Real-Time Classification of Bladder Events for Effective Diagnosis and Treatment of Urinary Incontinence

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***Abstract*—Diagnosis of lower urinary tract dysfunction with urodynamics has historically relied on data acquired from multiple sensors using nonphysiologically fast cystometric filling. In addition, state-of-the-art neuromodulation approaches to restore bladder function could benefit from a bladder sensor for closed-loop control, but a practical sensor and automated data analysis are not available. We have developed an algorithm for real-time bladder event detection based on a single *in situ* sensor, making it attractive for both extended ambulatory bladder monitoring and closed-loop control of stimulation systems for diagnosis and treatment of bladder overactivity. Using bladder pressure data acquired from 14 human subjects with neurogenic bladder, we developed Context Aware Thresholding, a novel, parameterized, user-tunable algorithmic framework capable of real-time classification of bladder events, such as detrusor contractions, from single-sensor bladder pressure data. We compare six event detection algorithms with both single-sensor and two-sensor systems using a metric termed Conditional Stimulation Score, which ranks algorithms based on projected stimulation efficacy and efficiency. We demonstrate that adaptive methods are more robust against day-to-day variations than static thresholding, improving sensitivity and specificity without parameter modifications. Relative to other methods, Context Aware Thresholding (CAT) is fast, robust, highly accurate, noise-tolerant, and amenable to energy-efficient hardware implementation, which is important for mapping to an implant device.**

***Index Terms*—Event Detection Algorithms, Urinary Dysfunction, Overactive Bladder, Spinal Cord Injury, Closed-loop Control, Incontinence**

I. Introduction

Urinary incontinence is a condition affecting 200 million people worldwide [1] and significantly reduces quality of life. Diagnosis of urinary incontinence can range from simple clinical evaluation based on history and a physical exam to more complex tests, such as a clinical urodynamics examination, to determine if the patient has stress urinary incontinence (SUI) or urgency urinary incontinence due to overactive bladder (OAB) or neurogenic detrusor overactivity [2]. During a clinical urodynamics test, the bladder is filled with saline at nonphysiologically high infusion rates for one or two cystometric fills. Two separate pressure sensors, one measuring vesical pressure via an intraurethral catheter, and the other measuring abdominal pressure via a rectal balloon catheter, are used to determine bladder activity. True detrusor pressure is calculated as the difference between the abdominal pressure and the vesical pressure, $P_{detrusor} = P_{vesical} - P_{abdominal}$. The detrusor pressure is then used to distinguish between bladder contraction events and abdominal-induced artifacts caused by coughs, laughs, or changes in posture [3]. The nonphysiologically high infusion rates allow for reasonably short examination times, but may irritate the bladder and confound pressure data, and the small number of cystometric fills provides little data for diagnosis. Extended ambulatory urodynamics testing can provide more data collected at physiologically normal fill rates [4], [5]. However, this two-sensor system provides an inconvenient and uncomfortable solution for extended ambulatory urodynamics testing. An alternative method of measuring bladder activity over extended durations at natural fill rates would improve diagnosis.

For treatment of urinary dysfunctions, electrical stimulation has been shown to effectively inhibit unwanted bladder contractions in both spinal cord injury patients [6]–[9] and neurally intact patients [10]. The Interstim (Medtronic, Minneapolis, MN) is an implantable open-loop, continuous-stimulation neuromodulator that is currently FDA approved for use in humans to control sensations of urgency [11]. A similar approach using stimulation has been shown to be effective for individuals with neurogenic detrusor overactivity [12]. Open-loop stimulation of the genital nerve is not ideal because the neural pathways could become habituated to continuous stimulation of sensory nerves, potentially reducing the effectiveness of stimulation over time. Stimulation settings may need to be adjusted over time, typically by the clinician. In addition, individuals with neurogenic detrusor overactivity require feedback of bladder activity in the absence of sensation to determine when to empty their bladders, and those with sensation may not wish for stimulation to be continuously active for reasons of comfort. Closed-loop or conditional genital nerve stimulation has been shown to be as effective as open-loop stimulation for increasing bladder capacity [12], [13] while reducing power consumption and stimulation time

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[14], potentially reducing the cost of this treatment modality over time. However, such approaches require feedback to determine bladder activity for closed-loop control.

Both diagnosis and stimulation to improve urinary continence can greatly benefit from a system capable of categorizing bladder events in real time from a single pressure sensor. Generally, these events can be categorized into three types: bladder contraction resulting in voluntary voiding; bladder contraction without voluntary voiding; and abdominal artifact (Figure 1). Two approaches have been tested for chronic bladder monitoring. One approach measures bladder activity by decoding neural signals from the peripheral nerves of the lower urinary tract, and has been used to estimate bladder volume or predict contractions [15]–[17]. However, the viability of this approach to determine bladder activity from nerve recordings is limited by the accuracy and stability of the decoding model and the mechanical stability of the neural interface. A second approach involves implantable sensors, which are capable of directly measuring bladder pressure [18]–[24]. This approach removes the need for an external, catheter-based sensor and does not have the drawbacks of a neural recording approach. It remains to be shown if a single sensor is sufficient to identify bladder events or if a second abdominal sensor is required to distinguish these from abdominal and motion artifacts.

