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# Multiclass SVM for Bladder Volume Monitoring using Electrical Impedance Measurements

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**Abstract**— Urinary incontinence is a common condition that impacts the quality of life from those who suffer from it. Electrical impedance measurements offer the potential for a non-invasive low-cost solution to monitor changes in the bladder volume. This work focuses on using a multiclass support vector machine (SVM) algorithm to classify the fullness of the bladder into three states; not full, full, and a boundary class. This paper applies this machine learning algorithm to both simulation and experimental data. The SVM model uses the recorded voltages from electrical impedance measurements as features, is trained and optimized using a Bayesian Optimization approach, and then 10-fold cross-tested to obtain a generalized error. This paper demonstrates that simulation data with a signal-to-noise ratio of 40 dB, and experimental data from a pelvis phantom, can be perfectly separated into the three classes defined above.

**Keywords**—bladder volume monitoring, machine learning, electrical impedance; classification algorithms

## I. INTRODUCTION

More than 200 million people throughout the world suffer from urinary incontinence [1]. The condition particularly affects the quality of life for the elderly, those suffering from neurological conditions, and children and adolescents with intellectual disabilities [2] – [6]. The current gold standard for bladder volume monitoring is through bladder ultrasound (2D and 3D) operated by a trained medical technician in a clinical setting [7]. A simple low-cost at-home solution would alleviate the burden on the health care system and help improve the quality of life for those suffering from urinary incontinence.

Electrical impedance (EI) techniques offer the possibility to continuously monitor changes in the bladder volume noninvasively and proactively. Small electrodes are placed on the skin around the pelvis and record the impedance between specific channels. As the bladder fills, there is an increased region of high conductivity that exists within the pelvic region. The changes in impedance between the electrodes can then be used to infer changes in the volume of the bladder.

Previous research focused on using EI data to create tomographic images from the measured voltages [8]. More recently, work has been done using machine learning algorithms to estimate the volume of urine in the bladder [9] and to classify the state of the bladder between ‘full’ and ‘not full’ [10]. In this work, we demonstrate that a multiclass support vector machine (SVM) classifier, using a radial-basis function kernel, can be used to classify data from both numerical simulations and phantom measurements of an electrical impedance system for bladder volume monitoring. The

extracted voltage recordings from these simulations and measurements are used to train and test a Bayesian optimized multiclass SVM model to classify the state of the bladder into 1 of 3 groups; ‘not full’ (NF), ‘full’ (F), and ‘boundary’ (B). As was shown in [10], the most common misclassification errors occur near the boundary volumes between ‘full’ and not ‘full’, as would be expected due to the strong correlation between the conductivity of the pelvic region and the bladder fullness [10]. The advantage of adding this boundary class is that in practical applications, knowing when the bladder is nearing a full state will allow for more frequent measurements. This has two benefits: we can save battery life by limiting the number of measurements when the bladder is classified as not full, and, by performing more frequent measurements in the boundary state, more precisely know when the bladder is full.

## II. METHODOLOGY

### A. System Overview and Data Collection

The numerical simulation data used in this work is the same data set used in the test case 1 in [10]. Simulation data was obtained for fourteen different bladder volumes from 40 – 420 ml. The numerical model consists of an elliptical cylinder finite element mesh (FEM) representing the pelvic region with a ring of 32 evenly-spaced electrodes along the outer wall. A uniform background conductivity of 0.2 S/m was assigned to the FEM and a conductivity of 1.75 S/m was assigned to the bladder region, to match the expected properties of human tissues [10]. Random gaussian white noise (RWGN) was added to each simulation frame, with signal-to-noise ratios (SNR) of 20 dB and 40 dB. While these values are below those reported for most EI devices in the literature [10], it accounts for the degradation of the signal quality that may arise in real-world scenarios due to movement and electrode positioning [10]. An example of this numerical model is shown in Fig. 1.

