Hypervolemia Screening for Dialysis Patient Healthcare Using Meta Learning Model-Based Intelligent Scaler

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1. Introduction

In dialysis patients, increase in salt intake leads to a high sodium content, which results in an increase in body water. Hypervolemia is a condition manifested by excess normal body water, resulting in increases in body sodium content and a consequent increase in extracellular body water. This fluid overload condition causes increased body weight, high blood pressure, and peripheral edema in the legs and arms. The serious complications accompanying this condition include heart problems and shortness of breath [1–3]. Sodium concentration is an important contributor to fluid balance in the human body. Extremely high levels of sodium cause congestive heart failure and cardiovascular system instability. Excess body weight increases blood pressure, while prolonged symptoms lead to restructuring of heart function and induction of heart failure and arrhythmias [4,5]. Therefore, maintaining adequate body weight, water volume, and blood pressure and reducing the sodium concentration are important in dialysis healthcare. This study intends to propose an intelligent scaler to estimate total body water (TBW) and maintain dry weight/body mass index (BMI). In clinical examinations, bioimpedance spectroscopy [1,6–8] has been used to measure TBW using single-frequency (50 kHz) and multi-frequency (5–1000 kHz) bioelectrical impedance and subsequently to assess the condition of hypervolemia or hypovolemia. A multi-frequency bioelectrical impedance analyzer [8,9] is a noninvasive technique using a pair of electrodes placed on the wrist and ankle. The resistance of intracellular and extracellular water (ECW) in body tissues can be estimated by the impedance and the phase shift at different frequencies. The slopes of normovolemia and hypervolemia characterize the variations in ECW with body weight (BW). Accumulation of excess fluid in the body leads to increase in BW. This causes a rapid rise in the slope...
of ECW versus BW [1]. However, ECW and BW measurements must be obtained at the beginning of each dialysis treatment and are used to determine the slopes over the normovolemia range in healthy subjects. The aforementioned clinical examinations are simple methods; however, they lack the sensitivity and specificity required to identify hypervolemia.

The anthropometric method is also a simple technique used for the determination of TBW before or after dialysis treatment. It can be easily represented using a mathematical statistical model, such as the Watson formula, Hume formula, Sahlgrenska formula, Lee formula, and Chumlea formula [2,8,10,11,12–14]. TBW can be estimated using the dialysis patient’s characteristics, including gender (S, male/female), age (A, years), height (H, cm), weight (W, kg), BMI, and diabetes. These formulas have been used to evaluate TBW in different populations. In addition, anthropometric methods are applied to estimate the urea distribution volume (approximately equal to TBW) and the ionic dialysance during dialysis. In the blood sample method, ionic dialysance is estimated largely independently of TBW from the ratio of predialysis and postdialysis blood urea levels [14]. The precise result of the urea distribution volume can be obtained using kinetic modeling and bioimpedance measurement. Hence, the ionic dialysance can be determined for the online monitoring without using blood samples. Among these methods, the Watson formula has been widely used to estimate TBW in dialysis patients. Its model uses linear regression with narrow margins of substantial error to estimate body water. The Watson formula has a < 2% margin of error [11] in estimating the TBW in a patient’s normal dry weight and provides a promising reference method for routine examinations. Thus, the ratio of estimated TBW to normal TBW provides a criterion to identify changes in water volume balance. In this study, based on the Watson formulas for female and male subjects, standard training patterns were established to train a machine learning model-based intelligent method.

In the clinical setting, the number of enrolled dialysis subjects will increase gradually in the current active database; such new dialysis subjects or existing subjects with updating new training patterns. For example, TBW estimation has a negative correlation with A in male subjects. The TBW estimation is proportional to individual desired body weight in female subjects. Therefore, maintaining W, for a male subject, the incremental training patterns are required to meet the modified individual standard with varying A. Hence, this study proposed a meta-learning model to address the incremental learning of new training patterns. In a traditional training strategy, the retraining process will take substantial time to learn overall training patterns and to adjust to overall network parameters. A large number of training patterns will affect training performance and classification efficiency. It manner will take much CPU executing time to finish the learning stage. An incremental learning strategy [15–19] consisting of a primary multilayer learning network and an agent network will be established as an intelligent scaler for hypervolemia and hypovolemia screening. The primary multilayer learning network is designed using a multiple regression model with the particle swarm optimization (PSO) algorithm [20–24]. In the meta-learning stage, the agent network is employed to screen the previous learned experiences. The meta-learning model can gradually enhance the optimization for adaptive applications with new incremental training patterns. Its model refines the partial parameters and can avoid the overtraining with a large number of training patterns.

