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Original Article

Using Akaike information criterion and minimum mean square error mode in compensating for ultrasonographic errors for estimation of fetal weight by new operators

Yueh-Chin Cheng [a], Yu Hsien Chiu [b], Hsien-Chang Wang [c,*], Fong-Ming Chang [d], Kao-Chi Chung [a], Chiung-Hsin Chang [d,**], Kuo-Sheng Cheng [a]

[a] *Department of Biomedical Engineering, National Cheng Kung University, Tainan, Taiwan*
[b] *Department of Healthcare Administration and Medical Informatics, Kaohsiung Medical University, Kaohsiung, Taiwan*
[c] *Department of Information Management, Chang-Jung Christian University, Tainan, Taiwan*
[d] *Department of Obstetrics and Gynecology, National Cheng Kung University Medical College and Hospital, Tainan, Taiwan*

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Abstract

Objectives: The accuracy of ultrasound (US) measurements is operator dependent. In order to decrease the operator-dependent errors in estimated fetal weight (EFW), a model selection analysis was undertaken to select significant compensation weighting factors on ultrasonographic parameters to support artificial neural network (ANN), and thus to enhance the accuracy of fetal weight estimation.
Materials and Methods: In total, 2127 singletons were examined by prenatal US within 3 days before delivery for ANN development, and another 100 cases were selected from new operators for evaluation. First, correlation analysis was used to analyze the differences between the prenatal and postnatal parameters. Second, Akaike information criterion (AIC) was used to determine the number of database partition and optimal weightings for compensating the input parameters of the ANN model. Finally, minimum mean squared error (MMSE) mode was utilized to determine the optimal EFW.
Results: EFW of the proposed compensation model using AIC and MMSE showed mean absolute percent error of 5.1 ± 3.1% and mean absolute error of 158.9 ± 96.2 g. When comparing the accuracy of EFW, our model using AIC and MMSE was superior to those conventional EFW formulas (all $p < 0.05$).
Conclusion: We proved that performing the parameter compensation (by AIC) and model compensations (by MMSE) for the ANN model can improve EFW accuracy. Our AIC−MMSE model of EFW will contribute to the improvement of accuracy when adding new US datasets measured by new operators.

Keywords: Akaike information criterion; artificial neural network; estimated fetal weight; minimum mean squared error; ultrasonography

Introduction

To assess estimated fetal weight (EFW) accurately in obstetrics is very important for choosing a good delivery procedure to best benefit both the mother and the infant. The accuracy of EFW is affected by multiple variables including various fetal ultrasound (US) parameters. For clinical practice in Taiwan, the EFW involves a combination of ultrasonographic measurement of fetal growth parameters, such as biparietal diameter (BPD), abdominal circumference (AC) and femur length (FL) with Hsieh's reported equations which are the major methods for the estimation of fetal weight. However, such regression methods are relatively acceptable in clinical obstetrics [1−5]. The accuracy of EFW remains to be

* Corresponding author. Department of Information Management, Chang-Jung Christian University, Tainan, Taiwan.
** Corresponding author. Department of Obstetrics and Gynecology, National Cheng Kung University Hospital, 138 Sheng-Li Road, Tainan 70403, Taiwan.
E-mail addresses: wangbb@mail.cjcu.edu.tw (H.-C. Wang), ahsin@mail.ncku.edu.tw (C.-H. Chang).

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improved. Clinical practice has found that the US-based EFW estimation yielded a 10% error for newborns weighing 2–4 kg; and >15% error was observed for newborn babies weighing <2 kg or >4 kg [6].

