ORIGINAL ARTICLE

Estimation of Urine Volume and Urine Conductivity Using Electrical Bioimpedance Based on the Neural Network Method

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Abstract

Purpose: Urine volume and urine conductivity monitoring allow better care for urinary tract infection disease. Urine volume and conductivity involve electrical bioimpedance change at the lower abdomen. In previous studies, bioimpedance has been only used for estimating the volume, and the estimation error significantly increases when the conductivity changes.

Materials and Methods: In this work, the neuron network technique is proposed to determine both the volume and the conductivity based on the measured bioimpedance data on a sixteen-electrode configuration. Nine architectures of neuron networks were investigated by simulation. Eleven body models were created, consisting of muscle, fat, pelvis bone, rectum, and bladder. Seven bladder sizes, eleven conductivities, and eight levels of Signal-to-Noise Ratio (SNRs) were simulated.

Results: The result showed that the neural network method could efficiently estimate with an average of 1.04% volume error and 2.85% conductivity error. The performance remained stable with a signal-to-noise ratio higher than 60 dB, but it may reduce 2-8 times at lower SNRs. The moderate fat content provided high performance. The performance would be worsened if the bladder size was very small and the conductivity was low. The performance was increased when the volume was moderate, i.e. 302 ml, and the conductivity was higher than 1.76 S/m. The 3-layer architecture with 1024, 512, and 2 neurons yielded the highest performance. The 2-layer architecture with hidden neurons higher than 512 provided a comparative performance with only 0.9-1.5% lesser performance.

Conclusion: Neural network technique can be used to estimate urine volume and urine conductivity with excellent performance.

Keywords: Urine Volume; Urine Conductivity; Bladder; Fat Content; Neuron Network.

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1. Introduction

Bladder dysfunction introduces an adverse impact on people. Dysfunctions may be caused by various pathophysiological conditions such as neurological disorders, muscular weakness, spinal cord injury, multiple sclerosis, and aging [1]. Losing bladder sensation to store or void the bladder severely impacts on an individual's well-being and quality of life. Clean Intermittent Catheterization (CIC) is a conventional method to empty the bladder by invasively inserting the catheter into the urethra. However, it may result in urinary tract infection or renal reflux [2]. It potentially leads to dysreflexia, severe paroxysmal hypertension, and several other disorders [3]. Bladder monitoring for urine volume and conductivity is one of the effective ways to help. However, manual inspection for the time to empty the bladder based on the experience of nurses or physicians for personal nursing may be inappropriate in the long term.

Ultrasound has been widely used in the clinic to measure bladder volume at the bedside [4]. However, although the accuracy and reliability are high, it requires professionals to operate and interpret. Using ultrasound as a routine procedure for continuous monitoring is still limited. Monitoring by measuring tissue bioimpedance is another promising option to determine fluid content [5-7] in the bladder, which is related to bladder volume [8-13] or pressure [14]. Principally, a small exciting current is initially introduced into the skin through a pair of electrodes. Bladder or urine volume change as well as the urine conductivity change will introduce corresponding voltages measurable on the skin which will be measured via additional pairs of electrodes. The measurement voltage is determined as the region bioimpedance that, therefore, can indicate the volume and the conductivity of urine in the bladder. [9] reported that every 50 ml of increasing bladder volume caused a 10-mV voltage increase. Conversely, [15-17] reported a negative relationship, and this relationship seems more rational since a volume increase indicates a region impedance decreases and implicitly a voltage decrease. The inconsistency could be due to the different measurement procedures or possibly improper control of other organs' activity. When the two-electrode configuration with 60 kHz 1 mA current was used, a change of the voltage of approximately 3% occurred at the 400 ml volume change [15]. Whereas, with the four-electrode configuration with 10 kHz 1 mA current, the maximum voltage changes of 8.1-21.5% weres found at the 1000 ml volume change (this depended on the measuring location) [16]. [18] also found based on the simulation that the voltage change was 4% with the adjacent current pattern (which is one of the most widely-used patterns) when the volume was changed by 150 ml, but it could be up to 7% when using the opposite current pattern. Another traditional way to use the voltage data when a measurement is performed at several locations of the abdomen is to reconstruct a 2-D impedance image of the bladder by Electrical Impedance Tomography (EIT) technique [17, 19, 20]. However, using the image to estimate the volume is inaccurate due to the image's reconstruction artifact [20]. It is also sensitive to noise and the urine's conductivity. Therefore, some studies did not directly determine the volume from the pixels in the reconstruction EIT image [15, 19]. Instead, the image was transformed to the global impedance of the lower abdomen. Like the previous way, the correlation between the global impedance and the volume was studied and it was reported to have a good correlation [17, 19]. [17] and [19] used 5 mArms at 50 kHz current on a 16-electrode scheme and performed on nine and ten volunteers, respectively. However, some inconsistent correlations were also found in [17]. This is possibly due to the non-linear effect of impedance change that needs individual calibration for estimation [21]. [19] found that volume estimation using impedance-based measurement was consistent with that using ultrasound devices. However, the impedance-based method showed a significant error when estimating residual urine. Furthermore, the measured impedance was also greatly interfered with body movement caused by abdominal muscle contraction and relaxation. Electrode configuration was also investigated in [19]. Using many electrode planes results in better bladder volume estimation.