The remainder of this article is organized as follows. Section 2 describes the methodology, including the anthropometric formulas, meta-learning model, and PSO algorithm. Sections 3 and 4 present the experimental results and conclusion, respectively.

2. Methodology

2.1. Anthropometric Formulas for TBW Estimation

Total body water (TBW) estimation is important information in dialysis patients for evaluating the degree of fatness and hypertension. The body weight is relative to one’s height and then to determine the body mass index (BMI), TBW in predialysis stage, and interialytic weight gain in postdialysis stage. The desired body weight (kg), $W_{des}$, of a dialysis patient is determined in terms of sex and height [10] as

Female: $W_{\text{female}} = 52 + (H - 1.58) \times 50$  

(1)

Male: $W_{\text{male}} = 62 + (H - 1.70) \times 60$  

(2)

where $H$ is height (m). According to the Watson formula [11], given the dialysis patients’ characteristics: (1) sex: $S$ (male = 1/female = 0); (2) age: $A$ (years); (3) height: $H$ (cm); (4) weight: $W$ (kg), two formats for male and female subjects are used to estimate TBW [2,8,11]:

Male ($S = 1$):

$\text{TBW}_{\text{male}} = -2.097 + (0.1069 \times H) + (0.2466 \times W)$  

(3)

TBW in females ($S = 0$):

$\text{TBW}_{\text{female}} = 2.447 - (0.09156 \times A) + (0.1074 \times H)$  

$+ (0.3362 \times W)$  

(4)

The other experienced anthropometric formulas for estimating TBW are shown in the Remark [2,8,11,12,13],
Remark:
• **Hume formulas:**
  Female \((S = 0)\):
  \[
  \text{TBW}_{\text{female}} = -35.270121 + (0.34454 \times H) + (0.183809 \times W)
  \]  
  (5)
  Male \((S = 1)\):
  \[
  \text{TBW}_{\text{male}} = -14.012934 + (0.194786 \times H) + (0.2962934 \times W)
  \]  
  (6)

• **Sahlgrenska formulas:**
  Female \((S = 0)\):
  \[
  \text{TBW}_{\text{female}} = -29.944 + (0.294 \times H) + (0.214 \times W)
  - (0.0004 \times A)
  \]  
  (7)
  Male \((S = 1)\):
  \[
  \text{TBW}_{\text{female}} = -29.944 + (0.294 \times H) + (0.214 \times W)
  - (0.078 \times A)
  \]  
  (8)

• **Lee formulas:**
  Female \((S = 0)\):
  \[
  \text{TBW}_{\text{female}} = -26.6224 + (0.262513 \times H) + (0.232948 \times W)
  \]  
  (9)
  Male \((S = 1)\):
  \[
  \text{TBW}_{\text{male}} = -28.3497 + (0.243057 \times H)
  + (0.366248 \times W)
  \]  
  (10)

The Watson formula provides an individual standard to estimate the TBW in normality dry weight for female and male subjects, as shown in the TBW (L) versus body weight (kg) graph in Figure 1. For female subjects, the TBW has a positive correlation with \(H\) and \(W\). The desired body weight, \(W_{\text{female}}\), can be determined using equation (1). Then, with equation (3), subject’s normality dry weight can be estimated as a reference for continuous TBW examination. For example, for a female subject 1.65 m tall, the normal values of \(W_{\text{female}}\) and TBW_{female} are 55.5 kg and 29.2 L, respectively. For a given individual, \(H\) is nearly constant throughout the year; thus, the TBW is proportional to \(W\) [52.9 Kg, 57.9 Kg] versus [28.6L, 29.8L], as seen in Figure 1(a). For male subjects, TBW also has a positive correlation with \(H\) and \(W\) but otherwise, has a negative correlation with \(A\), as seen in the characteristic lines from 45 years to 60 years in Figure 1(b). For example, in a 50-year-old male subject 1.65 m tall, the normal values of \(W_{\text{male}}\) and TBW_{male} are 59.0 kg and 35.3 L, respectively.