Recently, using artificial neural network (ANN) approaches to estimate fetal weight has become popular [7–9], and it is more accurate than the traditional regression methods. Farmer et al [7], Chuang et al [8], and Cheng et al [9] have reported that adopting the ANN model could provide more accurate EFW than before. However, the estimation is becoming more complex as more fetal parameters can be gathered; the error is still large for high birthweight (BW) or low BW fetuses; and clinical accuracy demand is increasing. Thus, the estimation models need to be further improved for better clinical benefit. The present study applied the Akaike information criterion (AIC) and minimum mean squared error (MMSE) mode to improve significant compensation weightings, and thus minimize the difference between EFW and actual BW.

Materials and methods

Overall experiment

Specifically, the aims of this study were: (1) to provide an MMSE-based criterion for the model compensation of errors between prenatal and postnatal parameters; and (2) to apply the proposed approach on a ANN-based fetal weight estimation model and evaluate the effect of the compensation. Fig. 1 depicts the flowchart of the proposed overall experiment. Several prenatal US parameters were inputted to the baseline ANN to derive the EFW. The error Δw was calculated by subtracting EFW from BW. The differences among prenatal and postnatal parameters, head circumference (HC), AC, and FL were evaluated as ΔHC, ΔAC, and ΔFL. The MMSE compensation model took Δw, ΔHC, ΔAC, and ΔFL into consideration and made adjustments to the input parameters of the ANN to see the compensation effect.

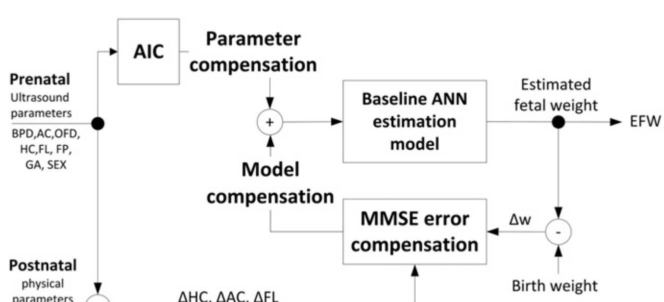

Fig. 1. The flowchart of overall experiments. AC = abdominal circumference; AIC = Akaike information criterion; ANN = artificial neural network; BPD = biparietal diameter; EFW = estimated fetal weight; FL = femur length; FP = fetal presentation; GA = gestational age; HC = head circumference; MMSE = minimum mean squared error; OFD = occipitofrontal diameter; SEX = gender; ΔHC = difference between the prenatal and postnatal parameters of HC; ΔAC = difference between the prenatal and postnatal parameters of AC; ΔFL = difference between the prenatal and postnatal parameters of FL; ΔW = difference between estimated and actual birth weights. + = summation of input data; − = subtraction of input data.

Data collection

Our retrospective study used the data collected from an educational hospital in Southern Taiwan: National Cheng Kung University Hospital. The participants included pregnant women with singleton pregnancies within 72 hours of delivery. This study was approved by the Institutional Review Board of National Cheng Kung University Hospital (IRB: ER-99-011). Informed consent was obtained from the pregnant women before examination. All the fetuses were examined by US scanner. The ultrasound measurements were undertaken by using conventional scanners (Aloka SSD-680, Tokyo, Japan; Medison Accuvix V20, Seoul, Korea; GE Voluson 730 Expert, Milwaukee, WI, USA) with 3.5–5.0-MHz convex transducers.

For the baseline ANN model, the collected data were screened to exclude those with missing data or unreasonable codes. The data were then used for developing an ANN model [9] to obtain the baseline threshold. A total of 2127 consecutive singleton fetuses were used in this study. The data for the fetuses were randomly divided into training and testing groups. The concept of v-fold cross validation and the same criterion of 7:3 were adopted to separate the training and the test datasets as in our previous study [8], and perform the evaluation five times. The model was trained using 1489 cases (70%) and tested with 638 cases (30%). The back propagation approach was used to train the network for optimizing the performance. MATLAB software package was adopted as the tool to perform the ANN algorithm. For evaluation of the proposed approach, we randomly chose 100 cases from the new operators with their examinations for the further experiment.

