Neural Network, Bioelectrical Impedance and Dual Energy X-ray Absorptiometry in the Assessment of Body Fat in Elderly Taiwanese Men

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***Abstract*—This article applied an adaptive linear neural network model to assess the body fat, Bioelectrical Impedance Analysis (BIA) to detect corresponding bioimpedances, and Dual Energy X-ray Absorptiometry (DEXA) to measure human compositions. This study employed these measured data to establish a linear neural network model for estimating body composition. After training and simulation, the neural network's numerical results revealed an accurate body fat assessment, which was obviously better than linear regression prediction methods proposed by literatures.**

I. INTRODUCTION

Human body having too much fat was called obesity which accompanied with diseases, such as heart disease, high blood pressure, diabetes, etc.[1-4]. Especially, the risk of elderly group is higher than the general public. The way to judge whether fat or not is to measure the body fat directly. However, the measuring methods refer to techniques of anthropometry, e.g. chemistry, electronics, and physics. Furthermore, body mass index (BMI), waist to hip ratio (WHR), underwater weighing, skinfold thickness measurements could not describe accurate actual distributions and contents of body compositions. Computerized tomography (CT), magnetic resonance imaging (MRI), dual energy X-ray absorptiometry (DEXA), etc. need special instruments, cost high, hard operation, which suit to a research or precise examination, but for a daily clinical examination[5-8]. Differently, BIA is a noninvasive, inexpensive, and portable method fit for a daily or routine clinical examination[9, 10]. Thus, BIA is a very convenient and popular technique for monitoring body composition and body fat of elderly group.

The BIA application principles presently based on some measuring techniques, such as underwater weighing or DEXA for specific subjects. Meanwhile, the same subjects were measured body segments' bioimpedances, anthropometry data, e.g. height, weight, age, sex, etc. to establish the linear regression prediction equations for body composition assessment.

However, linear regression equations based on independent variables (e.g. impedances of human body segments, weight, height, age, sex, etc.) could not accurately describe human body compositions. The major problem was using a linear relation equation to assess complicate body composition relations. Certainly, the linear regression equation would lead quite errors in assessing body fat for elderly or normal groups. Therefore, this study used adaptive linear neural network for the prediction algorithm which based on segments' bioimpedances, height, weight, age, etc. parameters of elderly group in Taiwan, and estimating errors to verify the proposed method.

Principles of bioelectrical impedance

The BIA measurements are performed using four electrodes[6]: usually two are attached at the wrist and two at the ankle. For the single-frequency measurement (typically at 50 kHz, 800 μA), a weak alternating current is passed through the outer pair of electrodes, while the voltage drop across the body is measured using the inner pair of electrodes from which the body's impedance is derived. To convert this information to a volume estimate, the basic assumption was used.

The resistance (R) of a length of homogeneous conductive material of uniform cross-sectional area is proportional to its length (L) and inversely proportional to its cross sectional area (A) (Fig. 1). Although the body is not a uniform cylinder and its conductivity is not constant, an empirical relationship can be established between the impedance quotient ($\mathrm{Length}^2/\mathrm{R}$) and the volume of water, which contains electrolytes that conduct the electrical current through the body. In practice, it is easier to measure height than the conductive length, which is usually from wrist to ankle. Therefore, the empirical relationship is between lean body mass (typically 73% water) and $\mathrm{Length}^2/\mathrm{R}$. Due to the inherent field inhomogeneity in the body, the term $\mathrm{Length}^2/\mathrm{R}$ describes an equivalent cylinder, which must be matched to the real geometry by an appropriate coefficient. This coefficient depends on various factors, among them also the anatomy of the segments under investigation. Therefore, errors occur when there are alterations in resistivity of the conductive material, variations in the ratio height to conductive length, and variations in the shape of the body and body segments (body segments behave as if they are in series with each other, with shorter and thicker segments contributing less to the total R).

Manuscript received April 29, 2008.

