Optimal Neural Network Architecture for Human Pubic Bone Parameters' Prediction in the Case of Incomplete Volumetric Data

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Abstract - **Obtaining a 3D surface model of the human pubic bone with sufficient accuracy is a difficult task due to its complex geometry. The task can be further complicated by the fact that some parts of the bones are often missing or damaged, resulting in the lack of complete volumetric data. Therefore, our idea is to create a parametric pubic bone model as the base for building 3D surface model with optimal number of parameters, using prediction techniques and artificial neural networks (ANN). The study is conducted at the sample of 32 polygonal models of the male right pubic bone. At the each bone 9 anatomical landmarks are located, and 12 parameters as linear distances between these landmarks are determined and their values are measured on the samples. These values represent the dataset from which different combinations as input and output variables are taken. Three-layer back-propagation architecture of Neural Networks (NN) is chosen, with 1, 2, 3 or 4 neurons in the input layer, while the hidden layer has 5, 10 or 20 neurons. Levenberg - Marquardt (LM) and Bayesian Regularization (BR) algorithm are used for training 15 different NN architectures. Correlation coefficients and Mean Square Errors as performance indicators for all NN architectures are measured and compared with the aim to select optimal number of input parameters and optimal NN architecture. The best results are obtained for 3 input parameters (d_1, d_3 and d_4), 5 neurons in hidden layer and BR training algorithm. The results of the study show that it is enough to localize 4 points and to measure the values of only 3 parameters, in order to get subject specific predictive bone model.**

I. INTRODUCTION

Building a personalized 3D surface model of the human pubic bone with sufficient accuracy is not an easy task, due to its free form geometry. This process implies certain knowledge about anatomy that is required for determining a sufficient number of anatomical landmarks. These landmarks are used for defining parameters as linear distances between them. In order to capture the complete geometry of the human pubic bone 8 anatomical landmarks and 10 parameters are selected. Also, one additional point at the ischium bone is selected and two additional parameters, treated as common for pubic and ischium bone, are chosen. Bearing in mind the fact that the identification and localization of these points and parameters' measuring is time consuming, optimizing the number of necessary landmarks and parameters is done by using prediction techniques, with the aid of ANN with optimal topology.

Traumas such as pubic fractures and pubic dislocations require use of personalized osteofixation materials or, in extreme cases, surgical treatment. For accurate positioning of reconstructive plates, fixators, screws, clamps and planning complex surgical operations it is crucial to have a 3D bone model at one's disposal, even in the cases when volumetric data are incomplete.

Prediction techniques for shape of organs or its parts in the cases where complete information is not present are performed with Principal Component Analysis (PCA), partial least squares and canonical correlation analysis, using morphometric parameters as scalar predictors [1]. Number of parameters is reduced using PCA procedure [2]. Iterative techniques for shape prediction with minimizing the Mahalonobis distance use landmarks' positions as boundary conditions for shapes. These landmarks are used to control the shapes [3]. Spherical topology for shape representation is used in spherical harmonic description [3] - [5].

Artificial neural networks allow modeling a multidimensional relationship of experimental data in different areas of bioengineering and biomechanics [6]. These adaptive models for data analysis have been used for evaluating the classification accuracy on pediatric fracture healing, using two methods: self-organizing feature map and multilayer perception (MLP) [7]. Automated detection and accurate diagnosis of developmental dysplasia of the hip on anteroposterior (AP) radiographs with convolutional neural networks was studied. The obtained results showed that there was no significant difference in the diagnosis made by the algorithm and the experienced radiologist [8]. The ability of convolutional neural networks to distinguish femoral neck fractures, trochanteric fractures, and non-fracture from AP and lateral hip radiographs was evaluated [9]. Estimation on Boehler's angle at calcaneus bone was done using ANN with one input layer of five neurons (5 parameters), two hidden layers and one output layer (Boehler's angle) with one neuron, and feedforward backpropagation training [10]. The prediction for 6 parameters of the human ankle bone was done using the set of demographics data (age, height and weight) as input and LM algorithm for neural network training [11]. 3D parametric model of the human mandible was obtained using ANN with measured values of morphometric parameters as input data and the X, Y and Z coordinate values as output data [12].

This study is guided by the idea to use ANN with optimal three-layer back-propagation architecture to find and identify complex patterns between parameters at the human pubic bone, with the aim to obtain optimal number of parameters. The proposed number of parameters is sufficient to get a patient-specific parametric model that is accurate enough for clinical practice. Furthermore, these parameters are easily recognized and measured from plain radiography that is the primary imaging modality in most cases. Proposed modeling approach represents the base for obtaining 3D surface model of the pubic bone, even in the cases when some parts of the bone are missing.