Ultrasonographic parameters assessment and correlation analysis

The fetuses were measured with US and yielded numerical parameters including: BPD, occipitofrontal diameter (OFD), AC, HC, and FL. Two nominal parameters, such as gender (SEX) and fetal presentation (FP) together with gestational age (GA) were also included in the prenatal data. Fetal AC was calculated by:

$$AC = \frac{\pi}{2} \times (APD + ATD) \quad (1)$$

where APD was abdominal anteroposterior diameter and ATD was abdominal transverse diameter. Similarly, the parameters BPD and OFD could be used to calculate the HC parameter as represented by Eq. (2).

$$HC = \frac{\pi}{2} \times (BPD + OFD) \quad (2)$$

GA was derived based on the date of the last normal menstrual period and confirmed by the first US scan. GA for all cases needs both the examination of the last menstrual period and US confirmation [4,10,11]. FP was divided into vertex and malpresentation groups according to US examination. Fetuses with breech or transverse presentations were represented in the malpresentation group. After the baby was delivered, the physiological parameters such as birth length (BL), chest circumference (CC), and HC could be measured.

The Kolmogorov–Smirnov test [12] was first applied to test whether they were normally distributed. Item analysis criteria such as internal consistency and correlation analysis were conducted to reveal the characteristics and discrimination of the prenatal US parameters and postnatal physical ones. The correlation and regression analysis among BPD, OFD, and HC was also performed. The relationship could be formulated as in Eqs. (3) and (4), where b_2 was a weighting factor and ε_2 the error term.

$$\mathrm{BPD} = b_2 \times \mathrm{OFD} + \varepsilon_2 \tag{3}$$

$$\mathrm{OFD} = \frac{(2\mathrm{HC}/\pi) - \varepsilon_2}{1 + b_2} \tag{4}$$

AIC and MMSE framework for compensating for ultrasonographic parameters

Analysis of the differences between prenatal and postnatal parameters aimed to achieve an optimal compensation on the ANN inputs. The feedback mechanism also benefited understanding of the error characteristics. Fig. 2 shows the determination algorithm for selecting the optimal weighting factors. There were two steps including parameter and model compensations. In the parameter space, the differences ΔHC, ΔAC and ΔFL between the prenatal and postnatal parameters were first uniformly partitioned into k subsets. AIC assessed each subset to determine an optimal number k of subsets. The above procedure was performed repeatedly until a minimum AIC value was determined. The selected subsets were then used to estimate a set of optimal weighting factors for the three differences. After the compensation in the parameter space, the compensated parameters were inputted to the developed ANN model to re-estimate the fetal weights. The difference Δw for each subset was then conducted into the MMSE-based estimation process to determine a set of the optimal model compensation weightings.

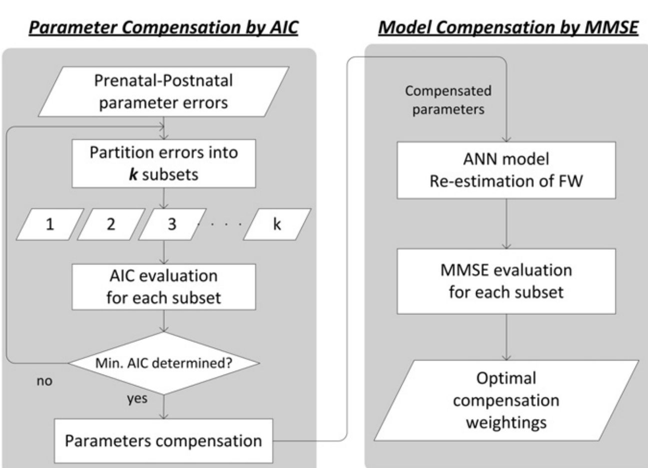

Fig. 2. The determination of the compensation weighting factors. AIC = Akaike information criterion; ANN = artificial neural network; FW = fetal weight; MMSE = minimum mean squared error.

