NEURAL NETWORKS BASED APPROACH TO ESTIMATE BODY FAT (%BF)

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Abstract: The amount of fat in human body composition relative to total body weight (%BF) is considered a determinant factor to a healthier and longer life. In this paper a neural network approach, that overcomes some of the current limitations of assessing %BF through skinfold thickness measurement with calliper devices, is presented. Neural networks recognised capabilities in modelling nonlinear problems can provide a valuable tool to deal with the inherent nonlinear behaviour of body tissues. The approach was tested on a sample of elder individuals, men and women, showing better performance when compared with two available alternative methodologies.

Keywords: Neural networks (NN), nonlinear models.

1. INTRODUCTION

The problems related to the amount of fat in human body composition can in general be associated with malnutrition problems, including obesity and overweight, and are increasing at a global scale affecting world health(WHO, 2009).

The assessment of the amount of fat in human body composition is therefore a key element in dealing with these problems. Although a variety of methods and techniques have been developed for body composition assessment, including % body fat (%BF), none can be considered as unique and complete as the ideal solution (Heymsfield et al, 2005; Heyward and Wagner, 2004). The consideration of multiple factors such as the costs involved with the equipment, the effects they have on individuals, the suitability for large scale and systematic evaluations, combined with the accuracy of the assessments made, give rise to the existence and improvement of various methods.

The Dual-Energy X-Ray Absorptiometry (DXA) method is currently considered one of the most advanced and sophisticated methods, capable of providing accurate assessments for adiposity and satisfying the requirements for reference values. In the work presented DXA values were used as the reference for the %BF.

In spite of the accuracy of the most advanced and sophisticated methods, including DXA, they are not yet suitable for large scale or systematic studies because they rely on bulky, invasive, complex and expensive equipment.

Various alternatives are available offering simpler and less expensive methods. Of these the work presented concentrates on anthropometry, as it remains the most applicable non-invasive technique for identifying over and undernutrition states of clinical and non-clinical samples (Heymsfield et al, 2005). A common, simple and inexpensive technique applicable in a large number of individuals relies on skinfold thickness measurement (Heymsfield et al, 2005; Frisancho, 2008) using skinfold calipers. They evaluate the subcutaneous adipose tissue thickness measured at different body locations which are then processed through mathematical models developed for body composition and used to provide an estimate of % body fat (%BF). Different types of models were developed, the simplest ones being based on two compartments (fat and non-fat tissues). Prediction equations were established based normally on the use of samples of individuals from populations and the application of statistical and mathematical techniques, such as regression analysis. The equations are normally derived for specific groups based on ethnicity, gender and age.

Using conventional calliper devices normally requires highly trained health technicians following standard procedures (Heymsfield et al, 2005; Frisancho, 2008). This significant dependence of the operator on the collection and subsequent processing of data justified the need for simpler models and equations. However the evolution of calliper devices such as the one developed by Restivo, et al, (2007) which currently provides unique characteristics such as better reliability, sensitivity, accuracy, data recording and monitoring, can also support the use of more sophisticated models and prediction equations. The development of a neural network (NN) model can be easily incorporated in such a device, opening up windows of opportunities to explore the specific capabilities of neural networks: modelling nonlinear functions, incorporation of different types of data in the model.

To test this new approach a sample of data (79) for elder people, i.e. older than 60 years, was used. The behaviour of body tissues of elder people pose specific problems which seem to amplify the nonlinearities involved (Heyward and Wagner, 2004), justifying even more the need for new models.

A neural network solution was developed providing at its output an estimate for the %BF when the gender, age, weight, height, and four skinfold measures were presented at its input. Using the DXA values as a reference, the NN solution provided better overall results (average, extreme values) when compared to the alternatives based on the Siri (Siri, 1961) and Brozek equations (Brozek, 1963) using the body density estimation from Visser (1994).

2. NEURAL NETWORKS APPLICATION

In spite of being subject to continuous developments, neural networks are nowadays available as a recognised technique with specific characteristics, and with potential to provide unique solutions to a vast range of problems (Bishop, 1997; Gupta, et al., 2003; Ripley, 1996). The inherent suitability to model nonlinearities, combined with the natural possibility to include different types of information in the same model, are indicators that can be used to define its applicability range. These characteristics result from its operation principles which are based on the use of multiple and interconnected processing elements, each implementing a simpler but nonlinear function. Such a structure, inspired from our knowledge of the human brain processing and capabilities, results in a mathematical model with a large number of parameters that must be specified during the design stage and which make a neural network solution normally a case specific technique.

Among the various structures possible the well-known feedforward structure illustrated in Fig.1 was selected. The input and output elements represent the codification of the problem into a neural net structure, and therefore are directly related to the information the user provides (inputs) as well as the results the user expects to be generated (outputs) by the model.