Previous work in event-driven or conditional stimulation has demonstrated the feasibility of detecting the onset of urinary bladder contractions from sensors implanted in the bladder wall using static thresholds [25], hereafter referred to as Static Detrusor Thresholding (SDT, Equation 1), or a hybrid of static and adaptive thresholds [22], referred to as Hybrid Detrusor Thresholding (HDT, Equation 2), summarized here:

$$SDT = \begin{cases} P_{det}(t) \geq T, & \textit{Stimulation On} \\ P_{det}(t) < T, & \textit{Stimulation Off} \end{cases} \tag{1}$$

$$HDT = \begin{cases} avg(30) + T \geq P_{det}(t), & \textit{Stimulation On} \\ avg(30) + T < P_{det}(t), & \textit{Stimulation Off} \end{cases} \tag{2}$$

If the detrusor pressure, P_{det}, at the current time, t, crosses a fixed threshold, T, then stimulation is turned on under the assumption that a bladder contraction is occurring. The HDT algorithm adds a moving average of the previous 30 seconds, $avg(30)$, to account for drift. Because these algorithms identify a bladder contraction by pressure exceeding a threshold value, they are prone to administer stimulation at inappropriate times, such as when an individual coughs. If these algorithms over-stimulate, then more power is consumed than necessary; the risk of habituation to stimulation is increased; and the user may be uncomfortable with stimulation at inappropriate times. To avoid false positives, a second sensor is required, but frequent resetting of the threshold may still be necessary.

This paper presents a Context Aware Thresholding (CAT) algorithm, which is a novel, tunable, wavelet-based adaptive algorithmic framework for rapid, accurate, and automatic detection of bladder events and rejection of artifacts without using a second, separate sensor. This algorithm has applications

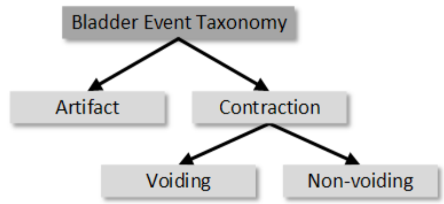

Fig. 1. Taxonomy of bladder events - artifacts, voiding, and non-voiding contractions. Automatic detection of these events can aid in diagnosis and treatment of lower urinary tract dysfunction.

in both real-time and offline processing of single-sensor bladder pressure signals, or as a stimulation trigger in a closed-loop system. The event detection algorithm is amenable to efficient hardware implementation, which is important for mapping it inside an implant unit. We have developed an automated method for tuning our system to an individual patient using a set of operational parameters, thus maximizing the efficacy and efficiency through the use of a novel conditional stimulation scoring function. This system was validated using a set of prerecorded data from human subjects with neurogenic bladder in an emulated real-time environment.

II. Methods

The primary objective of our algorithm was to detect and identify bladder events, including contractions and stress events, without requiring a second sensor. The system requirements included amenability to efficient hardware implementation and the ability to maintain a high level of accuracy despite artifacts and other sources of physiological or sensor noise [26], and take into account the potential variation in the patient population, changes in patient physiology over time, or hardware issues, such as loss of sensitivity or sensor drift. The system also needed to be reprogrammable and tunable to an individual.

A. Vesical Pressure Signal Processing

The basic algorithm structure includes three stages: initial filtering, wavelet transform, and adaptive thresholding (Figure 2). The signal is initially filtered using an exponential moving average (EMA) [27], with a low pass cutoff frequency of 0.01 Hz. EMA filtering is chosen because it allows the system to operate in an almost predictive manner by assuming that repeated spikes in pressure can potentially result in a true bladder contraction. For a hardware implementation, the computation is inexpensive, requiring very few operations and a single unit of delay, enabling real-time operation. Furthermore, by filtering close to DC, changes in pressure are effectively limited to those caused by passive stretching of the bladder. Contractions, which occur at higher frequencies, are sustained, and while slightly attenuated, remain present in the output. The output of the EMA is then processed by applying a multilevel discrete wavelet transform. We chose the Daubechies 4 wavelet as the basis function for use in the algorithm. This wavelet was chosen for its performance at extracting frequencies of interest for this application and its ease of implementation. Furthermore, the wavelets are constructed to minimize the number of filter coefficients required to approximate a given signal [28], reducing the computational burden on hardware implementation.