AIC database partition and subset number determination

Before the compensation, the errors of the postnatal-to-prenatal parameter difference were considered to be partitioned into complementary subsets to assert the model fitness. The number of subsets was determined by using the AIC [13,14]. The AIC is an analytical model selection method based on using analytical estimates of the prediction risk for regression. With a linear estimator it was possible to determine the effective number of parameters. The number associated with each model was calculated as in Eq. (5). The AIC value can be regarded as the decision criterion for the best subsets partition number.

$$\mathrm{AIC} = \ln V + \frac{2d}{N} \tag{5}$$

where V was the number of parameters in the model; d the complexity of the model; and N the number of observations. The criterion could be minimized over choices of d to form a tradeoff between the fit of the model and its complexity.

Based on the limitation of the testing data, we took the bias correction up to the term of order $N-1$ into the AIC using Eq. (6):

$$\mathrm{AIC_c} = \mathrm{AIC} + \frac{2m(m+1)}{N-m-1} \tag{6}$$

where m was the number of parameters in the model. After partitioning by AIC, the differences ΔHC, ΔAC, and ΔFL were then divided into d subsets for further experiments. Their values also needed to be normalized before the AIC determination. For a sequence of error data Δx_i, the normalized Δx_i^* could be calculated using Eq. (7):

$$\Delta x_i^* = \frac{\Delta x_i^* - \Delta x_{\min}}{\Delta x_{\max} - \Delta x_{\min}} \tag{7}$$

where Δx_{max} was the maximum error and Δx_{min} the minimum error.

The relationship between Δw and {ΔHC, ΔAC, ΔFL} was then estimated by the formula in Eq. (8).

$$\Delta w = \alpha \cdot \Delta\mathrm{HC} + \beta \cdot \Delta\mathrm{AC} + \gamma \cdot \Delta\mathrm{FL} + \varepsilon \tag{8}$$

where α, β, γ were weighting coefficients and ε the error term. Deriving these coefficients by statistical regression, we had the compensated HC′, AC′ and FL′ for the input of the original ANN model. The compensations were given by:

$$\begin{cases} \mathrm{HC} = \mathrm{HC} + \alpha \cdot \Delta\mathrm{HC} \\ \mathrm{AC} = \mathrm{AC} + \beta \cdot \Delta\mathrm{AC} \\ \mathrm{FL} = \mathrm{FL} + \gamma \cdot \Delta\mathrm{FL} \end{cases} \tag{9}$$

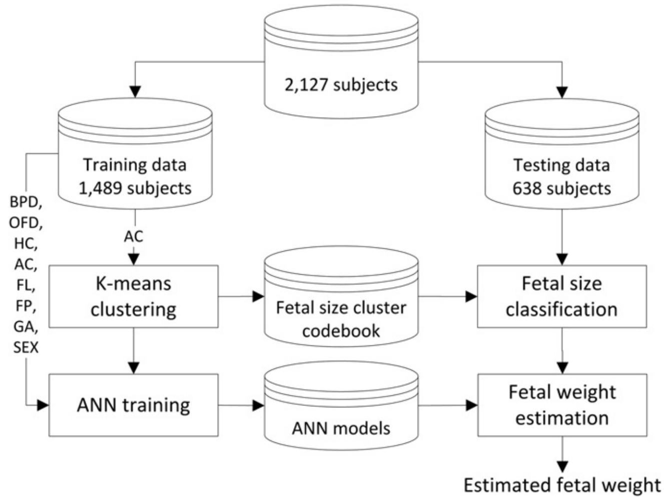

Fig. 3. Baseline artificial neural network estimation model. AC = abdominal circumference; BPD = biparietal diameter; FL = femur length; FP = fetal presentation; GA = gestational age; HC = head circumference; OFD = occipitofrontal diameter; SEX = gender.