II. Methodology

Study is conducted through few steps:

- determining landmarks and parameters on polygonal models of the pubic bone,
- measuring of parameters' values,
- data normalization,
- determining sets of input, output and hidden layers,
- testing neural networks with different training algorithms,
- selecting optimal neural network architecture,
- choosing the most appropriate set of input variables.

Polygonal models of 32 pubic bones samples were already converted from medical image in 3D polygonal geometrical model in Computer Aided Design (CAD) program. The sets of 8 anatomical landmarks, marked as 1 - 8, and 10 parameters labeled as d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10} and d_{11} are determined (Fig. 1). Because pubic bone is one of the constitutive parts of the hip bone, and with the aim to present connection with its adjacent ischium bone, 1 additional point (point 9, Fig. 1) and 2 additional common parameters for pubic and ischium bone, labeled as d_1 and d_{12} (Fig. 1) are included in the data set.

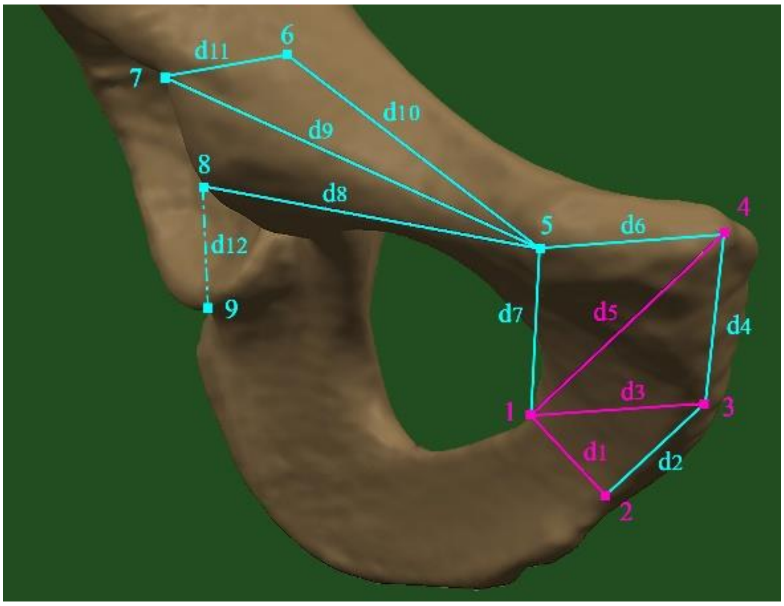

Figure 1. Selected anatomical landmarks and parameters at the human pubic bone (modified from [13])

The following anatomical landmarks are separated, [13]:

1 - the most anterior point of the obturator foramen,

2 - the most inferior point where inferior pubis ramus and ischium ramus are connected,

3 - the most inferior point on the inferior edge of the medial aspect of the pubic symphysis,

4 - the most superior point on the superior edge of the medial aspect of the pubic symphysis,

5 - pubic tubercle, as the most anterior point at the pubic bone,

6 - the deepest point in acetabular fossa,

7 - point at the acetabular rim where ilium and superior pubis ramus are connected,

8- the most inferior point of the anterior end of the lunate surface of the acetabulum, and

9 - the most inferior point of the posterior end of the lunate surface of the acetabulum.

The measured parameters values are normalized using min-max scaler and further used as initial dataset for ANN modeling.

Parameters that connect the points which can be easily recognized and determined (points 1, 2, 3 and 4, Fig. 1), are chosen as input variables, while all other parameters are used as output variables. These input variables (d_1, d_3, d_4 and d_5) in different combinations are taken as neurons for the input layer of the ANN. In that manner, 15 variants of input layers are made, consisting of 1, 2, 3 and 4 neurons (Fig. 2).

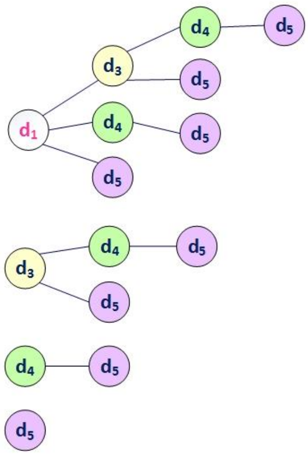

Figure 2. Parameters' combinations for input layers

For example, for input layer with 1 neuron 1 parameter is taken and 4 different ANN are tested. For input layer with 2 neurons 2 parameters are taken (e.g., d_1 and d_3, d_1 and d_4, etc.) which makes 6 cases for testing. For 3 neurons (e.g., d_1, d_3 and d_4) 4 cases are tested, while for 4 neurons only 1 case is tested.