Given the individual estimation, the family characteristic lines (45–60 years) are also the relationship of TBWs with Ws. Therefore, these family characteristic lines can be applied to screen for hypervolemia and hypovolemia.

For male subjects, TBWs vary with both \(W\) and \(A\), and for female subjects, TBWs vary with only \(W\). According to the Watson formula-based standard data, we can establish the training patterns to train the machine learning model, as input-output paired datasets, \([n_{\text{0}}, W_{\text{0k}}] - \text{[TBW}_{\text{0k}}\), \(n = 1, 2, \ldots, N, k = 1, 2, \ldots, K\), where \(N\) is the number of dialysis patients and \(K\) is the number of training patterns, as seen in Table 1. The multilayer machine learning model can be constructed using a learning algorithm in the learning stage, as seen in the diagram in Figure 2. In addition, as male subjects growing year by year, the incremental training patterns are required to meet the modified individual standard with varying \(A\). In an incremental learning strategy, a meta-learning model is used to achieve the learning task with new training patterns for adaptive applications. The proposed learning model is implemented using a multiple regression mechanism between inputs and outputs using the PSO learning algorithm.
2.2. Meta-Learning Model

Figure 3 depicts the structure of the meta-learning-based neural network, consisting of a primary network and an agent network. The primary network is a multilayer neural network, including input, pattern, summation, and output layers. The meta-learning model is used to screen for the appropriate changes in network parameters according to past experience of the primary network. The agent network is used to determine the desired target approach to new training patterns. Then, partial network parameters in the hidden layer are required to adjust using new training patterns. For multiple regression applications, the primary network is used to approximate the relationship between 2 input variables (S and W) and 1 output variable (TBW). The algorithm of the meta-learning intelligent model includes the following two stages: (1) to learn input–output paired training patterns using the PSO algorithm [20–23] and to estimate the near-global optimal solution and (2) to learn the new training data to tune the partial network parameters using the PSO algorithm. The learning procedures are summarized below.

- **Primary Network Learning Stage**

The input-output paired training patterns can be represented as follows:

\[
X_n(k) = [x_{n1}(k), x_{n2}(k)] - [y_n(k)] = [n, W_{nk} - [TBW_{nk}]
\]

where \(n = 1, 2, 3, \ldots, N\), is the number of dialysis patients; \(k = 1, 2, 3, \ldots, K\), is the number of training patterns for the individual patient. The total number of training data points is \(N \times K (K = 26\) in this study). These training patterns can be used to determine the structure of the primary network. We have two input nodes in the input layer and one output node in the output layer. The pattern nodes can be determined by the number of training patterns. Hence, the primary network learning stage is summarized as follows:

**Step 1)** for \(n \times K\) input training patterns, \(X_n(k) = [x_{n1}(k), x_{n2}(k)] = [n/N, W_{nk}/W_{max}]\), connecting weights, \(w_{ki} i = 1, 2, k = 1, 2, \ldots, N \times K\), are created between the input layer and the pattern layer by

\[
W^1 = [w_{k1}, w_{k2}]^T = \left[\frac{n}{N}, \frac{W_{nk}}{W_{max}}\right]^T
\]

where \(W^1 = [w_{ki}]^T\) is a \((N \times K)\) by 2 matrix; and \(W_{max} = 100.0\) kg. The body weights are normalized to the maximum values.

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Table 1. The input-output paired training patterns for female and male subjects.

| Sex, S | Input | Output |
|-------|-------|--------|
|       | Age, A | H (cm) | W (Kg) | TBW (L) |
| 1 (Male) | ↓ | ↓ | ↓ | ↓ | ↓ |
|        | 45 | 160 | 56.0 | 34.2 |
|        | 45 | 165 | 59.0 | 35.8 |
|        | ↓ | ↓ | ↓ | ↓ |
|        | 50 | 160 | 56.0 | 33.7 |
|        | 50 | 165 | 59.0 | 35.3 |
|        | ↓ | ↓ | ↓ | ↓ |
|        | 55 | 160 | 56.0 | 33.2 |
|        | 55 | 165 | 59.0 | 34.8 |
|        | ↓ | ↓ | ↓ | ↓ |
|        | 60 | 160 | 56.0 | 32.8 |
|        | 60 | 165 | 59.0 | 34.3 |
| 0 (Female) | ↓ | ↓ | ↓ | ↓ |
|        | – | 155 | 50.5 | 26.9 |
|        | – | 160 | 53.0 | 28.1 |
|        | – | 165 | 55.5 | 29.2 |
|        | – | 170 | 58.0 | 30.4 |