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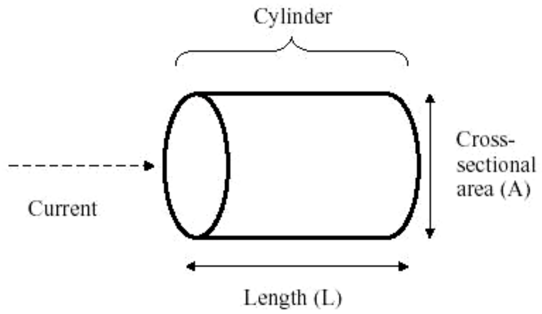


Fi. 1. Principles of BIA from physical characteristics to body composition. Cylinder model for the relationship between impedance and geometry. The resistance of a length of homogeneous conductive material of uniform cross-sectional area is proportional to its length (L) and inversely proportional to its cross sectional area (A). Hence resistance (R) = $\rho L/A = \rho L^2/V$; and volume (V)= $\rho L^2/R$; where ρ is the resistivity of the conducting material and V equals AL.

Fat-free mass

FFM is everything that is not body fat. A large number of BIA equations in the literature predict FFM. These equations vary in the parameters included in the multiple regression equations and their applicability in various subjects. Early BIA equations (before 1987) only included Length^2/Resistance . Later equations include other parameters, such as weight, age, gender, reactance, and anthropometric measurements of the trunk and/or extremities to improve the prediction accuracy. FFM can be determined by SF-BIA provided that hydration is normal and BIA equations used are applicable to the study population, with regard to gender, age, and ethnic group.

Adaptive Linear Neural Networks

The adaptive linear neural network was forward network model composed by one or multiple linear neurons, which had simple structure, stable and fast converge. The neuron model (Adaptive Linear Neuron, ADALINE) proposed by B. Widrow and M.E. Hoff in 1960 was the first and classic linear neural network model. The linear neural network employed a linear function as a transfer function, and the input could be an arbitrary. ADALINE used the least mean squares (LMS) and Widrow-Hoff learning rule to minimize the mean square error and thus moves the decision boundaries as far as it can from the training patterns.

The linear neuron employed a linear transfer function which calculated the neuron's output by simple returning the value passed to it, implied by Fig. 2.

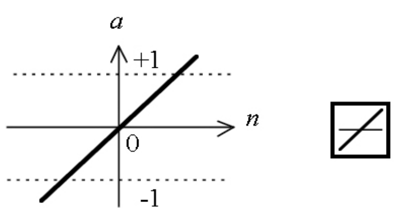


Fig. 2. Linear Transfer Function

Output of a linear neuron could be an arbitrary, Fig. 3 indicated a input vector of a single adaptive linear neuron:

$$\mathbf{P} = [p_1, p_2, p_3, \ldots p_R]^T \qquad \textbf{(1)}$$

The notation R presented the Rth input.
Single linear neuron's output vector **a** defined as:

$$a = \mathbf{Wp} + b \qquad \textbf{(2)}$$

, and $\mathbf{W} = [W_{1,1}, W_{1,2}, \ldots, W_{1,R}]^T$.

The adaptive linear network shown in Fig. 4 had one layer of S neurons connected to R inputs through a matrix of weights **W** and bias **b**.

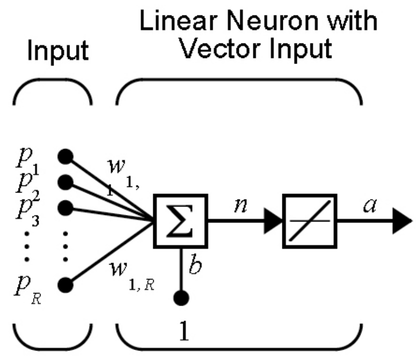


Fig. 3. Single linear neuron model.