The machine learning method is another way to exploit the voltage information to estimate the bladder or urine volume [10, 20], which benefits from a smaller computation load. Voltage information can be transformed to volume directly without the need for reconstruction. [20] simulated the volume change based on a single-plane electrode scheme and estimated the volume by a 3-layer neuron network. However, even though the relative estimation error of less than 2% was found, this error was still more significant than that estimated by using global impedance. The error was even more prominent when the noise was higher and when urine conductivity was varied. Recently, [10] investigated

the use of support vector machines and the k-Nearest-Neighbours technique to classify the bladder state as full and not full. Electrode configuration was a single-plane 32-electrode scheme with 5 mA at 50 kHz current, and the study carried out simulation and phantom tests. For all methods, accuracies ranging between 73% and 100% were found, and they were all tolerant to noise (even at the signal-to-noise ratio of 20 dB). The k-Nearest-Neighbours technique showed a larger error at large bladder volumes but a smaller error at small volumes. The variance of urine conductivity caused an estimation error of the bladder volume of up to 200%. It is worth noting that only bladder and skin geometry were included in these studies. It could be noticeable that, to our knowledge, urine conductivity has not been estimated or used by any studies to date. Since urine conductivity may affect the performance of volume estimation, including urine conductivity in the training process may improve estimation performance comparatively. Furthermore, a kidney infection is an unexpected consequence of Clean Intermittent Catheterization (CIC) to empty the bladder. Knowing urine conductivity could be a benefit as an indicator for determining patient well-being as well.

In this study, the urine (or bladder) volume and urine conductivity were estimated by various configurations of neuron networks based on simulation. Urine conductivity was here included to improve the performance of the estimation used in various circumstances. The simulation was carried out in a 2-plane configuration with 16 electrodes. The body model included bladder, pelvis bone, and rectum geometry. Fat was also added with 11 schemes. Seven bladder sizes were generated, and values of urine conductivity were investigated.

2. Materials and Methods

2.1. Simulation Model and Electrode Configuration

Voltage information in the simulation was obtained from 11 geometries of a lower male body where the fat amounts were different. A Finite Element Method (FEM) model of each geometry was constructed (Figure 1) Each model contained five different tissues: muscle, fat, pelvis bone, rectum, and bladder (Figure 2a and 3) Fat was added around the lower body as shown in Figure 3. Since the maximum urine volume in an adult is 400 ml and it could be down to 118 ml in some cases [22, 23], seven sizes of the bladder were simulated with the volume of 153, 220, 264, 302, 341, 377, and 399 ml (Figure 2b) Therefore, 77 models were used where the number of elements was between 199,043 and 208,902. The conductivity of the muscle, fat, bone, and rectum (large intestine contents) was based on 10 kHz, i.e., 0.34083 [16], 0.02383 [16], 0.02043 [16], and 0.35 siemens per meter (S/m) [24], respectively. Eleven conductivities of urine (filled in the bladder) were simulated i.e., 0.50, 0.71, 0.92, 1.13, 1.34, 1.55, 1.76, 1.97, 2.18, 2.39, and 2.60 S/m.

