SELECTION OF AN ARTIFICIAL NEURAL NETWORK MODEL TO DIAGNOSIS MOUTH-BREATHING CHILDREN

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Abstract: A number of factors can lead to changes in body posture, basically determined by alterations in the natural curvature of the spine. Such changes, in turn, may also result in secondary health problems. Mouth breathing is thought to be one of these problems. Experiments with healthy nasal breathing individuals have showed that when they are forced to breathe through their mouth only the natural shape of their spine curves change. However the characterization of the spine curvature in mouth breathers has not been done yet and the matter lies on the personal experience of the health professional. This study reports on the preliminary findings of a broader research which attempts to characterize the changes in the behaviour of the spine, caused by mouth breathing, by using artificial neural network modelling and data from 52 subjects. Four different models – backprogation, learning vector quantization (LVQ), and self-organizing map (SOM) – were tested for best performances in sensitivity and specificity in diagnosing mouth and nasal breathing children. Competitive-learning-based algorithms – LVQ and SOM – presented the best performance for current data set.

1 INTRODUCTION

Breathing is the first vital function developed at birth becoming the main body function, and as such should be cared for. Chronic mouth breathing is associated with pediatric, allergy-related and otorhinological complaints.

The narrowing of the pharynx has been reported to be associated with forward extension of the neck in the attempt to straighten the pharyngeal tube in order to improve the reduced air flow through it (Solow, 1984).

The skull, mandible, cervical portion of the spine, and upper airways can be viewed as a system in which the positioning of its parts are closely related. Mouth breathing, a physiological change in the correct respiratory process, determines postural changes due to the altered, interrelated performance of the muscles in each of the parts that integrates the above mentioned system (Rocabado, 1979; Ribeiro, 2003). Studies on body posture of mouth-breathing children have reported as characteristic features of

these individuals: forward positioned head and shoulders, lordosis, protruded scapulas, frontal depression of the thorax, and protruded abdomen (Aragão, 1991; Liu, 2003). However, no studies further characterizing the posture of mouth breathers are currently available.

A computer-aided tool could be useful for health professionals if it could characterize the postural changes caused by mouth breathing. Artificial neural networks (ANN) (Haykin, 1999) have been used successfully in treating and analyzing biomedical data[7]. ANN can provide a faster data analysis when associations between factors and outcomes are not linear or when there are a great number of factors (high dimensionality) to be analyzed (Lisboa, 2002). Furthermore, ANN can lessen the influence of confounding variables (noise) (Reggia, 1993).

The aim of this study is to report the preliminary findings regarding the selection of an ANN model for identifying mouth-breathing children through the analysis of their posture.

2 MATERIALS AND METHODS

The data used in this study was collected at Imaging Department and Pediatric Otorhinolaryngology Department at Federal University of São Paulo (UNIFESP), Brazil. Fifty two children were assessed including 30 previously diagnosed as mouth-breathing subjects and 22 nasal breathers. The variables collected for analysis are shown in Table 1.

Table 1: Study variables.

Anthropometrics	Diaphragm	Posture
Sex	Right side Excursion (PD)	Cervical Curvature
Age		Lumbar Curvature
Weight	Left side Excursion (PE)	Thoracic Curvature
Height		Pelvis Positioning

The imaging of diaphragm excursion was obtained by videofluoroscopy and recorded for analysis using Adobe Photoshop® (Adobe Systems Inc.) software. Due to the limited size of the fluoroscope screen, the imaging of the left and right sides of the diaphragm was recorded separately. The posture of the participating children was assessed using photographs of the subjects' left-side view on which angles formed by key body features were analyzed using a specially developed software (Software for Posture Evaluation, SAPO) (Duarte, 2006). Figure 1 shows these key features and the angles they determined.
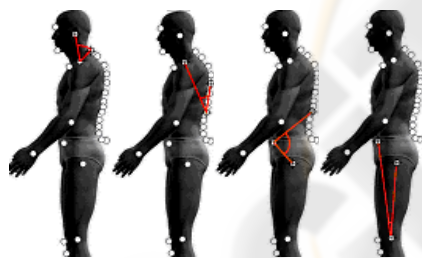

Figure 1: Representation of key points, and respective angles they formed, used in the posture assessment: (a) cervical curvature; (b) thoracic curvature; (c) lumbar curvature; (d) pelvis positioning.

The data collected were used to determine the ANN model that showed the best performance among a number of models which included, backpropagation (BP) (Haykin, 1999), learning vector quantization (LVQ) (Kohonen, 1997), and self-organizing map (SOM) (Kohonen, 1997). Such a comparison was carried out through Matlab® development tool (The MathWorks Inc., Natick, MA, USA) and implementation packages SOM Toolbox package (Vesanto, 2000) for SOM and LVQ models and the Neural Networks Toolbox® (The MathWorks Inc., Natick, MA, USA) for BP model.