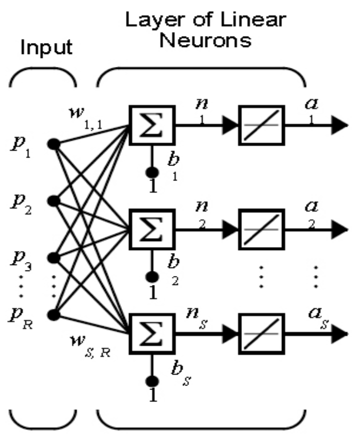


Fig. 4. Linear neural network structure diagram.

The target of the linear neural network was to find a fit matrix **W** of weight, which could make output most approximation to the target output **a** after input any signal vector to a neuron. This method needed a training set composed by some training pairs which contained given input vector **P** and relative target output **t**. If there were g training pairs in the training part, indicated as $\{p_1, t_1\}, \{p_2, t_2\}, \ldots, \{p_g, t_g\}$. $t_1, \ldots, t_g$ were relative target output, and input/output training pairs were:

$$E[e^2] = E[(t-a)^2] = c - \mathbf{x}^T\mathbf{h} + \mathbf{x}^T\mathbf{R}\mathbf{x} \qquad \textbf{(3)}$$

Mean square error was:

$$e^2 = (t-a)^2$$

where, $\mathbf{x} = [\mathbf{W} \quad b]^T$, $\mathbf{z} = [\mathbf{p} \quad 1]^T$, $a = \mathbf{x}^T\mathbf{z}$, $c = E[t^2]$, $\mathbf{h} = E[t\mathbf{z}]$, and $\mathbf{R} = E[\mathbf{z}\mathbf{z}^T]$ **(4)**

LMS algorithm proposed by Hagan [11], weight function **W** and bias **b**, could obtain by iterating **(5)~(7)**.

$$e(k) = t(k) - a(k) \quad \textbf{(5)}$$

$$\mathbf{W}(k+1) = \mathbf{W}(k) + 2\alpha e(k)\mathbf{P}^T(k) \quad \textbf{(6)}$$

$$\mathbf{b}(k+1) = \mathbf{b}(k) + 2\alpha e(k) \quad \textbf{(7)}$$

Maximum Stable Learning Rate should be $\alpha < 2/\lambda_{max}$, and λ_{max} was the maximum value of the input correlation matrix. k indicated iteration times.

When doing converge analysis, Maximum Stable Learning Rate should be determined first and let **W**(0) be an arbitrary. Using the result obtained from **(4)** and then iterating **(5)~(7)** individually, when the difference between **W**(k+1) and **W**(k) smaller than a range, the iteration would be stop and weight matrix **W**, bias **b** would be decided.

Dual-Energy X-ray Absorptiometry

Dual-energy X-ray absorptiometry (DEXA), first developed for assessment of bone mass, provides information on total fat mass (FM) and fat-free mass (FFM) and their distribution in the trunk and upper and lower limbs. Over the past decade, DEXA has been increasingly used to assess body composition in research and clinical practice, including applications to direct treatment. Its rapid uptake can be attributed to its ease of use, availability, and low radiation exposure. However, although the precision of the technique for body-composition outcomes is well established, insufficient attention has been paid to accuracy. Many validation studies have used as the reference method a technique that itself has unknown accuracy, thereby limiting confidence in the findings.

II. METHODS

Subjects

This work studied a radom group of 12 Taiwanese men, aged from 60~70 y (mean age 65±3.6yrs, weight 73±6.8kg, height 166±5.9cm) from healthy population. Body weight was measured to the nearest 0.1 kg, with the subjects dressed in light clothing. Bare foot standing height was measured to the nearest 0.1 cm by using a wall-mounted standiometer.

Bioelectrical resistance(R) and reactance (Xc) were measured by a BIA analyzer (QuadScan 4000; Bodystat, Douglas, United Kingdom) with four operating frequencies of 5, 50, 100, 200 kHz at 200μA. But, only the current at 50 kHz would be applied for analysis in this investigation.