Sixteen electrodes in two planes were used, as shown in Figure 4. The number of electrodes is sufficient and suitable for skin attachment [18, 25]. The first and second planes were at 880 and 800 mm from the feet. The circumferences of the body at the planes are shown in Table 1. The models were used to calculate the boundary voltage information according to Equations 1-4 [26] where σ is the conductivity distribution, x is a point in the volume Ω, u is the potential distribution, n is the normal vector on the boundary surface s, I_{el} is the injection current applied at excitation electrodes, V_{el} is the boundary voltage measured at electrodes, z_{el} is the electrode contact impedance, and V_{el} is the volume at the electrode surface. Principally, a small current is injected into a pair of boundary electrodes and the corresponding voltage is measured on other electrodes. The current is applied on different pairs (i.e. different excitation patterns) to observe different responses due to different regional conductivity distributions.

$$\nabla \cdot \left(\sigma(x)\nabla u(x)\right) = 0 \qquad x \in \Omega \tag{1}$$

$$\int_{el} \sigma(x)\frac{\partial u(x)}{\partial n} ds = I_{el} \qquad x \in \Omega_{el} \tag{2}$$

$$\sigma(x)\frac{\partial u(x)}{\partial n} = 0 \qquad x \notin \Omega_{el} \tag{3}$$

$$u(x) + z_{el}\sigma(x)\frac{\partial u(x)}{\partial n} = V_{el} \qquad x \in \Omega_{el} \tag{4}$$

The number of current patterns was 24, all in the adjacent pattern. The total number of measurements was 456. The current was set to 1 mA_{rms}, and the contact impedance was set to 1200 Ω. Eight degrees of Signal-to-Noise Ratio (SNR) were implemented i.e., 110, 100, 90, 80, 70, 60, 50, and 40 dB. Voltages were repeatedly generated with different random seeds from each SNR. Therefore, there were 135,520

datasets of voltage data. EIDORS software (https://eidors3d.sourceforge.net/) was used to generate the voltage datasets [26].

2.2. Dataset Preparation and Neural Network Architecture

Voltage data was associated with both circumferences (at the height of the electrode places) to use as the input of neural networks. Therefore, the number of the input was 458. Two outputs were expected, i.e., urine volume and urine conductivity. The dataset was divided into three sets, i.e., training, validating, and testing datasets with the ratio of 60%, 20%, and 20%, respectively. Nine neural architectures (based on the multilayer perceptron: MLP) with two or three layers were investigated in this study, i.e., (two-layer architecture) 458-32-2, 458-128-2, 458-512-2, 458-1024-2, and (three-layer architecture) 458-512-128-2, 458-512-256-2, 458-1024-128-2, 458-1024-256-2, and 458-1024-512-2. The first and the last numbers are the input and output numbers, respectively. The second number is the number of neurons in the hidden layer next to the input layer. The third number for the three-layer architecture is the number of neurons of the next hidden layer.

Sixty percent (81,312 data) of the dataset was prepared for the training dataset. Another 20% and 20% (27,104 data each) were used for the validating and testing dataset. Input and output were normalized before training. The activation functions used for all hidden layers and the input layer were ReLU (Rectified Linear Unit), and those of the output layers were Linear. Dropout layers were added and were varied with the rates of 0%, 10%, 30%, 50%, and 70% to gain the best estimation. The batch size was also varied with 32, 64, 128, and 256. Adam optimizer was selected with a training parameter of 0.9 and 0.999 of Beta1 and Beta2, respectively, and with learning rates of $1x10^{-4}$, $1x10^{-5}$, $1x10^{-6}$, and $1x10^{-7}$. These hyperparameters, i.e., dropout rate, batch size, and learning rate were empirically investigated to have the minimum training and validating loss. The maximum number of epochs for all cases was set at 10000 while the early stopping setting was applied, determined from the validation loss keeping a minimum of 50 times. The loss function was MSE (mean squared error) function. The training was performed on Keras machine learning version 2.2.4 based on the Tensorflow platform (https://www.tensorflow.org/) version 2.10. The prediction accuracy was determined from the Mean Absolute Percentage Error (MAPE) as shown in Equation 5, where N is the number of estimates, T is the target (exact) value, and E is the estimation value. In our case, T is the true simulated value of the urine volumes or of the urine conductivities; and E is the prediction value of the urine volumes or of the urine conductivities.

