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Linear Regression for Estimating Bladder Volume with Voltage Signals

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Abstract— **Urinary incontinence is a common condition that can severely impact the lives of those who have it. Bladder volume monitoring solutions that exploit the electrical differences of different tissues in the pelvis have the potential to help medical personnel in the decision-making process with urinary incontinence. In this work, we investigate linear regression as a means of assigning bladder volume to the measured voltage values. We found that linear regression outperforms the previously studied machine learning regression algorithms by nearly a factor of 4. This linear regression approach is also more effectively able to handle volumes outside the training boundaries in comparison to previous work in the field. More work is needed to further improve the estimate of bladder volume based on the voltage signals, especially at high noise levels.**

Keywords— Bladder Volume Monitoring, Machine Learning, Regression, Voltage, Electrical Impedance, COST EMF-MED

I. Introduction

Urinary incontinence affects over 200 million people throughout the world [1]. In particular the condition affects children and adolescents with intellectual disabilities [2], the elderly [3], [4] and those with neurological conditions [5]. Urinary incontinence can severely impact the quality of life of these individuals [6], [7].

Methods of measuring the electrical properties of tissue at both low and high frequencies can be used to monitor the bladder volume and aid in providing clinical feedback to the clinician that can enhance decision-making with urinary incontinence [8]. To determine the bladder volume, the data can be associated with the bladder volume by metrics [9], [10] or by machine learning [10].

Currently, neural networks (NN) have been employed at low-frequency for bladder volume monitoring (BVM) using voltage as input [10]. However, the performance of the NN was found to deteriorate when pushed outside training boundaries, such as in the extrapolating of unseen bladder volumes [10]. Bladder volume has been shown to have a 'near' linear trend with electrical properties [8]. Thus, a better machine learning algorithm may be linear regression for extrapolating bladder volume.

In this work, we perform numerical simulations of an electrical impedance system for BVM. These simulations provide us with a series of voltages at each electrode that are dependent on the bladder volume. We then apply a linear regression model to estimate the bladder volume of future unknown bladder scans, and compare this performance to existing machine learning regression within the field.

II. Simulation Data Gathering & Data Preparation

A 32 electrode, elliptical cylinder finite element model (FEM) of the pelvis was created in the EIDORS package [11] for the data generation, as shown in Fig. 1. The FEM contains an ellipsoid representing the bladder, that ascends upwards and widens in the FEM as the bladder volume is increased. Further detail on the simulation model can be found in our previous work [12]. This FEM shape is the current simulation standard for BVM with electrical impedance techniques. The number of electrodes corresponds with the electrical impedance hardware from our previous experimental studies [12].

Voltage data was collected for the bladder volumes [50:5:400] ml for training and testing with an injection current of 6 $mA_{p\text{-}p}$ and an electrode "skip of 4" pattern. Thirty frames of 1024 measurements were taken for each bladder volume with 40 dB of noise added (the signal-to-noise equation is outlined in [12]). This noise level caters for severe circumstances [12]. After removing injection measurements and averaging all voltages for a specific measurement pair, each frame was reduced to 29 voltages. These 29 voltages formed the inputs, x, into our linear regression model, $y(x)$:

$$y(x) = \alpha + \sum_{i=1}^{29} b_i x_i \tag{1}$$

where α is the y-axis (bladder volume) intercept and b_i is the coefficient for i^{th} input.

Overall the dataset consisted of 2130 frames with labels of bladder volumes. The training and test data formed a 50%-50% split. The dataset was randomised before training and testing.

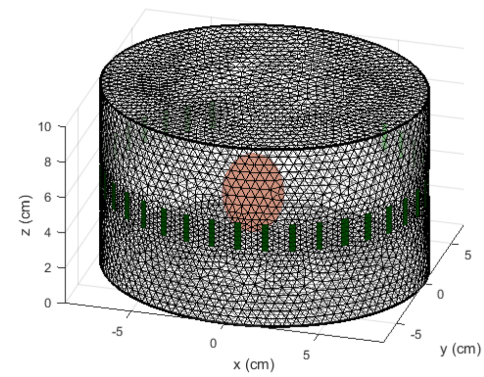

Fig. 1. Simulation FEM for data generation. Within the FEM, the bladder (orange) is represented as an ellipsoid that ascends vertically, mimicking the urinary bladder in the pelvic cavity. The electrode positions are shown as green rectangles.

To compare fairly with current literature, an unseen bladder volume dataset was created consisting of bladder volumes that differ from those in the training set: [22:5:428] ml. After testing, the regression model was performed on the unseen bladder volume dataset, consisting of 2460 frames.

III. Results & Discussion

The procedure of shuffling of the dataset, training, testing and running on the unseen volume dataset was repeated 10 times and the results were averaged. Tables 1 and 2 outline the performance metrics, including the root mean squared error (RMSE), for the linear regression on the test set and on the unseen bladder volume dataset, respectively.

Current literature used relative volume error as the primary assessment metric of the NN for bladder volume regression [10]. For the NN, the mean relative volume error was 193.38% and the standard deviation (STD) of the relative volume error was 213.21% on the unseen bladder volume dataset [10] (with the same level of noise as implemented in this study). Linear regression reduces the mean relative volume error by 3.9 times, while the STD of the relative volume error was reduced by a factor of 2.25.

Note that [10] removed bladder volumes that required the NN to extrapolate, where we did not. The volumes outside of the training boundaries severely deteriorated the performance of the NN. We trained the dataset on the noisy data, where [10] trained on ideal data. We believe training on the noisy data is more representative of real-world environments. Thus, the work here suggests linear regression as, currently, the best choice of machine learning regression for BVM.

However, more work is needed to reduce the RMSE that is currently quite high for applications where the exact bladder volume is needed, such as reporting to the clinician at what volumes involuntary voiding occurs.

TABLE I. Test set results after 10 repetitions. Standard deviation (STD) reported for each metric over the 10 runs.

Metric	Value
RMSE	56.73 ± 1.11 ml
Relative Volume Error	30.53 ± 0.92%
STD of the Relative Volume Error	41.53 ± 2.15%

TABLE II. Unseen volume dataset results after 10 repetitions. Standard deviation (STD) reported for each metric over the 10 runs. In parentheses are the values from the NN [10] .

Metric	Value
RMSE	62.38 ± 0.32 ml (N/A)
Relative Volume Error	49.30 ± 0.37% (193.38%)
STD of the Relative Volume Error	94.69 ± 0.71% (213.21%)

IV. Conclusion

We have shown that a linear regression model outperforms the use of a neural network to predict the bladder volume from electrical impedance simulations. Further work is needed in reducing the error with bladder volume assignment using machine learning.

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