DEXA (Lunar Prodigy; GE Medical Systems, Madison, WI) was used for the measurement of whole-body composition, including fat mass, lean body mass (comprising muscle, internal organs, and body water), and bone mineral densities. %BF was calculated from entire body mass (including bone mineral densities) by using the manufacturer's software (Encore 2003 software version 7.0). The subjects had undergone no nuclear examination, and the female subjects were not pregnant at the time of examination. All scans were performed while the subjects were wearing two piece light clothing, and all metal items were removed from the volunteer to ensure accuracy of the measurement. DEXA measurements were performed while the subject was lying in a supine position. The typical scan time was 20 min, depending on height. The radiation exposure per whole-body scan is estimated to be $20\,\mu Gy$, which is lower than the daily background level.

The precision of FFM and BMC assessment, as determined by three repeated weekly measurements on three subjects, was 2.5 and 1.0%, respectively. The precision of appendicular LTM assessment was ≦2.5%. The difference between body mass measured by DEXA and Weight measured by scale was 1 ± 1 kg. In spite of its statistical significance ($p<0.0001$, paired t-test), this difference is of no practical relevance.

Model establishment and result determination

This study compared results and errors of fat free mass prediction equations proposed by Roubenoff and Lohman [12, 13] for estimation body composition of elderly men by means of bioimpedance, such as **(8)**, **(9)** implied individually.

$$FFM = 9.1536 + 0.4273\frac{Ht^2}{R_{50}} + 0.1926Wt + 0.0667 \quad \textbf{(8)}$$

$$FFM = -11.41 + 0.600\frac{Ht^2}{R_{50}} + 0.186Wt + 0.226 \quad \textbf{(9)}$$

Which FFM indicated fat free mass (Kg), Ht implied height (cm), R_{50} indicated resistance of human body with frequency 50 kHz introduced current (Ω), Wt meant weight (Kg), X_c was reactance of human body(Ω).

According to **(8)** and **(9)**, this study defined input signals as $p_1 = \frac{Ht^2}{R_{50}}$, $p_2 = \text{weight}$, $p_3 = X_c$, output target as $t_1 = FFM$ for adaptive linear neural network, and subjects' anthropometry data and measured results shown in table 1.

Table 1 Subjects' anthropometry data and measured results.

Item	Mean	±	S.D.
Age(years)	65.3	±	3.6
Height(cm)	166.4	±	5.9
Weight(kg)	73.2	±	6.8
BMI(kg/㎡)	26.6	±	3.4
Resistance	535.9	±	29.1
Reactance	75.6	±	8.6
FFM(%) by DEXA	70.4	±	5.7

To determine Weighting function $\mathbf{W}_{i,j}$ and bias $\mathbf{b}_i$ (i,j=1,2,3) needed to guess initial values and input/output training pairs according to weighting function. This study employed **(4)~(7)** for numerical calculation, iteration, and training to satisfy error range. Simultaneously, applying the above process to the application soft Matlab for writing programs and getting simulation results and differences to target values, as shown in Figure 5.

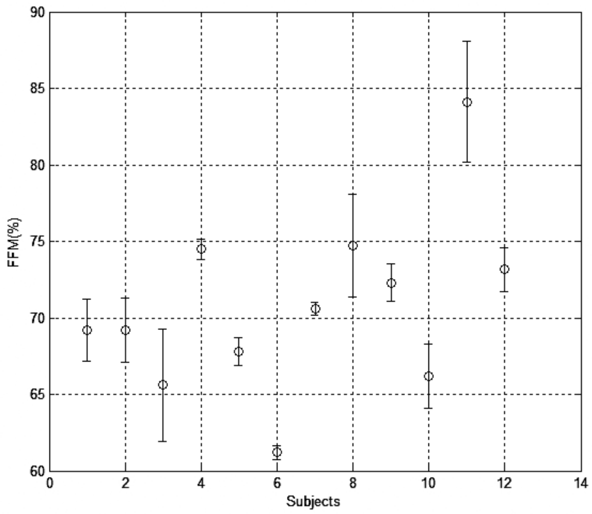


Fig. 5. Results and errors of training target.