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Figure 2. The structure of meta-learning model.
**Step 2)** for \( K \times N \) output training patterns (desired target), the connecting weights, \( w_{nj}^n \), \( j = 1, 2 \), are created between the pattern layer and the summation layer by

\[
W^2 = \left[ \frac{\text{TBW}_{nk}}{\text{TBW}_{\text{max}}}, 1 \right]^T
\]

where \( W^2 = [w_{nj}^n]^T \) is a \((K \times N)\) by 2 matrix; \( \text{TBW}_{\text{max}} = 40.0 \) L is the maximum TBW. These connecting weights are also normalized to the maximum values and are associated with the two input variables. The connecting weights from the overall pattern nodes to the summation node, \( \Sigma g_k \), are set as 1.

**Step 3)** compute the output of the pattern node, \( g_{nk} \),

\[
g_{nk} = \exp \left[ -\sum_{k=1}^{K} \frac{(x_i - w_{nj}^n)^2}{2\sigma_i^2} \right], \quad i = 1, 2
\]

where \( X_0 = [x_1, x_2] = [n/N, W/\text{TBW}_{\text{max}}] \) is the testing pattern; \( s_n \) in equation (14) are the smoothing parameters and can be determined using the optimization algorithm, such as PSO algorithm.

**Step 4)** compute the output, \( y(k) \), in the output layer, as

\[
y_n(k) = \sum_{k=1}^{K} w_{nj}^n \times g_{nk}^n / \sum_{k=1}^{K} 1 \times g_{nk}^n = S_L(k) / \sum_{k=1}^{K} g_{nk}^n
\]

Final Output:

\[
Y = y_n(k) \times \frac{\text{TBW}_{\text{max}}}{\text{TBW}_{\text{nor}}} \begin{cases} < 1, \text{undervolemia} \\ \approx 1, \text{normal} \\ > 1, \text{hypervolemia} \end{cases}
\]

Residual Volume (L):

\[
V = \pm (Y - 1) \times \text{TBW}_{\text{nor}}
\]

where the final output, \( Y \), is used to indicate the changes in fluid volume balance; the symbol ‘+’ means ‘hypervolemia condition’; and the symbol ‘-’ means ‘hypovolemia condition’.

For a mean squared error function (MSEF), the PSO algorithm is used to refine the optimal parameter \( s \) in...
the primary network. The PSO algorithm is intended to adjust the optimal parameter and to minimize the objective function \(MSEF\), as

\[
MSEF = \min \left( \frac{1}{K} \sum_{k=1}^{K} \left[ T_n(k) - y_n(k) \right]^2 \right) \leq \epsilon \quad (18)
\]

where \(T_n(k)\) is the desired target, \(T_n(k) = TBW_{nk/\text{TBW}_{\text{max}}}\) for the \(k\)th training patterns.

- **Meta-Learning Stage**

For the new training patterns, the agent network as an inducer is employed to decide the degree of similarity or dissimilarity between the untrained patterns and the existing training patterns. Then, the meta-learning stage triggers the sub-network to learn the new training patterns using the PSO algorithm and to refine the partial smoothing parameters of the sub-network. The Gaussian functions are designed to screen for the degree of similarity as follows:

\[
g_n^\prime = \exp \left[ -\frac{1}{2\sigma^2} \times (ED_n^\prime)^2 \right] \quad (19)
\]

\[
ED_n^\prime = \sqrt{\sum_{i=1}^{2} (\Delta x_n^i)^2}, \Delta x_n^i = |x_{0i} - x_{n^i}| \quad (20)
\]

\[
X(0) = [x_{01}, x_{02}] = \left[ \frac{n \ W_{\text{male}}}{N'}, \frac{W_{\text{max}}}{W_{\text{max}}} \right] \quad (21)
\]

\[
X(n') = [x_{n'1}, x_{n'2}] = \left[ \frac{n' \ W_{n',\text{male}}}{N'}, \frac{W_{\text{max}}}{W_{\text{max}}} \right] \quad (22)
\]

where \(n' = 1, 2, 3, \ldots, N', N'\) is the number of dialysis patients; \(W_{n',\text{male}}\) are the normal weights of male or female subjects; \(ED_n^\prime\) is the Euclidean distance; and \(\sigma\) is the smoothing parameter determined at the primary network learning stage.