$$MAPE = \frac{1}{N}\sum_{1}^{N}\left|\frac{T-E}{T}\right| \quad (5)$$

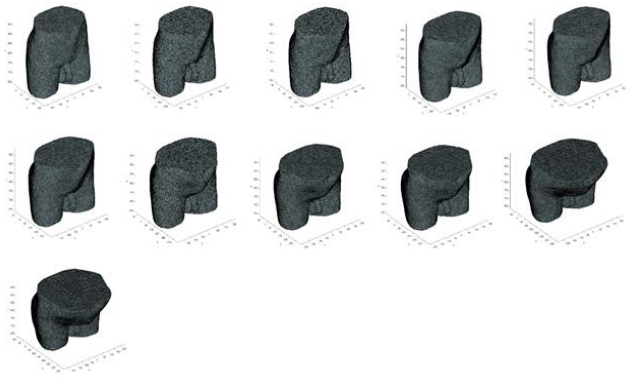

Figure 1. Lower body geometries with different fat content

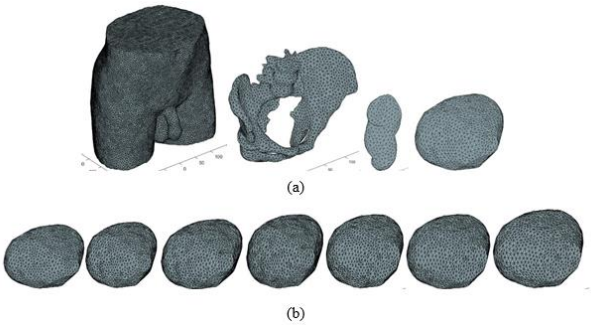

Figure 2. (a) (From the left to the right) Muscle, pelvis bone, rectum, and bladder, (b) Various sizes of bladder used in the study: 153, 220, 264, 302, 341, 377, and 399 ml

3. Results

3.1. Network Architectures

The estimation results regarding the architectures used are shown in Table 2. Overall, the 2-layer networks gave the best estimation error of 1.6% for the volume estimation and 3.9% for the urine conductivity estimation.

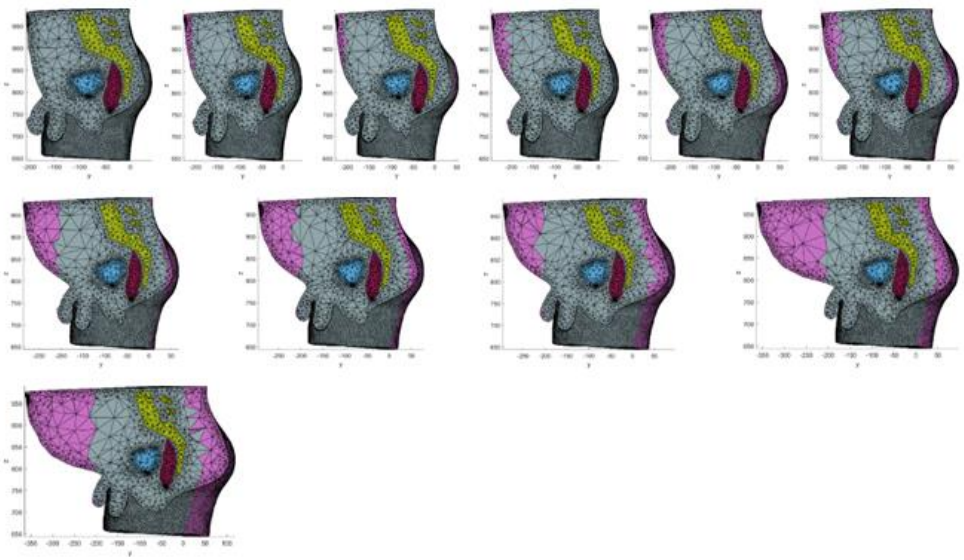

Figure 3. Model sections, each consists of muscle (grey) pelvis bone (yellow), rectum (dark red), bladder (blue), and fat (pink)