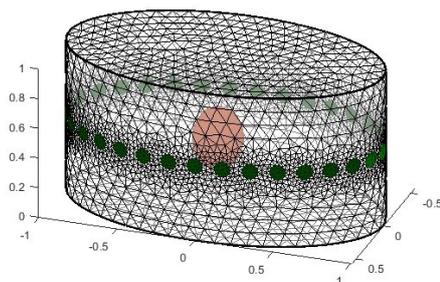


Fig. 1. Image of the simulation model, shown with a bladder volume of 240 ml (green circles indicate electrodes, and red ellipsoid is the bladder).

The phantom measurements are collected using a Swisstom Pioneer Set with 32 electrodes in a 44-cm belt. The electrodes are placed on the outside walls of a pelvic model fabricated from a polyurethane mixture [10]. The bladder is modelled by various sized ellipsoids with a conductivity of 1.68 S/m. Data is collected at 50 kHz with bladder volumes between 40 – 420 ml. An image of the experimental setup is shown in Fig. 2, and more details of the experimental setup can be found in [10].

### B. Data Preparation

For both the simulation and experimental data sets, the measurements from the injection electrodes were removed, resulting in 928 measurements per frame. These 928 measurements represent the 928 features used per observation for the classifier. The data sets were then sorted into three classes; NF, with bladder volumes less than 250 ml, F, with bladder volumes greater than 300 ml, with the B class consisting of measurements from when the bladder volume is between 250 and 300 ml. The simulation data set consists of 1400 observations; 600 in the NF class, 600 in the F class, and 200 in the B class. The experimental data set consists of over 10000 observations, a subset of these 10000 observations were taken to get a data set that matched the simulation data set size exactly (600 in both NF and F classes, and 200 in the B class).

### C. Classification Algorithm Implementation

This work presents the first implementation of a one-vs-one multiclass SVM classifier, with a radial basis function kernel for EIT data. The classifier is trained and then tested with both the simulation and the experimental data. The performance of the classifier is optimized by using a Bayesian optimization procedure during 10-fold cross validation to determine the SVM box constraint and kernel scaling factor that lead to the lowest generalized error across the ten runs. The training data set consists of 90% of the data, with the other 10% held out for testing. The final classifier is trained with the optimized SVM model parameters and then tested on the (previously unseen) 10% testing data set. This procedure of training and testing is repeated 10 times (with each run using a different training and testing set) to obtain a generalizable classification error.

## III. RESULTS

For the simulation data set with a SNR of 40dB and the experimental data sets, there was perfect classification across all test runs. For the simulation data set with 20 dB SNR, a confusion matrix is shown in Table 1, showing the mean, and the standard deviation, across the 10 test runs. The table reports the percentage of correctly classified observations (highlighted in green) and the rate of misclassification and to which class the misclassification occurred (shown in yellow and pink).



Fig. 2. Image of the pelvic phantom, showing the electrode belt. The bladder is held in the pelvic region by the wooden stick.

TABLE I. AVERAGED RESULTS OVER 10 TEST RUNS FOR 20 DB SIMULATION DATA. THE CONFUSION MATRIX WITH PERCENTAGE OF CASES CLASSIFIED IN EACH CLASS; STANDARD DEVIATION SHOWN IN PARENTHESIS.

	NF	B	F
NF	90.93 (3.18)	6.62 (2.66)	2.45 (2.43)
B	19.26 (9.53)	59.55 (11.22)	21.19 (11.89)
F	3.58 (3.65)	6.18 (2.67)	90.24 (5.43)

## IV. CONCLUSION

We have shown that a multiclass SVM can be used to successfully classify EI measurements into three bladder volume states. By performing a Bayesian Optimization procedure to optimize a radial basis function multiclass SVM, it is possible to obtain perfect classification results with experimental data and simulation data with a SNR of 40 dB, demonstrating that this may be a useful signal processing step for a final device for bladder volume monitoring.

## ACKNOWLEDGMENT

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