MMSE compensation

According to the compensated parameters HC′, AC′ and FL′ of the selected subsets, the re-estimation of the fetal weight was performed as EFW′. Among all the partitioned training data, we applied the MMSE [15] criterion to determine the optimal estimate of EFW′ based on the collected data. The MMSE was formulated as in Eq. (10).

$$\mathrm{MMSE} = \underset{k}{\operatorname{argmin}} \frac{\sum_{i=1}^{k}\left(\mathrm{EFW}_i' - \mathrm{BW}_i\right)^2}{k} \tag{10}$$

where k was the number of subsets in different partitions. After the MMSE processing, the overall optimal compensation weighting for Eq. (8) was determined by choosing the minimal MMSE among the various AIC subsets. The weighing was used to generate adjusted fetal parameters and applied to the ANN inputs for estimation of BW. Accuracy comparison between the baseline and the compensated EFW was conducted to validate and assess the proposed approach.

Accuracy comparison and performance evaluation

The baseline model for estimating fetal weight was based on the back-propagation ANN architecture proposed by Cheng et al [9]. The model was composed of an input layer with eight inputs, a hidden layer, and an output layer. The input of the ANN was grouped according to fetal AC value. Three groups, low, normal, and high BW, were determined using k-means clustering algorithm [16,17]. Eight significant features including BPD, OFD, HC, AC, GA, FL, SEX, and FP were selected by stepwise regression [18,19] as input parameters in the group-based ANN model. Fig. 3 depicts the training and testing flowchart for the ANN-based fetal weight estimation.

The error of fetal weights estimated by the proposed model was compared with regression-based formulas listed in Table 1, including Hsieh's formula 1B [4], Hsieh's formula 2B [4], Hadlock's formula [3], and Shepard's formula [1]. Two indexes were adopted for assessing the accuracy: mean absolute error (MAE) and mean absolute percent error (MAPE). The equations are represented as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\mathrm{EFW}_i - \mathrm{BW}_i\right| \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\mathrm{EFW}_i - \mathrm{BW}_i\right|}{\mathrm{BW_i}} \times 100\% \tag{12}$$

where n was the number of fetuses. The significant level was defined as 0.05. Data management and statistical analysis were performed using SPSS for Windows version 15.0 (SPSS Inc., Chicago, IL, USA) and STATISTICA version 8 (StatSoft Inc., Tulsa, OK, USA). As described above, our study used 100 cases as the input of the trained ANN model. Based on the proposed error-compensation model, the fetal parameters were adjusted and re-fed to the ANN. The results of weight estimation with/without the compensation were compared to assess the accuracy of the proposed compensation model, and the accuracy evaluation was compared between the proposed compensation model and commonly used EFW formulas.

Results

Data description

The range of BWs of 2127 babies was between 500 g and 4736 g and was used for the ANN model development [9]. GAs ranged from 21 to 43 weeks. All the US parameters were tested using the Kolmogorov−Smirnov test ($p < 0.05$) and the results

Table 1
Four conventional formulas of estimating fetal weight.

References	Formulas
Hsieh's formula 1B (1987)	$\log_{10}\mathrm{EFW} = 5.6541 \times 10^{-3} \times \mathrm{AC} \times \mathrm{BPD} - 1.5515 \times 10^{-4} \times \mathrm{AC}^2 \times \mathrm{BPD} + 1.9782 \times 10^{-5} \times \mathrm{AC}^3 + 5.2594 \times 10^{-2} \times \mathrm{BPD} + 2.1315$
Hsieh's formula 2B (1987)	$\log_{10}\mathrm{EFW} = 9.4962 \times 10^{-3} \times \mathrm{AC} \times \mathrm{BPD} - 0.1432 \times \mathrm{FL} - 7.6742 \times 10^{-4} \times \mathrm{AC} \times \mathrm{BPD}^2 + 1.7450 \times 10^{-3} \times \mathrm{BPD}^2 \times \mathrm{FL} + 2.7193$
Hadlock's formula (1985)	$\log_{10}\mathrm{EFW} = 1.304 + 0.05281 \times \mathrm{AC} + 0.1938 \times \mathrm{FL} - 0.004 \times \mathrm{AC} \times \mathrm{FL}$
Shepard's formula (1982)	$\log_{10}\mathrm{EFW} = 1.2508 + 0.166 \times \mathrm{BPD} + 0.046 \times \mathrm{AC} - 0.002646 \times \mathrm{AC} \times \mathrm{BPD}$

