Abstract—Quadriplegia and paraplegia are disabilities that result from injuries to the spinal cord and neuromuscular disorders such as cerebral palsy. Patients suffering from quadriplegia have varied levels of impaired motor movements, hence, performing quotidian tasks like controlling home appliances is challenging for quadriplegics. The use of hand and eye gestures to perform these tasks is a plausible remedy, but available solutions often assume considerable limb movement, are not fit for long-term use, and may not be applicable to quadriplegics with varied range of motor impairments. To address this problem, we present the design, implementation, and evaluation of a multi-sensor gesture recognition system that uses comfortable and low power wearable sensors. We have designed an EOG-based headband using textile electrodes and a glove that uses flex sensors and an accelerometer to detect eye and hand gestures. The gestures are used to control appliances remotely in a home setting and we show that they have good accuracy, latency, and energy consumption characteristics.

I. INTRODUCTION

Quadriplegia \(^1\) and paraplegia are forms of paralysis that can result from spinal cord injury, neuromuscular disorders such as cerebral palsy, multiple sclerosis, and strokes \([4], [2]\). In the United States, there are more than 270,000 patients with Spinal Cord Injury (SCI) that suffer from varied motor impairments \([5]\). While some patients suffer from complete limb and mobility impairments, others have limited motor abilities. A quadriplegic faces challenges performing day to day activities, and in many cases has to depend on external help at home or assisted living facilities to perform daily chores — about 86% of the SCI patients are sent to private homes and 6.6% are discharged to assisted living facilities \([5]\). The reliance on nurses, healthcare professionals, and assisted living facilities can impose a substantial economic burden on the patient \([3]\). Statistics show that a person with a disability can spend up to $177K per year on assisted living \([5], [2]\).

Hand and eye gestures have been used in the past for performing daily activities for patients with disabilities. Several sensors such as EOG sensors \([11]\), gaming consoles \([7]\), and cameras \([10]\) are used to track eye movement and hand gestures. These gestures, can consequently be used for controlling home appliances, security systems, and alarms. These systems are, however, limited in several ways in their applicability to quadriplegics. First, several of the sensors for gesture recognition are expensive and not fit for long term usage. For instance, eye tracking systems require IR cameras and EOG sensors use wet electrodes that can cause skin irritation and often lead to noisy data when used in the long term. Secondly, a specific sensor for gesture recognition may not be applicable to a wide range of paralysis patients. For instance, EOG sensors will have poor gesture recognition accuracy for patients suffering from ocular disabilities, while hand and finger gestures would not work for patients with complete limb paralysis (a class A tetraplegic). Moreover, sensors such as cameras and gaming consoles assume considerable limb movement and may not be suitable for patients with motor disabilities. Finally, while sensor systems for gesture recognition exist, end-to-end cyber-physical systems for practical applications such as home automation are scarce.

We present the design, implementation, and evaluation of a multi-sensor gesture-based home automation system extensible to varying degrees of paralysis. Our system uses multiple wearable devices to detect hand and eye gestures with low latency and high accuracy. Specifically, we have designed a headband with textile-based EOG sensors to capture eye movements and a wearable glove with flex sensors and an accelerometer to capture hand gestures. A key novel feature of our system is a set of simple yet robust gesture recognition algorithms that can be implemented in hardware and on computationally weak micro-controller platforms. Analyzing data at the edge sensor devices mitigates privacy concerns with storing medical data at backend servers, and has better latency and energy performance compared to systems that offload data to backend servers for analysis. The gestures from the glove and headband device are fused on a smartphone that controls home appliances such as lamps using a webservice and a custom home automation system. Fusing data from multiple sensors allow gesture recognition for a wide variety of paraplegia patients. For example, eye movement acts as an accurate gesture recognition modality for patients with impaired eye movements.

II. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The overall architecture of our proposed gesture-based home automation system is illustrated in Figure 1. We next describe how the different components of our home automation system architecture meets our design principles.