In clinical urodynamics, the effects of artifacts are negligible as patient motion and activity level are controlled, and a global threshold can work well for detecting bladder contractions. However, for ambulatory urodynamics without an abdominal reference sensor, a fixed threshold is vulnerable to patient movement and sensor drift. Thus, an adaptive threshold, which considers local trends in the data, may be more robust in a real-world, ambulatory setting. We investigated two statistical methods of adaptive thresholding, which consider either the mean and standard deviation or the quantiles within a given window size.

Using standard-deviation-based thresholding, the algorithm labels a contraction when the approximation of the vesical pressure rises two standard deviations above the window mean. Similarly, artifacts are considered to occur when the detail coefficients, or outputs from the high pass filters, rise by the same amount. At this stage the original signal is heavily processed. Therefore, any residual artifacts will cause spikes in the detail coefficients, enabling detection. Since the bladder pressure approximation does not change significantly between subsequent windows, the mean need not be recomputed for each sample, providing a trade off between power savings and accuracy in hardware implementation.

Using the quantile-based adaptive thresholding, the values in the window are sorted by rank order. Samples in either the approximation or detail coefficients exceeding a threshold percentile are considered bladder events or artifacts, where the threshold percentile may be adjusted by the physician. Since the list remains partially sorted, new samples can be rapidly inserted into the list. Furthermore, separate significance threshold values for approximation and detail coefficients allow algorithm tuning based on the desired detection and false positive rates.

B. Algorithm Optimization and Output

The ability to optimize algorithm performance for a specific user is crucial to the successful implementation of the framework. To enable user-specific optimization, we introduced a set of tunable input parameters into the system. To provide this level of flexibility, the tunable parameters included (1) sample buffer length, (2) approximation coefficient sensitivity, and (3) detail coefficient sensitivity. The sample buffer length refers to the time in seconds of history to retain, while the approximation and detail coefficient sensitivity refer to the percentile required for a new input value to be classified as the start of a contraction or artifact, for approximation and detail coefficients, respectively. A high value for the sample buffer length could result in a prohibitively large history buffer. At each level of the discrete wavelet transform, however, the data rate is halved, so it is possible to store a longer history with fewer samples while retaining the general trend of the signal. Furthermore, in a hardware implementation, this reduces the area overhead, delay, and power consumption for computing the local threshold. The second and third parameters affect the probability that the algorithm will attribute pressure increases to actual bladder contractions or artifacts, and they can be individually adjusted to achieve the desired performance.

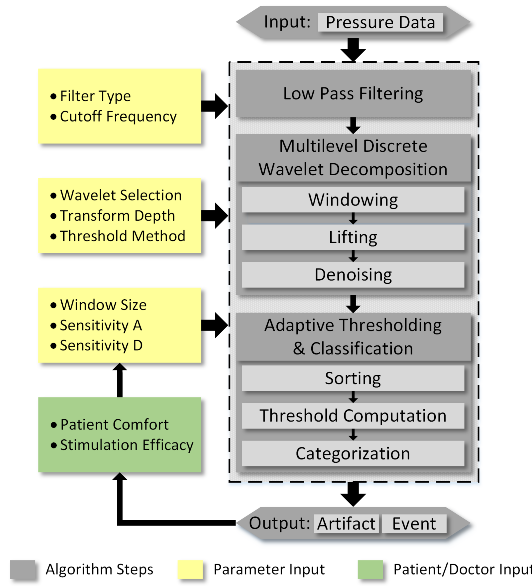

Fig. 2. The algorithm flow, with feedback. Low pass filtering, wavelet transform, and adaptive thresholding are used to categorize contraction events and artifacts. Patient comfort and stimulation efficacy are not evaluated by the algorithm, but can be considered when adjusting parameter values.

We defined three quantifiable metrics from the output of the algorithm: (1) the success or failure of event detection (X), effectively the true positive rate; (2) the number of false positives detected per contraction event (Y), and the duty cycle of the stimulator, which measures the time the stimulator is on divided by the total duration of the recording (Z). Together, these metrics aggregate the effectiveness of the algorithm at detecting an unwanted bladder event with sufficiently short delay to prevent the unwanted event with electrical stimulation. We defined a cost function termed the Conditional Stimulation Score (CS Score) that combines these three metrics to tune the algorithm and to compare performance to other algorithms:

$$CS\_Score(x, y, z) = x^2 - \left(\frac{y}{100} + \frac{|z|}{10}\right) \tag{3}$$

$$x = \frac{\textit{Events Detected}}{\textit{Total Events}}, \tag{4}$$

$$y = \frac{\textit{False Positives}}{1 + \textit{Events Detected}} \tag{5}$$

$$z = \frac{DC_{actual} - DC_{ideal}}{DC_{ideal}} \tag{6}$$

$$DC_{actual} = \frac{T_{stim_on}}{T_{total}}, \; DC_{ideal} = \frac{T_{contraction}}{T_{total}}$$

Due to the importance of a high detection rate, the percentage of true positives (x) is squared in order to penalize input parameters resulting in a value below 1, while perfect detection remains unchanged. False positives (y) and duty