AC = abdominal circumference; BPD = biparietal distance; BW = birth weight; EFW = estimated fetal weight; FL = femur length.

Table 2
Statistics of prenatal and postnatal ultrasound parameters of the selected 100 cases.

Types	Prenatal			Postnatal			
Parameters	HC (cm)	AC (cm)	FL (cm)	BW (g)	HC (cm)	CC (cm)	BL (cm)
Mean	32.4	32.9	7.0	3122.5	33.3	32.3	49.1
SD	1.2	1.4	0.2	285.2	1.3	1.4	1.5

AC = abdominal circumference; BW = birth weight; BL = birth length; CC = chest circumference; FL = femur length; HC = head circumference; SD = standard deviation.

revealed that all numeric data had non-normal distributions. The numerical parameters with the significant discrimination included AC, BPD, OFD, HC, FL, and GA. AC had a strong positive correlative with BW ($r = 0.81$, $p < 0.01$) and was selected as the basis of grouping fetuses, including the low BW group (Group I, $r = 0.92$, $p < 0.01$, $n = 102$), normal BW group (Group II, $r = 0.61$, $p < 0.01$, $n = 1{,}044$), and high BW group (Group III, $r = 0.64$, $p < 0.01$, $n = 981$). In Group I, the input layer included three parameters of GA, BPD, and AC ($R^2 = 0.95$, $n = 102$). In Group II, the input layer included six parameters of AC, BPD, GA, FL, SEX, and HC ($R^2 = 0.72$, $n = 1044$). In Group III, the input layer included five parameters of AC, BPD, SEX, FL, and FP ($R^2 = 0.61$, $n = 981$).

For evaluating our approach, 100 cases were conducted for the outside testing with BW >2 kg. The mean and standard deviation for prenatal parameters were: HC, 32.4 ± 1.2 cm; AC, 32.9 ± 1.4 cm; and FL, 7.0 ± 0.2 cm; and for postnatal parameters: BW, 3122.5 ± 285.2 g; HC, 33.3 ± 1.3 cm; CC, 32.3 ± 1.4 cm; and BL, 49.1 ± 1.5 cm (Table 2). The Spearman correlation between prenatal and postnatal parameters had a positive coefficient: FL and BL was $r = 0.44$ ($p < 0.05$), AC and CC was $r = 0.51$ ($p < 0.05$), and prenatal HC and postnatal HC was $r = 0.51$ ($p < 0.05$).

Evaluation of parameter compensation by AIC and MMSE

We compared the AIC values for 3–10 subsets partition. Fig. 4 shows the AIC with different subset number of ΔHC,

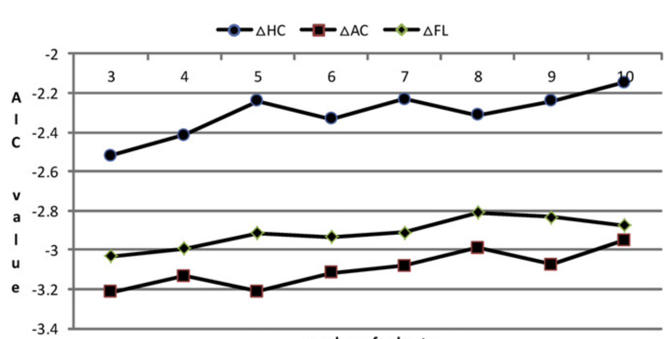

Fig. 4. The AICs with different number of subsets for ΔHC, ΔAC, and ΔFL. AC = abdominal circumference; AIC = Akaike information criterion; FL = fetal length; HC = head circumference; ΔHC = difference between the prenatal and postnatal parameters of HC; ΔAC = difference between the prenatal and postnatal parameters of AC; ΔFL = difference between the prenatal and postnatal parameters of FL.