The structure of each ANN model was as follows:
- Backpropagation - Network structure: 20 nodes in the first hidden layer, 5 nodes in the second hidden layer and 1 node in output layer. Training function: Levenberg-Marquardt. Maximum number of epochs to train: 100. Minimum performance gradient: 10^{-10};
- LVQ - Network structure: 3 x 3 nodes. Vectors prototypes initialization: linear. Neighbourhood relationship: hexagonal. Running length: 100. Learning rate used in training: 0.001;
- SOM - Network structure: 3 x 3 nodes. Vectors prototypes initialization: linear. Neighbourhood relationship: hexagonal. Neighbourhood function: gaussian.

The performances of these ANN models were measured by determining the rates for sensitivity and specificity obtained with each model, when carrying out the leave-one-out cross-validation (Burnham, 2004). Receiver Operating Characteristic (ROC) (Metz, 1978) curve analysis was used to determine the association ANN model-input pattern with the best performance among those showing higher rates of sensitivity and specificity.

Some investigation of factors potentially associated with the shaping of spine curves – body weight, height and excursion of the diaphragm – was also carried out by inputting them either separately or in combination with the data collected regarding spine curvature (Table 2).

Table 2: Different input patterns used to determine the influence of potential influencing factor on spine curvature. The number between brackets indicates the number of variables of a same subset.

Input Pattern (IP)	IP Label
spine curvatures (4) and diaphragm excursion (2)	IP 1
spine curvatures (4), diaphragm excursion (2), weight (1) and height (1)	IP 2
spine curvatures (4)	IP 3
diaphragm excursion (2)	IP 4
weight (1) and height (1)	IP 5

3 RESULTS

The sensitivity and specificity rates attained with each of the study input patterns and each of the study ANN model varied from 0.76 to 1 and from 0.57 to 0.99 respectively (Table 3).

The areas under the ROC curves for LVQ and SOM inputting IP3 were 0.94 and 0.90, respectively, for SOM inputting IP2 was 0.92 and inputting IP1 0.97.

Table 3: Specificity (sp) and sensibility (se) values calculated through leave-one-out algorithm for different data sets and for all ANN models analyzed in this study.

RNA Models	SOM		LVQ		BP	
Input Pattern	sp	se	sp	se	sp	se
PE1	0.97	0.97	0.99	0.90	0.98	0.94
PE2	0.98	0.95	0.96	0.96	0.86	0.94
PE3	0.98	0.93	0.98	0.97	0.96	0.90
PE4	0.88	0.87	0.88	0.90	0.88	0.90
PE5	0.80	0.76	0.67	0.76	0.67	0.76

4 DISCUSSION

The area under the ROC curve for IP2 (all variables studied) inputted in SOM (0.92) indicates that this input pattern improves the performance of SOM but is still bellow the performance of LVQ using a much simpler set of input variables (IP3).

However, a previous statistical test not shown in this study (t-Student test) presented a statistically significant association between the data collected on the excursion of the diaphragm and the child being a mouth breather. This association seems to reflect on the area under the ROC curve (0.97) calculated for SOM model when the variables associated with spine curvature and diaphragm excursion (IP1) was inputted.

Despite the input of the data referring to the diaphragm excursion (IP1 and IP2) yielding a better performance of SOM, the fluoroscopic investigation is an additional medical examination that is not usually performed in the clinical practice. Therefore, if we are to deal with such limitation, LVQ model associated with the input of variables of spine curvature only (IP3) can presently be a good alternative model due to its high rates of sensitivity and specificity.

Including the variables weight and height to the set spine curvature and diaphragm excursion (IP1) to form IP2 resulted in lower performance of SOM model according to ROC curve analysis. This agrees with previous statistical analysis (Student's t-test) showing that the variation of weight and height between mouth and nasal breathers was not statistically significant.

Pesonen et al. (1996), Markeya et al. (2003), and Ng & Chong (2006) compared the performance of SOM and BP models in different tasks of classification of biomedical data and found that BP had higher rates of specificity and sensitivity. This was not the case in the present study. In fact, training in SOM is unsupervised, which would support its worse performance in data classification as compared with models using supervised training. A potential explanation for the best performance of SOM over BP in the present study is the limited set of data (52 patients) for training and validation currently available.

As previously mentioned, the present report is part of a broader biomedical study. So far, the use of computer-aided modelling focused the development of a reliable diagnosis tool. This is deemed to be the first step to develop a second and perhaps more important tool that could indicate the severity of changes in body posture and assist the decision making regarding the prescription of a physiotherapeutic treatment for such condition. ANN modelling is a resource that could overcome the complexity of such task.

5 CONCLUSIONS

The best rates of sensitivity and specificity were attained for variables associated with the spine curvature only (IP3) inputted in LVQ model. A further comparison of performance using IP3 was carried out between SOM and LVQ models using their respective ROC curves which showed that the area under the curve for LVQ model was larger (0.94) than that for SOM (0.90).

Although supervised learning ANN models, such as BP model, have been reported to yield better rates of sensitivity and specificity, the present study found that SOM and LVQ, both competitive-learning-based algorithms, had better performance.

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