The degree of similarity is parameterized using Gaussian functions, \(g_n^\prime \in [0, 1]\), varying between the values 0 and 1. If any new pattern, \(X(0)\), is similar to any existing dataset, \(X(n')\), the \(ED_n^\prime\) will have small values, as \(ED_n^\prime \to 0\) and index, \(g_n^\prime \to 1\); otherwise, \(ED_n^\prime \gg 0\) and \(g_n^\prime \to 0\), as follows:

\[
g_{\text{max}} = \arg\max (g_1, g_2, \ldots, g_{\text{max}}, g_n') \quad (23)
\]

Index, \(c^* = n'\), while \(g_{\text{max}} = g_n'\), and

\[
\alpha_n' = \begin{cases} 1, & c^* = n' \\ 0, & \text{otherwise} \end{cases} \quad (24)
\]

where Index, \(c^* = n'\), is the ranking order at its maximum value among the existing datasets, \(X(n')\). In this study, a sorting algorithm, such as a bubble sort or a quick sort [25,26], is used to determine the maximum value on the ranking order, \(c^*\). Then, the pattern nodes are updated when the degree of similarity is higher between the nearest training pattern and the current input pattern. Therefore, the input and output connecting the weights are also updated from the ‘current input nodes’ to the ‘nearest pattern nodes’ and from those to summation nodes, \(S_k\) and \(\Sigma g_k\), respectively. Index, \(\alpha_n' = 1\), will trigger the meta-learning task using the PSO algorithm to tune appropriate changes in the smoothing parameter with the new training patterns.

- **PSO Algorithm**

For the objective function \(MSEF\) as equation (18), the PSO algorithm is employed to refine the smoothing parameters in \(n'\)th sub-network and to minimize the mean squared error. Let \(\sigma_g^p\) be the current center position of the \(g\)th agent at iteration number, \(p\), and agent, \(g = 1, 2, 3, \ldots, G\), where \(G\) is the population size. Multiple patterns form a population and are represented by a \(G\)-dimensional vector, as \(\delta^p = [\sigma_1^p, \sigma_2^p, \sigma_3^p, \ldots, \sigma_G^p]\). The modification of the center position \(\sigma_g^p\) during computing can be represented by velocity \(\Delta \sigma_g^p, \Delta \delta^p = [\Delta \sigma_1^p, \Delta \sigma_2^p, \Delta \sigma_3^p, \ldots, \Delta \sigma_G^p]\). As shown in Figure 4, the mathematical representation of each item position is given by

Center Position: \(\sigma_{n'g}(p + 1) = \sigma_{n'g}(p) + \Delta \sigma_g(p + 1)\) \quad (25)

Velocity: \(\Delta \sigma_g(p + 1) = \alpha_n'[\Delta \sigma_g(p) + c_1 \text{rand}_1(\text{obest}_g - \sigma_{n'g}(p))] + c_2 \text{rand}_2(\text{obest} - \sigma_{n'g}(p))\) \quad (26)

where \(\text{obest}\) is the global best in the population, and \(\text{obest}_g\) is the individual best. The parameters \(\text{rand}_1\) and \(\text{rand}_2\) are the uniform random numbers between 0 and 1. When the index \(\alpha_n' = 1\), it will trigger the PSO algorithm to refine the smoothing parameters. Weights \(c_1\) and \(c_2\) are time-varying acceleration coefficients [19–22], as follows:

\[
c_1 = (b_1 - a_1) \frac{p}{p_{\text{max}}} + a_1, \quad c_2 = (b_2 - a_2) \frac{p}{p_{\text{max}}} + a_2 \quad (27)
\]

where the first term, \(c_1\), is the ‘cognitive component,’ the second term, \(c_2\), is the ‘social component,’ \(a_1, b_1, a_2,\) and \(b_2\) are constant values, of which the experienced values are \(c_1\) from 2.5 to 0.5 and \(c_2\) from 0.5 to 2.5, respectively [22,24], and \(p_{\text{max}}\) is the maximum number of allowable iterations. When \(c_1\) is a higher coefficient, the search region will expand. Multiple particles are
allowed to determine the individual best solution around the search space by adjusting the searching points. By monotonously decreasing the coefficient $c_1$ and increasing the coefficient $c_2$, the search region will centralize to the global best solution and continue fine-tuning until the end of the search stage [23]. The term $p/p_{\text{max}}$ is used to control the coefficients $c_1$ and $c_2$ at each search stage. The following two convergent conditions are available for terminating the learning stage: (a) the objective function $MSEF$ is less than the pre-specified value, $\varepsilon$, and (b) the iteration numbers achieve the maximum allowable number $p_{\text{max}}$.