ΔAC, and ΔFL. The minimum AIC value for ΔHC was −2.52, ΔAC was −3.03, and ΔFL was −3.22. The minima all occurred when the number of subsets was set to 3. Thus, partitioning the testing dataset into three subsets yielded the minimum AIC. Accordingly, the weighting coefficients for α, β, and γ were then derived using Eq. (8). Table 3 shows the weighting values for the selected subsets.

These weightings were further used to derive the compensated values HC′, AC′, and FL′. Taking the first subset as an example, the AIC compensation was calculated by using Eq. (13):

$$\begin{cases} HC = HC + 0.24 \cdot \Delta HC \\ AC = AC + 0.35 \cdot \Delta AC \\ FL = FL + 0.41 \cdot \Delta FL \end{cases} \tag{13}$$

The BPD and OFD correlation was also derived as shown in Eq. (14):

$$BPD_i = 0.318 \times OFD_i + 5.657 \tag{14}$$

Subset 3 with MMSE was chosen to determine the optimal weightings for further model-based compensation. The compensated parameters AC′, FL′, BPD′, and OFD′ were inputted into the ANN model.

Accuracy comparison of fetal weight estimation

The evaluation results of MAPE and MAE based on the baseline model without the compensation were 5.4 ± 3.2% and 165.6 ± 97.5 g, respectively; the results using the proposed compensation model were 5.1 ± 3.1% and 158.9 ± 96.2 g, respectively. Experimental results showed improvement of the EFW accuracy. The accuracy evaluation was compared between the proposed compensation model and regression-based formulas. As shown in Table 4, the MAPE and MAE of the proposed compensation method were 5.1 ± 3.1% and 158.9 ± 96.2 g, 6.3 ± 3.4% and 195.3 ± 102.2 g for the Hsieh 1B model, 6.3 ± 3.4% and 195.1 ± 102.9 g for the Hsieh 2B model, 6.8 ± 5.4% and 214.2 ± 174.7 g for the Hadlock model, 6.4 ± 3.5% and 198.3 ± 101.9 g for the Shepard model, and 5.4 ± 3.2% and 165.6 ± 97.5 g for the baseline without compensation Cheng's ANN model, respectively. The Friedman test showed that MAPE and MAE had significant differences among the six methods (Table 4). The results of the multiple-comparisons procedure showed that the MAPE and MAE of five pairs had significant differences. The five pairs were compared as below: (1) the proposed method and the Hsieh's formula 1B method; (2) the proposed method and the Hsieh's formula 2B method; (3) the proposed method and Hadlock's

Table 3
Weightings for the selected three subsets by Akaike information criterion.

Subsets	α	β	γ
Subset 1	0.24	0.35	0.41
Subset 2	0.44	0.12	0.44
Subset 3	0.83	0.14	0.03

α, β, γ are weighting coefficients.

Table 4
Comparison of the accuracy of estimating fetal weight among AIC−MMSE model and conventional formulas (n = 100).

Methods	MAPE ± SD (%)	p value[a]	MAE ± SD (g)	p value[a]
Hsieh's formula 1B (1987)	6.3 ± 3.4%	<0.01	195.3 ± 102.2	<0.01
Hsieh's formula 2B (1987)	6.3 ± 3.4%	<0.01	195.1 ± 102.9	<0.01
Hadlock's formula (1985)	6.8 ± 5.4%	<0.01	214.2 ± 174.7	<0.01
Shepard formula (1982)	6.4 ± 3.5%	<0.01	198.3 ± 101.9	<0.01
Cheng's ANN model (2012)	5.4 ± 3.2%	<0.01	165.6 ± 97.5	<0.01
AIC−MMSE model (This series)	5.1 ± 3.1%	—	158.9 ± 96.2	—

AIC = Akaike information criterion; ANN = artificial neural network; EFW = estimated fetal weight; MAE = mean absolute error; MAPE = mean absolute percent error; MMSE = minimum mean square error; SD = standard deviation.