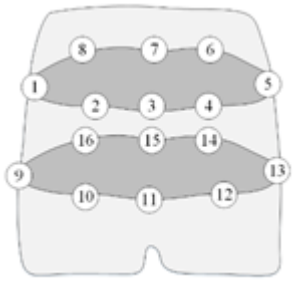

Figure 4. Position of the electrodes

Table 1. Circumferences of different models

Model	Circumference at the lower electrode plane (mm)	Circumference at the upper electrode plane (mm)	Fat volume (ml)
FAT1	921.0	889.5	0
FAT2	922.8	901.3	411
FAT3	938.9	917.1	614
FAT4	957.3	976.4	2157
FAT5	993.2	1002.4	3041
FAT6	1020.5	1032.6	4113
FAT7	1027.2	1066.7	5084
FAT8	1124.5	1173.1	9573
FAT9	1159.2	1204.0	11498
FAT10	1257.1	1374.5	19069
FAT11	1296.3	1414.2	21735

Table 2. Estimation Performance

Architecture	MAPE of urine volume (%)	MAPE of urine conductivity (%)
2-layer		
458-32-2	6.0293	12.3632
458-128-2	3.2455	7.5136
458-512-2	1.8929	4.3735
458-1024-2	1.6093	3.9180
3-layer		
458-512-128-2	2.0062	4.3096
458-512-256-2	1.5276	3.8174
458-1024-128-2	2.1243	4.2490
458-1024-256-2	1.3884	3.4104
458-1024-512-2	1.0229	2.8500

The 3-layer networks showed insignificant differences of 1.04% and 2.85% for the volume and the conductivity estimation error, respectively. The volume estimation was more accurate than the conductivity by 2.4 times. In the case of the 2-layer architecture, using the number of neurons that was less than 512 resulted in a significantly larger error for both predicting parameters. In general, the larger number of neurons resulted in a smaller error. For all cases, the number of neurons of the layer before the output layer had a more substantial influence on having a small error. For example, in the 3-layer architecture, the double of neurons from 128 to 256 can reduce the error by 0.48%-0.74% and 0.49%-0.84% for the volume and the conductivity estimation, respectively. It is also noticeable that the number of neurons

of the hidden layer next to the input layer for the case of 3-layer architecture had a lesser influence.

3.2. Training Hyperparameters

The training hyperparameters were investigated. However, due to a large number of results, only the investigation on the 458-1024-512-2 network is shown here, as in Figure 5. The extensive learning rate resulted in an inferior error. The minimum learning rate ($1x10^{-7}$) resulted in enormous computation time, but no significant improvement could be observed (Figure 5a) When smaller batch sizes were employed, a slight improvement could be observed. Still, this improvement was not comparable to the substantial increase in the computation time (Figure 5b) In the case of dropout rate, in general, the increase in dropout rate caused an increase in error (Figure 5c) It is beneficial to notice that even at zero percent dropout rate, the estimation was still able to converge.

3.3. Estimation Performance

The result of the noise susceptibility investigation is shown in Figure 6. When the SNR was over 60 dB, the prediction performance was stable. The performance was slightly reduced at 60 dB, 2-3 times at 50 dB, and 6-8 times at 40 dB for both estimates (however, the performance of the urine conductivity estimation was worse.) The errors could be up to 3.6% and 10.3% for the volume and conductivity estimations, respectively. In the case of fat content variance, the error was small at the moderate body size (moderate fat amount), i.e., the hip circumference between 1002-1066 mm (Figure 7) The error varied between 0.6% and 1.6% for the volume estimation, significantly larger in the range of 1.7% and 6.4% for urine conductivity estimation. The sizeable fat content tended to have a poorer estimation outcome, especially for the urine conductivity estimation.