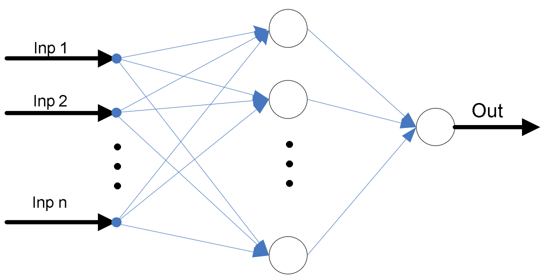

Fig. 1. Neural networks feedforward structure representation.

The number of internal (i.e. hidden) elements is one of the design parameters which have to be defined during the design stage. Each one of the interconnections between the various elements is characterised by a number (weight) which appears at the NN output. Finding the weights which minimize an error, obtained when comparing the neural network output with the known correct solution for each instance of the problem, is normally known as the training or learning phase. This type of NN belongs to a class of supervised neural networks.

Developing a NN solution requires previous knowledge of correct solutions for specific instances of the problem. The selection and availability of this data is therefore of great importance in the design of a NN approach and its generalization ability. The data used is normally split into a training set, testing set and a validating set. The training and validation sets are used during the training phase. The test set consists of cases not used during the training phase being used for evaluation of the NN generalization ability.

3. DESIGN A NEURAL NETWORK TO ESTIMATE %BF

Having chosen a feedforward type NN (Fig.1) the following sections describe the various phases of the design process to obtain a NN that is capable of estimating %BF for an individual, older than 60 years of age, being given some of its anthropometric measures.

3.1 Data representation and encoding

The data used consisted of 79 cases, 47 women and 32 men, of individuals with 60 or more years of age.

The data was randomly split into 55 cases for training (70%), 12 cases for testing (15%) and 12 cases for validation (15%).

Using the feedforward type NN the representation of the problem into a NN, consisted of using 8 inputs: gender, age, weight, height and four skinfold measurements (triceps, biceps, subscapular, suprailiac). One element in the output, represented the %BF.

Having different types of data in the inputs and outputs, normalizing the input/output values was included in the codification process.

3.2 NN training phase

Using the Levenberg-Marquartd learning algorithm, the training phase consisted of an iterative sequence of steps:

- defining a number of internal elements (i.e. hidden layer);
- starting the training phase, during which the training set is presented to the NN and the corresponding outputs are compared with the target value (DXA %BF), using the mean square error (mse) performance function. At each presentation (i.e. epoch) the weights are adjusted in order to minimize the error function using the Levenberg-Marquartd algorithm;
- observing, as in (Fig. 2) the behaviour of the performance function on the training, validating and test data sets, the training process can be stopped accordingly;
- repeating these steps until a satisfactory solution is obtained.

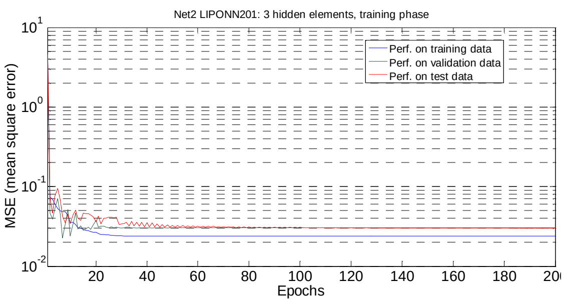

Fig. 2. Performance measure (mse) during training of NN with 3 hidden elements (Net2): training, validating and testing data sets.

In the experiments made 3, 6 and 10 hidden elements were tried. Also for each of these cases several runs were made starting from different initial, randomly selected, weights; various settings for the parameters of the learning algorithm were also experimented.

At each training presentation (epoch) the performance measure on the training data will, naturally, always decrease, as it represents the data on which the learning algorithm operates. This behaviour normally should not be the same for the validating and testing data sets performance graphs. This can be explained by the training process favouring the specialization of the NN on the data used for training, limiting its generalization ability. This effect can be amplified with an increase of the NN size (i.e. nº of hidden elements). This effect is clearly observed (Fig 2 to Fig. 4), which gives an indication that the NN with 3 hidden elements seems to be capable of providing better results.

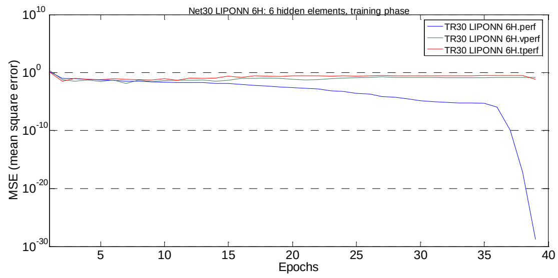

Fig. 3. Performance measure (mse) during training of NN with 6 hidden elements (Net3): training, validating and testing data sets.

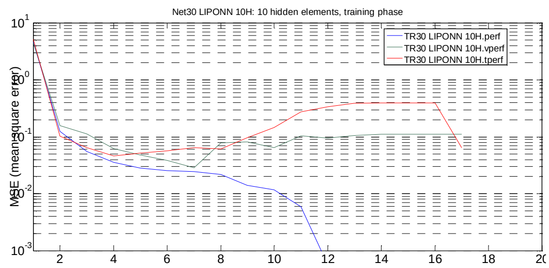

Fig. 4. Performance measure (mse) during training of NN with 10 hidden elements (Net5): training, validating and testing data sets.