3. Experimental Results and Discussion

3.1. Meta-Learning Model Training

The proposed meta-learning model was carried out in the LabVIEW graphical programming software (NI™ Corporation, Austin, Texas, USA) at the PC level, as depicted on the graphic user interface in Figure 5. As shown in Table 1, the structure of the primary network could be determined using the input–output pairs of training patterns, such as the combination of $(n/N, W_{nk}/W_{\text{max}})$ and $(\text{TBW}_{nk}/\text{TBW}_{\text{max}})$, $n = 1, 2, \ldots, N$, $k = 1, 2, \ldots, K$. The configuration consisted of 2 input nodes, 2 summation nodes, and 1 output node, as depicted in Figure 3. We had 10 dialysis patients ($N = 10$, 4 female and 6 male subjects, aged 45–60 years) and 26 training patients ($K = 26$) for each subject. Thus, the total number of training patterns was $10 \times 26 = 260 (N \times K)$. We had 260 pattern nodes $(g_{n1}, g_{n2}, g_{n3}, \ldots, g_{nk}, \ldots, g_{nK})$ in the pattern layer. As shown by the three-dimensional representation in Figure 6(a), these paired training patterns were used to create the connecting weights between the input layer and the pattern layer and between the pattern layer and the summation layer, respectively. The primary network established a multiple regression model with two input variables and one output variable using the PSO algorithm.

![Figure 4. The PSO searching space.](image4)

![Figure 5. The graphic user interface for hypervolemia and hypovolemia screening (Intelligent Scaler).](image5)

![Figure 6. The input-output paired training patterns for meta-learning model. (a) The input-output paired training patterns for three-dimensional representation (10 subjects), (b) The new input-output paired training patterns for three male subjects ($1\#$, $4\#$, and $6\#$) with adding ages.](image6)
In the learning stage, the PSO algorithm with time-varying acceleration coefficients \(\{a_1 = 2.5, b_1 = 0.5, a_2 = 0.5, b_2 = 2.5\}\) was given by the population size \(G = 10–30\) for each computing iteration and the maximum allowable number, \(p_{\text{max}} = 50\), for the optimal smoothing parameter searches. We performed at least 5 runs with different random center positions, \(\delta^0 = [\sigma_1^0, \sigma_2^0, \sigma_3^0, \ldots, \sigma_n^0]\) and given population sizes, \(G\). For the convergent condition, \(\epsilon \leq 10^{-2}\), the average optimal smoothing parameter, \(s_{\text{opt}} = 0.003096\), could be guaranteed to minimize the mean squared error, MSEF. Its optimal solution lists decreased monotonously and could reach the convergent condition. Its iteration computations could take \(\leq 25\) iteration computations. As shown in Figure 7(a), there was only a slight improvement in optimal parameters by increasing the population sizes from 10 to 30 particles [25,26]. In addition, the learning stage increased the average number of computation iterations to minimize the MSEF from \(p \times 10\) to \(p \times 30\) evolution computations (from \(19 \times 10\) to \(23 \times 30\) evolution computations), and the average CPU time increased from 30.5993 to 74.7180 s. To reduce the computation iterations, we suggest the convergent condition for modeling the intelligent network using the PSO algorithm, including \(\text{MSEF} \leq 10^{-2}\), population size, \(G = 20\), and maximum iteration numbers, \(p_{\text{max}} = 25\).