The overall estimation performance for the urine volume and urine conductivity is shown in Figure 8 and Figure 9. The moderate bladder size, i.e., 302 ml, and the high conductive urine, i.e., greater than 1.76 S/m resulted in a small estimation error (it could be down to 0.77% and 2.44% for the volume and the conductivity estimation, respectively.) The smallest bladder size, i.e., 153 ml, caused approximately 70% larger error in the volume estimation and a 30% larger error in the conductivity estimation. The slightest conductive urine caused the increase of both errors by approximately two times.

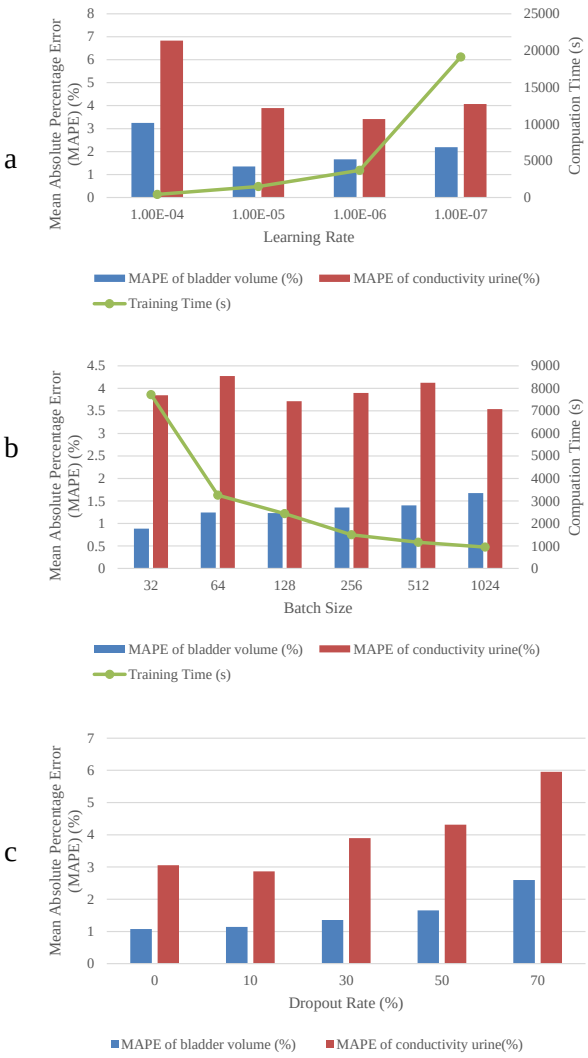

Figure 5. (a) Estimation error and computation time of different learning rates, (b) Estimation error and computation time of different batch sizes, (c) Estimation error of different dropout rates