[a] The estimation errors (MAPE and MAE) of the AIC−MMSE model were smaller than those of the conventional formulas and our previous ANN model using the Friedman test and multiple-comparisons procedure.

method; (4) the proposed method and Shepard's method; and (5) the proposed method and the Cheng's without compensation ANN model. Our proposed approach was significantly better than four regression methods and Cheng's without compensation ANN model by Friedman test.

Discussion

We showed an efficient AIC−MMSE compensation framework based on our proposed ANN model for improving EFW accuracy with another 100 cases selected from new operators. The baseline ANN model adopted an AC grouping approach to reclassify the input parameters of the ANN model and showed its ability to estimate fetal weight more accurately than the classical regression models [9]. However, the ANN model is highly dependent on the training cases. In order to be applicable to unseen or incomplete data, the model needs to be recalculated, which may not be possible in practice.

Motivated by the central limit theorem in statistics, the distribution of an average tends to be normal, even when the distribution from which it is averaged is non-normal. Although the error compensation model was trained with a small number of 100 cases, the cases were reasonably partitioned into several subsets and then conducted with a cross-validation process into the selection of the optimal weighting factors and further the minimization of the estimation errors to be averaged. Then the compensated parameters, HC', AC' and FL', and their optimal weighting coefficients for the differences, ΔHC, ΔAC and ΔFL were estimated and used for the further ANN development. Experiments for optimal partition using AIC could achieve a satisfactory performance with regard to the complexity, the limited data size, and the number of subsets. The range of three to seven subsets was evaluated to find the minimal AIC, and the results suggested that three subsets showed a tradeoff outcome in selecting the optimal partition.

The present study, based on error between the prenatal and postnatal fetal parameters, utilized an AIC−MMSE approach to compensate the input parameters of Cheng's ANN estimation model, to reduce further the estimation error of fetal weight. Through the correlation analysis, the prenatal FL was significantly correlated with postnatal BL ($r = 0.44$, $p < 0.05$), and AC and CC ($r = 0.51$, $p < 0.05$). The BPD and OFD, which could be derived from HC, showed their correlation (r = 0.51, $p < 0.05$). This approach could also provide useful formulation in dealing with the problem of data incompleteness. Although the optimal number of subsets was determined, the corresponding compensation weighting coefficients were obtained and conducted into the MMSE processing for the advanced model compensation. The weighting coefficients with minimum estimate of errors became an alternative way to compensate the inputs of the baseline ANN model without recalculation.

In conclusion, our study attempted to eliminate noise factors between ultrasonographic parameters and actual BW before delivery by using a new model of AIC−MMSE. Although the baseline ANN model could achieve a significant difference from other methods, the data heterogeneity among the high variability and broad-ranged parameters needs to be minimized. According to our results, the proposed novel approach using AIC−MMSE shows potential improved accuracy in comparison with our previous study. Although it could be argued that the performance depends on the limited data set, a further thought is that more training data and real observations (infants) are needed to improve the evaluation performance. As shown by the effects in the evaluation of the parameter and model compensation, determination of number of subsets and normalization of parameters play important roles in this task. The kind of development is highly empirical and needs to collect data from many individuals. In addition, the assessment of fetal weight as well as fetal growth is still crucial to prenatal diagnosis and genetic consultation [20–27]. We believe our novel ANN model and the improved work in this task could provide valuable information in assisting the related assessments in daily practice.

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