**Gestures:** Our system supports three types of gestures: (1) eye movement gestures (left and right eye movements); (2) finger flexing gestures (pointing a single finger or a set of fingers from their bend position); and (3) hand rotation gestures (rotating the arm clockwise or anti-clock wise). These set of gestures are used to control a menu-based Android smartphone.
Lamps

Home Automation Application

Data

analysis

system currently supports toggling the state of an appliance—i.e., if the device is on, it can be switched off, and vice versa.

**Wearable sensors:** Our wearable sensors consist of a comfortable wearable glove and headband device with inbuilt sensors to capture gestures.

**Headband:** Implementation of assistive devices that use eye movement use two signals—the vertical EOG to detect up and down eye movements and the horizontal EOG used to detect right and left movements [1]. In our approach for partial paralysis patients, we use the horizontal EOG acquired through a headband and complement the inputs available through the headband using a glove (with flex sensors and an accelerometer). Therefore, the overall system does not compromise on the number of sensor inputs to detect gestures.

Conventional wet EOG electrodes are Ag/AgCl based. These electrodes use a polymer gel to improve skin contact. These electrodes, however, dry out, that makes the EOG biopotential data noisy and can cause skin irritation. To mitigate these problems, we have designed novel conductive textile electrodes (silver coated nylon) in our headband to capture the EOG biopotentials, illustrated in Figure 2 (a). The dry textile electrodes can be built into items of daily use like headbands. Textile electrodes are flexible and have the best skin conforming properties and can improve a user’s comfort level. Through experimentation we have confirmed that our electrodes have similar sensitivity as Ag/AgCl electrodes. We have also designed custom power supply and data acquisition PCBs that provide hardware signal conditioning and power gating and hosts a MSP430 micro-controller and an ultra-low power Bluetooth module.

**Glove:** To capture hand gestures, we have designed a wearable glove with 5 flex sensors one on each finger and a 3D accelerometer (used as a tilt sensor). Figure 2 (b) illustrates our assistive glove device. The flex sensors are resistors fabricated on plastic whose resistance changes with the angle of bend. The angle of bend is sensed by measuring the voltage drop across a 10K Ω resistor in series with the flex sensor in a potential divider configuration. The flex sensor and the accelerometer interfaces with a data collection board that houses the micro-controller and the Bluetooth module. A key difference between the detection of eye movement gestures and finger gestures is that the flex sensor do not need to be sampled at a high rate to detect hand gestures. Moreover, the finger bending gestures can be detected using simple thresholding based signal processing. We leverage this property to design a low power asynchronous gesture recognition and data collection system. The micro-controller and the Bluetooth module are woken up only when the hardware logic detects a valid finger gesture.

Figure 2 (c) illustrates a part of the circuit that interfaces with a single flex sensor. This circuit is replicated five times for each flex sensor. The outputs from the flex sensor is fed into two open drain switches. These switches are built with a 4-bit comparator whose thresholds are set using a digital to analog converter (DAC), programmable from the micro-controller. If the set thresholds are \( V_t \) (low threshold) and \( V_h \) (high threshold), and \( V_f \) is the voltage output of the flex sensor, the first switch evaluates \( V_f > V_t \) and the second switch evaluates \( V_f < V_h \). If the comparison returns true, the switch outputs a ground voltage (logic 0) or else it outputs \( V_{cc} \) (logic 1). The outputs from a single switch is part of a 10-bit interrupt line that is pulled up with a resistor. Each interrupt line ties to an input port of the MSP430 micro-controller. If any one of the 10-bit lines is pulled low (logic 0), the MSP430 is interrupted from a sleep mode and is woken up. The micro-controller can then figure out from the interrupt lines which finger was flexed, and determine the hand gesture. This obviates the need to keep the micro-controller on all the time and poll the flex sensor output using energy intensive analog-to-digital converters. The DAC latches in the voltage thresholds for the switches, and has a very low power sleep mode that can be triggered by an external clock. Hence, the micro-controller does not need to be switched on to maintain the programmed thresholds. Our 3D accelerometer interfaces with the micro-controller using a 4-wire SPI interface. The accelerometer is used to detect hand rotation gestures.