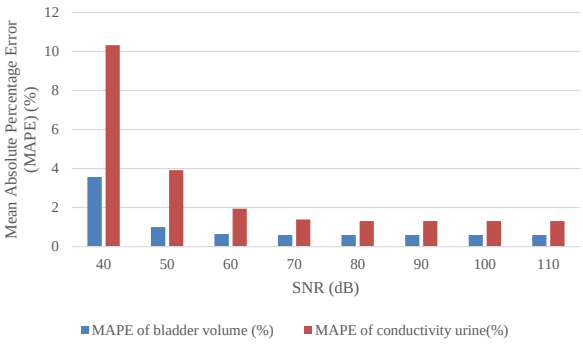

Figure 6. Estimation error of different SNRs

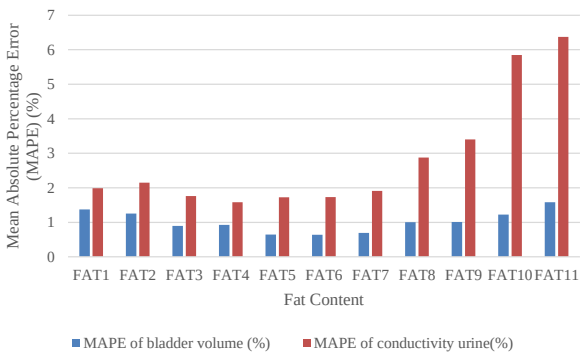

Figure 7. Estimation error of different fat contents

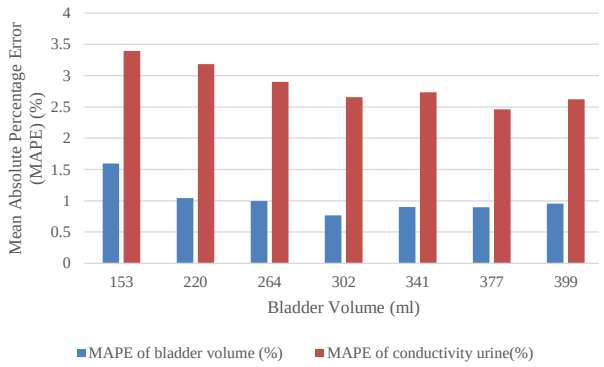

Figure 8. Estimation error of different urine volumes

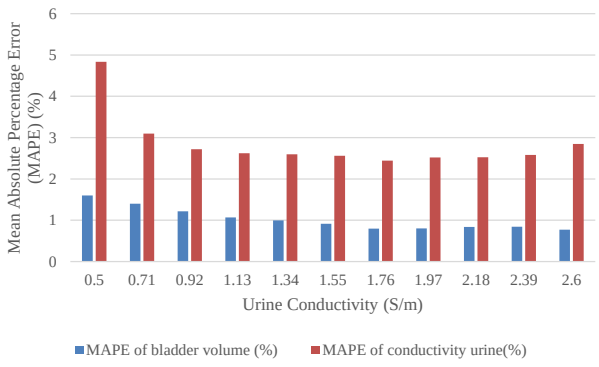

Figure 9. Estimation error of different urine conductivities

4. Discussion

The neural network method has been demonstrated by simulation that it can be used to estimate the bladder or urine volume and urine conductivity in different circumstances. The estimation errors for the volume and conductivity in this study were less than 1% and 2.9%, respectively. This was consistent with that reported in [10], which was simply based on binary classification between full and not full bladder state. The error found in [10] was approximately between 1% and 3%. [20] also used the neuron network method for continuous monitoring bladder volume in a body geometry and found that the error was between 0.81% and 1.94% (a simulation basis). However, [10] and [20] did not include fat, bone, and rectum and did not estimate urine conductivity. [20] reported that when the conductivity was changed, the estimation error of the volume could be significantly increased by 200%. Even though the simulation situations in this study are more complicated and the urine conductivity is varied, with the proposed architecture, the estimation errors are approximately the same degree of error as reported in the previous studies. Furthermore, [10] and [20] used a single-plane electrode configuration. The single-plane electrode configuration could be too simple in the estimation, as [19] recommended using multiplane electrode configurations. In this study, a 2-plane scenario was applied. Regarding the network architecture, the extensive network structure, i.e., 3 layers and lots of neurons, outperformed the rest. The estimation error of the 458-1024-512-2 network, the most extensive architecture, was only 1.02% and 2.85% for the urine volume and urine conductivity, respectively. A further investigation also found that the coefficient of determination of this architecture is 99.53% and 97.92% for the urine volume and urine conductivity, respectively, which all are high. However, the 2-layer architecture with a higher number of neurons is still attractive since the performance insignificantly decreased, but the training time is considerably reduced. The performance depends on the number of layer neurons before the output layer rather than the number of layers next to the input layer (for the 3-layer structure), as expected, since the sensitivity of the layer close to the output layer is higher than those are close to the input layer. This is regarding the characteristic of the backpropagation algorithm. The small learning rate surprisingly resulted in a poorer outcome. This was because the estimation loss decreased too slowly, and the early stopping condition was met before the optimum fit. In the case of batch size, the computation time increased exponentially with the small batch size while the performance was slightly increased. This phenomenon would be worse if the number of neurons was increased. Therefore, a large batch size is then advised here. In the case of dropout rate selection, a higher dropout rate caused a larger error, which is rational since the rate of forgetting in training weights is higher. The optimal dropout rate is 10%. It is interesting that even with a zero

dropout rate, the estimation outcome was slightly different from that used in the best dropout rate, i.e., 10%. This could indicate a low degree of complexity for this estimation problem. And this could reinforce the previous opinion that the 2-layer architecture should be adequate.

