their marks in the practical exam.

Cluster 3: Students perform few figures with a high quality, but all figures are with low/medium difficulty. As these students practice not too much, their marks in the practical exam are lower than their figures marks, getting low/medium marks instead of high marks (they develop a low number of figures with a quite good quality).

5 Conclusions

The results obtained in this study illustrate the identification of six groups of personnel and the unique opportunity to consider individual actions according to each group based on the parameters shown in the Figure 4 (increasing the number of figures in some of them, or increasing the difficulty of some figures in other, etc.).

Moreover, the results show that using PCA, MLHL and CMLHL algorithms allows significantly improving the training process when personnel needs high level skills, especially in fields such as aviation, engineering, medicine, etc., where the number of skills to be assessed simultaneously is large.

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