### 3.2. Retrain with Updating New Training Patterns and Adding Incremental Training Patterns

In the meta-learning stage, by updating the new training patterns in the existing datasets, the degrees of similarity could be computed using equations (19)–(23), where the smoothing parameter of equation (19) was assigned with \(\sigma = 0.003096\). For example, updating the new training patterns for dialysis patients, \(1\#\), \(4\#\), and \(6\#\), the degrees of similarity were as shown in Figure 7(b). The total 78 (3 × 26) of new input-output pairs updated the connecting weights. The indexes, \(g_{\text{max}} = g_4 = g_6 = 1.0000\), were the absolute maximum values, and then the index \(\alpha' = 1\) was employed to trigger the learning task to adjust the optimal smoothing parameters using equations (25)–(27). We used the same primary network structure with 2 input nodes, 260 pattern nodes, 2 summation nodes, and 1 output node. Its optimal solution lists also decreased monotonously and could rapidly reach the convergent condition for \(\leq 22\) iteration computations \((p \leq 22, G = 20, \leq 22 \times 20\) evolution computations), as seen in Figure 7(c). For the same convergent condition, the average optimal smoothing parameter, \(s_{\text{opt}} = 0.002086\), guaranteed to minimize the mean squared error. Then, the smoothing parameters of pattern nodes \((g_{1}^{1}, g_{2}^{1}, g_{3}^{1}, \ldots, g_{26}^{1})\), \((g_{1}^{2}, g_{2}^{2}, g_{3}^{2}, \ldots, g_{26}^{2})\), and \((g_{1}^{3}, g_{2}^{3}, g_{3}^{3}, \ldots, g_{26}^{3})\) were updated using the optimal smoothing parameter. Hence, the proposed meta-learning model could screen the previous learned experiences and refine the partial parameters of the primary network. This learning strategy could avoid adjusting whole smoothing parameters and could reduce the learning time for on-line applications.

In addition, the numbers of current training patterns was 260 \((N = 10)\) in the current database, and 130 new training patterns \((5\text{ subjects, } 11\#–15\#)\) were added as shown in Figure 8. In the meta-learning stage, by feeding the incremental training patterns, the connecting weights \(w_{ki}^{n}\) and \(w_{kj}^{n}\) \(n = 11, 12, 13, \ldots, 15\), could be set from the input nodes to the new pattern nodes, \((g_{11}^{1}, g_{12}^{1}, g_{13}^{1}, \ldots, g_{26}^{1})\), \((g_{12}^{2}, g_{13}^{2}, g_{14}^{2}, \ldots, g_{26}^{2})\), \((g_{13}^{3}, g_{14}^{3}, g_{15}^{3}, \ldots, g_{26}^{3})\) and from those to the respective summation nodes. Then, the PSO algorithm was used to tune the smoothing parameter and could also rapidly reach the convergent condition for \(\leq 20\) iteration computations. The optimal parameter, \(s_{\text{opt}} = 0.003758\), was also obtained to minimize the mean squared error. While new subjects were enrolled in the current database, the proposed meta-learning model had the capability of processing numerical computations for expandable training patterns. Therefore, the database could be automatically enhanced by updating new training patterns or adding incremental training patterns to the current active database.

### 3.3. Case Study in Dialysis Patients

Experimental data obtained from dialysis patients were used to validate the proposed intelligent scaler, as shown in Table 2. In the predialysis stage, an electronic weighing chair was used to take personalized physiological measurements, including pressures and weights, as shown in Figure 9. For example, for a male \((\text{No. } 2\#)\), \(A = 50\) years, \(H = 1.60\) m, and \(\text{BMI} = 21.8\) kg/m², the baseline weight, \(W_{\text{male}} = 56.0\) kg, was estimated in the predialysis stage. This patient had hypertension and uncomfortable symptoms, a condition such that a change in weight of \(+ 2.0\) kg would result in a higher systolic blood pressure and fluid volume imbalance. Inadequate control of fluid volume and appropriate weight was an important causative factor of cardiovascular symptoms (left ventricular hypertrophy) and mortality. The proposed intelligent scaler provided an early screening method for the predialysis stage. Given the patient number and weight \((2, 58.0\) kg\), the intelligent scaler estimated the residual volume as \(V = 0.6699\) L and indicated the hypervolemia condition as a final output of \(y = 1.0198 > 1.0000\). This subject could be designated as a patient with increasing weight.
Figure 7. The meta-learning based intelligent network training. (a) The optimal smoothing parameter and mean squared error versus the number of iteration computing for primary network training, (b) the similarity degrees screening in meta-learning stage, (c) the optimal smoothing parameter and mean squared error versus the number of iteration computing for updating the new training patterns.
that led to a ‘hypervolemia condition.’ The results provided a suggestion to remove extra weight and achieve the appropriate BMI and dry weight. In dialysis healthcare, dialysis patients have a guideline to control drink, food, pressure, and dry weight. This finding confirmed that the proposed model could detect fluid volume near-balance or imbalance (residual volume in liters) in dialysis healthcare. The overall experimental results for 10 subjects (No. 1#–10#) are presented in Table 2 and Figure 10.