3.3 NN using phase

The evaluation of the trained NNs consisted on submitting all the available data sets through the NNs and analysing the error obtained for each case relative to the correct (i.e. DXA) values. Table 1 presents the aggregate values of the Total Error (√mse), and extreme (Max, Min) values for the training and testing data sets. The results were obtained using NNs with different number of hidden elements: 3 (Net1 and 2), 6 (Net3 and 4) and 10 (Net 5 and 6); each case with the training process stopped at different stages: 1st at best validation value, 2nd at maximum epoch number.

Table 1 NNs performance (i.e., [%BF]) on the training and testing data sets.

	Training			Test		
	$\sqrt{mse}$	Max	Min	$\sqrt{mse}$	Max	Min
Net1:3Ha	3.01	8.52	-6.71	2.84	3.90	-4.19
Net2:3Hb	2.33	8.21	-5.01	2.61	2.09	-4.67
Net3:6Ha	2.83	7.55	-6.83	4.14	3.84	-9.58
Net4:6Hb	0.00	0.00	0.00	8.62	12.25	-22.36
Net5:10Ha	2.38	8.72	-3.96	3.82	3.73	-7.25
Net6:10Hb	0.00	0.00	0.00	9.50	12.87	-26.43

The results presented on Table 1 confirm that the neural networks (Net1, Net2) with 3 elements in the hidden layer overperformed the networks with 6 and 10 elements.

Analysing in more detail Net 1 and Net2 through the error function plots of Fig. 5 and Fig. 6 it is visible that Net2 performs better, being the one selected for final comparison with the two alternative methods.

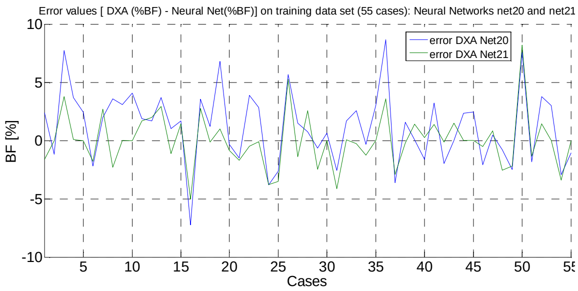

Fig. 5. Mean square error (mse) in [%BF] on the training data set (Net1 and Net2).

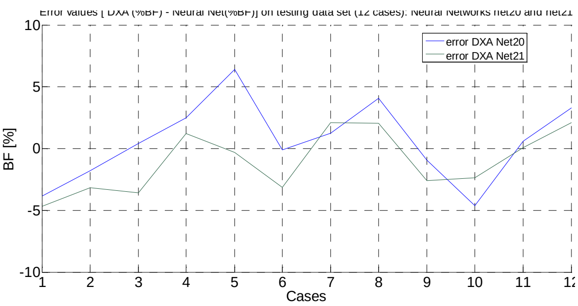

Fig. 6. Mean square error (mse) in [%BF] on the testing data set (Net1 and Net2).

3.4 *NN compared with Siri and Brozek equations*

The neural network solution to estimate %BF is compared to the Siri (1961) and Brozek (1963) equations using the body density given by the Visser (1994) methodology. The performance of each method can be evaluated comparing the values obtained with these three alternatives against the reference used (i.e. DXA %BF). Fig. 7 and Fig. 8 show these graphs for the training and testing data sets. It can be observed that the NN solution performs siginificantly better, not only on the training data, but also on most of the cases of the testing data set.

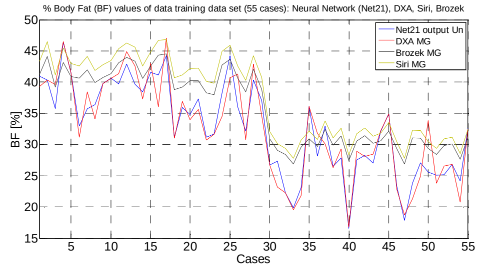

Fig. 7. %BF on the training data set: Net2, DXA, Brozek and Siri.

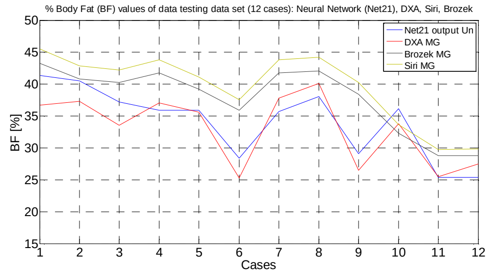

Fig. 8. %BF on the testing data set: Net2, DXA, Brozek and Siri.

4. CONCLUSIONS

The work presented was motivated by the belief that better approaches can be developed to model body composition. At this stage it was shown that a NN is a valuable tool on this process. Although the specific problem considered, elder individuals are in lack of more complete models, the neural network solution performed well and provided an integrated solution for both genders. As in other cases, expanding the NN application remains dependant on the availability of data.

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