Number of hidden neurons is determined by trial-and-error method. All proposed NN with 5, 10 or 20 neurons in hidden layer are trained with back-propagation LM and BR algorithm using nntraintool in Matlab 2018R. Dataset is randomly divided into three parts in proportion 70:15:15 (22:5:5), respectively for training, validation and testing set for LM, while BR did not not require a validation data set. Performances for all tested neural networks architectures are measured using correlation coefficient (R) and Mean Square Error (MSE).

III. SOLUTION/DISCUSSION

The best results are obtained with 3 neurons input layer, 5 neurons in hidden layer with sigmoid activation function, and 9 neurons in output layer with linear activation function. Inputs' data in the form of 32x3 matrix represent the values of parameters d_1, d_3 and d_5, while the targets' data in the form of matrix 32x9 represent the values for parameters d_2, d_4, d_6 - d_{12}. Proposed solution for optimal ANN architecture is presented in Fig. 3.

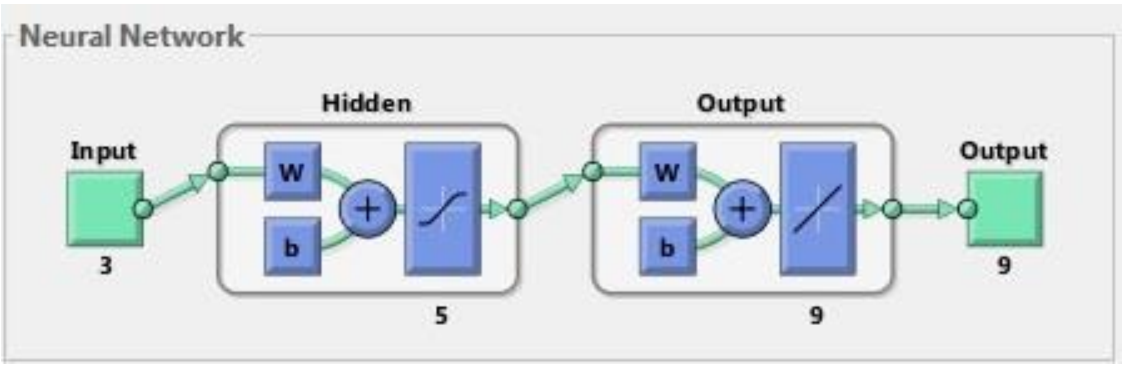

Figure 3. NN architecture for human pubic bone parameters' prediction

BR algorithm proved to be a better solution for training ANN in regard to LM algorithm, which is understandable since the scale of the sample is small. LM algorithm for proposed ANN architecture gives values of R for training 0.599572, for testing 0.37043, for validation 0.40943 and for all 0.51733, while the values for MSE are 0.0366896, 0.0754097 and 0.0601901 for training, testing and validation. In the case of BR algorithm, R values are 0.70413 and 0.6234 for training and testing, respectively, while the value for the whole sample is 0.69448 (Fig. 4).

Values of MSE are lower than in the case of LM algorithm (0.0340393 for training and 0.0257383 for testing). Best training performance is 0.034039 at epoch 161 (Fig. 5). The plot shows the L-shaped distribution and follows the horizontal line trend. The worst performances are noted in the solutions with 1 neuron in the input layer.

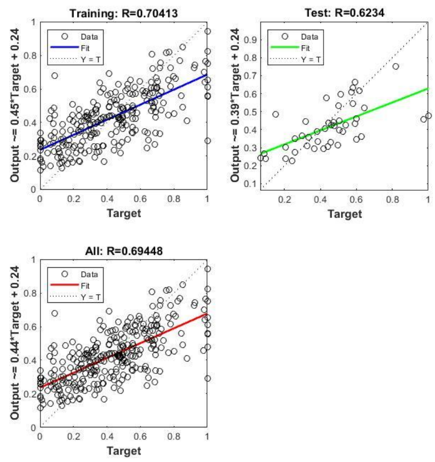

Figure 4. Linear regression between target and predicted values

A small value of MSE near zero determines that the ANN’s output and the target data are well trained, as it is presented in Figure 5.