### 4. Conclusion

Adequate fluid volume status and blood pressure control are both important clinical issue for dialysis patient healthcare. This study intended to develop an assistive tool to estimate the TBW and residual volume. Then, daily sodium, food, and drink could be restricted to improve patient malnutrition. The meta-learning model was proposed to design an intelligent scaler to

![Figure 8](image)

**Figure 8.** The incremental input-output paired training patterns for five new subjects (11# ~ 15#).

![Figure 9](image)

**Figure 9.** Electronic weighting chair for weight and pressure measurement.

### Table 2. The experimental results for dialysis patients.

| Patient No. | Sex | Baseline W (kg) & BMI | A (year) | Change in W (kg) | H (m) | (1) (L) | (2) (L) | (3) (L) | Meta Learning Model (L) | Residual Volume, V (L) |
|-------------|-----|-----------------------|---------|------------------|------|---------|---------|---------|-------------------------|------------------------|
| 1           | 1   | 56.0                  | 45      | + 1.5            | 1.60 | 29.3904 | 33.7452 | 31.0493 | 34.7103                 | 0.5043                 |
| 2           | 21.8                       | 56.0                  | 50      | + 2.0            | 1.60 | 29.3904 | 33.7452 | 31.0493 | 34.7103                 | 0.6699                 |
| 3           | 59.0                  | 45      | + 0.2            | 1.65 | 31.6155 | 35.6080 | 33.3633 | 35.8188                 | 0.0672                 |
| 4           | 59.0                  | 60      | + 1.6            | 1.65 | 31.6155 | 35.6080 | 33.3633 | 34.8621                 | 0.5379                 |
| 5           | 21.6                      | 62.0                  | 45      | + 0.4            | 1.70 | 33.8407 | 37.4708 | 35.6773 | 37.4317                 | 0.1345                 |
| 6           | 21.4                      | 62.0                  | 50      | + 1.8            | 1.70 | 33.8407 | 37.4708 | 35.6773 | 37.4266                 | 0.6052                 |
| 0           | 0                           | 50.5                  | ––      | −1.2             | 1.55 | 25.8309 | 31.1417 | 27.8196 | 26.6299                 | −0.2959                |
| 8           | 21.0                      | 53.0                  | ––      | + 0.5            | 1.60 | 27.7259 | 32.8563 | 29.9506 | 28.2001                 | 0.1233                 |
| 9           | 20.7                      | 55.5                  | ––      | + 1.3            | 1.65 | 27.8424 | 33.0045 | 30.13369 | 29.5484                 | 0.3206                 |
| 10          | 20.0                      | 58.0                  | ––      | −0.8             | 1.70 | 31.5157 | 36.2857 | 34.2123 | 30.1815                 | −0.1973                |

*Note: 1. Symbol (1) means Lee formulas; 2. Symbol (2) means Hume formulas; 3. Symbol (3) means Sahlgrenska formulas; 4. n/e means normality TBW (TBW\(_{nor}\))/ estimated TBW.*
screen for hypervolemia and hypovolemia conditions. Its learning model was a learning-to-learn scheme to retrain by updating new training patterns or adding incremental training patterns. The proposed intelligent system gradually enhanced the optimization to tune network parameters using the PSO algorithm. Thus, the optimization scaler could always be maintained with a refined database by adding new dialysis subjects or existing subjects with newly updated training patterns. The proposed intelligent scaler with individual subject number and body weight are applicable to all gender and age groups for hypervolemia and hypovolemia screening. In addition, this new assistive tool could be implemented to advance the dialysis treatment for multipatient use in the hemodialysis room.

In clinical applications, the screening results could offer indicators for dialysis treatment, such as

- lower the dry weight;
- extend the dialysis time;
- increase the frequency of dialysis; and
- lower the sodium dialysis.

Therefore, we might have a cross-sectional reference to direct dry weight management and control dialysis volume during dialysis treatment.

**Disclosure statement**

No potential conflict of interest was reported by the authors.

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