**Signal processing algorithms:** We next describe our eye turn detection and hand gesture recognition algorithm that can be implemented on computationally weak micro-controller devices.

**Eye turn detection algorithm:** EOG data suffers from motion artifacts (head movement), muscle noise, and noise from electromagnetic interference (EMI). Some of these noise artifacts, such as EMI, is filtered by our differential amplifier circuit in hardware, however, raw sensor data needs to be filtered further before thresholds can be used to detect eye turns. Using FFT on the EOG data with and without motion artifacts, we have experimentally determined that the primary band where the signal to noise ratio is maximum—signal is defined as the frequency amplitudes when the eye is moved, and noise is defined as the frequency amplitudes of the motion artifacts like head movement—lies in the 6-15 Hz range. We leverage this insight to design our eye turn detection algorithm. The first step of the algorithm, uses a butterworth filter to filter frequencies below 5 Hz. Step 2 removes the baseline drift of the signal by subtracting the mean value from the signal. Subtracting the mean from the signal helps remove slow baseline drift, which we have found to be common for our EOG signals. The next step smoothen the signal using a windowing-based integration. This assures that transient noise spikes are not confused with eye movements. We then apply two adaptive thresholds, to determine if an eye turn has been
registered. Similar to detecting $R$-peaks in ECG signals [6], the first threshold is calculated as the sum of the fractions of the signal’s local noise and signal peaks. The second threshold corresponds to half of the signal’s maximum value. This maximum value is updated for data received every second if the new maximum value obtained lies within an interval of the previous maximum value. This interval is used to ensure that the thresholds are not updated due to sudden noisy data due to sharp head movement or low amplitude data obtained due to no eye movement for prolonged periods of time. Since both thresholds are applied on the smoothened signal, they assure that only legitimate eye turns pass the threshold. If the signal is above these thresholds, then the algorithm infers that a eye turn has occurred. The direction of the eye turn depends on whether the eye turn is negative or positive. We also calculate a confidence with the detection as the ratio of the power in the 5-15Hz spectrum (signal) and rest of the frequencies (noise).

**Hand gesture recognition algorithms:** The flex sensors are most immune to noise caused by hand tremors or hand movements, however, the flex sensor voltages corresponding to a straight finger and a bend finger have a large separation. Therefore, setting proper thresholds can filter noise due to motion artifacts, which is possible to set using our thresholding circuit. Accelerometer data, however, is susceptible to hand, body, and tremor motion for patients with neuromuscular impairments. We, therefore, first calibrate our algorithm with the accelerometer readings for the neutral position (horizontal fist) and determine the relative change in accelerometer values when the fist is rotated by 90 degrees in either direction. We divide the range of values into bins. When a patient uses the device, the micro-controller samples $n$ accelerometer readings and creates a probability distribution function using the apriori determined bins. If the sum of the probabilities of all the bins above 45° (or less than -45°), $p_{sum}$, is greater than 0.6, the system outputs a hand rotation gesture $^2$

**Sensor fusion:** A paralysis patient may choose to use eye movements, finger gestures, rotation gestures, or a combination of these gestures to control home appliances, using the phone application. If a patient uses only one sensor device, the fusion algorithm controls the user interface on the phone if the confidence of the gesture recognized is greater than 0.5. However, if two sensors are used for the same gesture, the algorithm uses a weighted sum, $(c_h \cdot I_h + c_g \cdot I_g)/2.0$, where $c_h$ and $c_g$ are the confidences associated with the gestures recognized by the headband and the glove, and $I_h$ and $I_g$ are indicator variables that are 1 if a gesture is recognized, and 0 if a gesture is not recognized. If the weighted sum is greater than 0.5 (better than chance), the system assumes that a gesture has been performed. Note that the glove sends an update to the phone only if it detects a gesture, therefore, the absence of a message, indicates that a gesture has not been recognized.