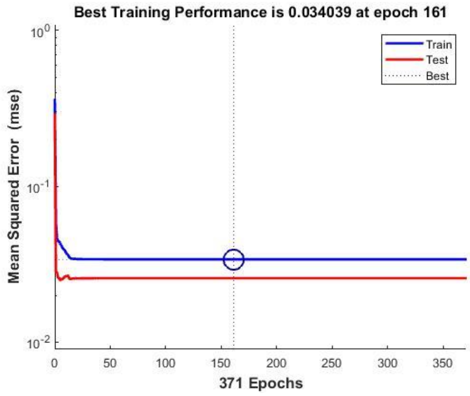

Figure 5. BR performance plot

IV CONCLUSION

Proposed ANN architecture allows quick parameter' predictions for the complete human pubic bone. Taking into account that the values for R indicate a significant but not perfect adaption of outputs to the targets, some improvement should be made with increasing the number of input/output data. The acquired landmarks and parameters values could be taken either from right or left pubic bone, which is of particular importance if one of the bones is damaged.

ACKNOWLEDGMENT

The presented research is part of the project III41017 - Virtual Human Osteoarticular System and its Application in Preclinical and Clinical Practice, which is sponsored by the Ministry of Education, Science and Technology development of the Republic of Serbia for the period of 2011–2019.

REFERENCES

[1] R. Blanc, C. Seiler, G. Székely G, L-P. Nolte, and M. Reyes, "Statistical model based shape prediction from a combination of direct observations and various surrogates: Application toorthopaedic research," *Medical Image Analysis*, vol. 16, pp. 11561166, 2012.

[2] R. Sierra, G. Zsemlye, G. Székely, and M. Bajka, "Generation of variable anatomical models for surgical training simulators", *Medical Image Analysis*, vol. 10, pp. 275-285, 2006.

[3] G. Zsemlye, "Shape prediction from partial information", Ph.D. dissertation, Zurich: Swiss federal institute of technology, October 2005.

[4] M. Styner, K. Rajamani, L. Nolte, G. Zsemlye, G. Székely, et al., "Evaluation of 3D correspondence methods for modelbuilding," *Lecture Notes in Computer Science*, vol. 18, pp. 63-75, 2003.

[5] A. Besbes, Image segmentation using MRFs and statistical shape modeling, Ph.D. dissertation, Paris:Ecole Centrale Paris, 2010.

[6] G. Enzo, Artificial Neural Networks and Predictive Medicine: a Revolutionary Paradigm Shift, In: *Artificial neural networks methodological advances and biomedical applications*, K. Suzuki, Ed. InTech, Rijeka, Croatia, 2011, pp. 139-148.

[7] S. Malek, R. Gunalan, S.Y. Kedija, C.F. Lau, M. Mosleh, et al., "A Primary Study on Application of Artificial Neural Network in Classification of Pediatric Fracture Healing Time of the Lower Limb", In: 10th International Conference on Practical Applications of Computational Biology & Bioinformatics. Advances in Intelligent Systems and Computing, vol. 477, Springer International Publishing, 2016, pp. 23-30.

[8] H. S. Park, K. Jeon, Y. J. Cho, S. W. Kim, S .B. Lee, et al., "Diagnostic Performance of a New Convolutional Neural Network Algorithm for Detecting Developmental Dysplasia of the Hip on Anteroposterior Radiographs," *Korean J Radiol*, vol. 22(4), pp. 612-623, April 2021.

[9] Y. Yamada, S. Maki, S. Kishida, H. Nagai, J. Arima, et al., "Automated classification of hip fractures using deep convolutional neural networks with orthopedic surgeon-level accuracy: ensemble decision-making with antero-posterior and lateral radiographs," *Acta Orthopaedica*, vol: 91(6), pp. 699-704, 2020.

[10] İ. Ota, S. Akkoyu, Y. Taştemur, and M. Çimen, "Boehler’s Angle Estimations in Calcaneus Bone by Using Artificial Neural Networks," *Cumhuriyet University Faculty of Science Science Journal (CSJ)*, vol. 36(5), pp. 57-63, 2015.

[11] R. Daud, H. Mas Ayu, M. S. Salwani, S. H. Tomadi, M. R. A. Kadir, et al., "Artificial Neural Network: The alternative method to obtain the dimension of ankle bone parameters," *Journal of Engineering and Applied Sciences*, vol. 12(10), pp. 2782-2787, 2017.

[12] J. Mitić, N. Vitković, M. Manić, S. Petrović, M. Rashid, et al., "Application of Artificial Intelligence Methods for the Reconstruction of the Geometric Model of the Body of the Human Mandible," *IMK-14 – Research & Development in Heavy Machinery*, vol. 24(2018)2, pp. 61-64

[13] M. Tufegdžić, Creating of 3D solid model of the human hip bone in the case of incomplete input volumetric data," Ph.D. dissertation, Faculty of mechanical engineering in Niš, University of Niš, 2017.