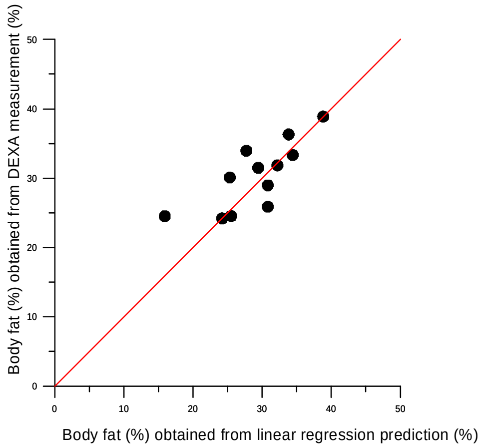
Substitution input variables, such as height, weight, resistance, reactance for **(9)** and **(10)** could obtain corresponding FFM values. Here, this investigation utilized 2-compartments human composition model, and fat mass (FM) would be obtained by weight subtract FFM.

$$\text{FFM}(\%) = \text{FFM} / \text{weight} \qquad \textbf{(10)}$$

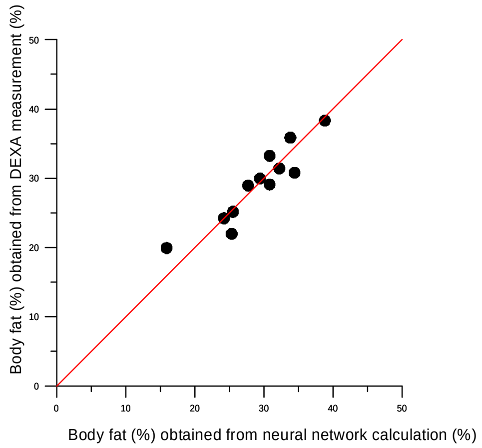
$$\text{fat}(\%) = 100\% - \text{FFM}(\%) \qquad \textbf{(11)}$$

Application RMS (root mean square) to estimate accuracy

This study uses root-mean-square (RMS) error to judge accuracy. The red line (y=x) indicated results obtained from linear regression or neural network prediction equal DEXA's measurement. The RMS of Fig. 6(a) and (b) respectively are 3.08 and 0.04. Therefore, the method utilized adaptive linear neural network is more accurate than the linear regression prediction method.



(a)



(b)

Fig. 6. Comparisons of body fat (%) measured from DEXA to calculated results from linear regression and linear neural network models.

III. Result and Discussion

BIA is a non-invasive, cheap, easy to use, acceptable technique for body composition assessment. Besides, multiple frequencies BIA have quantity information for human body compositions, and many studies try to obtain more all round and accuracy results. Through all kinds of numerical analysis methods, the goal of BIA is attempting to find an accurate and easy way to pass through the clinical validation test.

Owing to prediction equations based on bioimpedance, ethnic group, gender, health condition for FFM assessment, these considerable equations are need to modify to fit elderly group. Although, some prediction equations could be proposed for modification reference further, these equations still need to be verified by clinical examination.

Many scientists established FFM assessment equations on the basis of bioimpedance in their studies, which owned their merits and still progressed continuously. All scientists search equations which could describe body compositions more accurately. Because of influence with age, ethnic group, gender, illness, habits, the study need a lot of work to amend all kinds of equations. According to the basis of body composition, if FFM was determined, the other tissue could estimate via the ratio of medical certifications of human body composition.

This investigation used adaptive linear neural network model to assess FFM, which were based on anthropometry (e.g. height, weight, age, gender, bioimpedance) of health elderly men in Taiwan. According to results in this article, the assessment model employed adaptive linear neural network is better than multiple linear regression in estimating body fat. After training, iteration, and simulation to verify the errors, this investigation proposed an adaptive linear neural network model to apply for assessing FFM with BIA. This numerical algorithm model without large mathematical computing could be set into a chip system with limited operation ability, which could easily develop as a commercial portable bioimpedance analyzer and improve elder health.

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