Noise susceptibility in this study was consistent with that reported in [20]. However, this is not comparable with that reported in [10], where the noise level could be down to 20 dB-SNR. However, the study of [10] was performed based on a binary classification of the state of "full" and "empty" bladder, which may not be comparable. Interestingly, the very small or no fat content and the large fat content caused poor estimation performance. This is rational since the estimation of the small and the large fat content requires extrapolation in the estimation. Fitting the neural network outputs at the moderate fat content was then easier. This manner seems similar to [20], where a poorer estimation outcome was noticeable at the two ends of the estimation range of bladder volumes. Additionally, this could be explained by the massive fat content degrading the sensitivity to the conductivity change inside the bladder region. Therefore, the large fat content had a larger error than the smaller or no fat content.

The bladder or urine volume estimation was significantly more accurate than the urine conductivity estimation. Since urine is more conductive than the surrounding tissue, the larger volume results in higher sensitivity. The estimation error of the volume was similar to the fat content, i.e., the smallest and the most significant size tended to have a larger error. The large size of the bladder is supportive of estimating urine conductivity. The larger volume tends to have higher accuracy because of the higher sensitivity. This causes a larger voltage response on the skin. The small bladder size was more complex in all cases to estimate due to the low sensitivity.

Urine conductivity could vary according to salt or water intake, which was practically difficult to control. The estimation of the volume is then advisable to include urine conductivity as a crucial parameter. Urine conductivity can result in the increase of the volume estimation error to 2 times. Regarding the estimation error of the urine conductivity, the error was high at the low and high conductivity, similar to the urine volume estimation. The very low conductivity had a more significant error due to the conductivity being close to the surrounding tissues. The low conductivity also caused difficulty in estimating the urine volume for the same reason.

Neural network classifier requires a long training time, but after finishing training, the trained model could predict in hundred milliseconds. The training duration depends on the architecture, the training parameters, and the number of training data. In this work, with the 458-1024-512-2 network, the training duration was between 16 minutes and 2 hours. The prediction time was less than 1 second. Compared with the traditional method to estimate based on image reconstruction [17, 19, 20], the voltage information needs to be reconstructed first. Regarding [27, 28] which used approximately the same number of measurements and the number of 3D FEM model elements, the reconstruction time of each data was 40 minutes while 900 Mbytes memory was needed. Moreover, to estimate the volume or the conductivity, further processing time is also required. This indicates that estimation based on neural network technique can substantially reduce estimation time by at least 2400 times. Therefore, this is unavoidable for the traditional method to reduce the fineness of the FEM model or to use a 2D FEM model to reduce the computational time and resources, and this will impact the accuracy of the estimation. Estimation with a neural network classifier then can reduce computation time and resources while the estimation accuracy remains high.

It is worth mentioning that this work is based on simulation. Validation of experiment data is necessary. According to the result, we highly recommend collecting both the volume and urine conductivity during the experiment to have better prediction results.

5. Conclusion

This study implemented the neuron network method to estimate the bladder or urine volume and urine conductivity. Simulation results on a complex body structure showed that the neuron network method could be used with various body sizes, urine volumes, and urine conductivities, and it is also noise tolerant. Compared with other methods like ultrasound or global impedance monitoring, this method is simple and fast, and requires less computation. The performance in the case of volume estimation is higher than in the case of urine conductivity estimation. The estimation performance could be reduced when the body size is too

slim or too fat, as well as when the bladder size is very small, or the urine has very low conductivity.

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