**Home automation system:** We have implemented a home automation system that uses z-wave networked thermostats and energy meters [9]. The energy meters act as switches that can turn appliances on and off. Commands are sent to the meters and thermostats from a centralized dual radio (z-wave and Wi-Fi) Vera2 Gateway [8], through a cloud-based webservice that is invoked by our smartphone application when triggered by the sensors.

## III. System Evaluation

We evaluate our gesture-based home automation system on four male subjects. We set up a small home automation testbed using two lamps and z-wave meters and gestures are used to control these appliances. Our evaluation focuses on system accuracy, latency, and energy consumption.

**System accuracy:** In our first set of experiments, we measure the accuracy of recognizing gestures using the headband, the glove, and a combination of both devices. The subjects wore both devices and were asked to perform gestures at regular intervals. For every subject, close to 100 gestures were recorded. We record the time when the gestures were performed and calculate the percentage of false positives and false negatives incurred by our system. A false positive is registered if the system recognizes a gesture when the subject did not perform one, and a false negative corresponds to missing a gesture. Table I shows the accuracy of recognizing individual gestures and the accuracy of using sensor fusion for our subjects. Using sensor fusion, the system can detect between 86% to 97% of all gestures, with 3% - 14% false positives. The false positives are high in some cases since the subjects were not trained to perform two gestures simultaneously. However, the sensor devices complement each other and fusing data improves the overall accuracy of the system. For example, subject #3 suffers from impaired right

<table>
<thead>
<tr>
<th>Subject</th>
<th>Eye (FP, FN)</th>
<th>Hand (FP, FN)</th>
<th>Fused (FP, FN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>5%, 45%</td>
<td>1%, 3%</td>
<td>3%, 7%</td>
</tr>
<tr>
<td>#2</td>
<td>4%, 13%</td>
<td>8%, 5%</td>
<td>6%, 0%</td>
</tr>
<tr>
<td>#3</td>
<td>16%, 31%</td>
<td>9%, 7%</td>
<td>9%, 12%</td>
</tr>
<tr>
<td>#4</td>
<td>0%, 10%</td>
<td>2%, 0%</td>
<td>14%, 2%</td>
</tr>
</tbody>
</table>

TABLE I

**False positives and false negatives for our system.**

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$^2p_{sum}$ is also used as the confidence associated with the detection.
eye muscle movement, and hence the accuracy for headband gestures is low. The glove gestures are, however, detected with 9% false positives. Subject #1 has very high accuracy when using the glove device. However, the headband incurs 45% false negatives, but the fused accuracy is close to 94% without any false negatives. The high false negatives occur since the dimensions of the headband and the electrode placement need to be tuned to a user. Since head dimensions vary from subject to subject, for all subjects except subject #3 the sensors did not lie at the optimal location to collect EOG data.

**System latency:** Latency is an important usability concern. If the system incurs high latency to control appliances, the patients might eschew it. To evaluate the end-to-end latency, we measure the total time taken to control a lamp using a gesture, and analyze the time for various subtasks in Figure 3. The headband batches data every second and transmits the data to the smartphone, and hence incurs a 1 second latency. The batching helps in minimizing the use of the Bluetooth module. The glove, on the other hand, processes the sensor data on the micro-controller. From Figure 3 we first observe that the end-to-end latency is less than 3 seconds, which is within a user-perceived tolerance. One of the largest latency bottlenecks is the time to invoke the webservice over the 4G connection (1 +/- 0.3 second). This result illustrates the advantage of pushing computation to edge devices.

**Energy consumption:** The wearable sensors and the smartphone are battery powered. For a paralysis patient, low power consumption is an important design goal since it minimizes the number of battery recharges. We profile the power consumption of the sensors using a digital multimeter and on the smartphone using a custom application that tracks residual battery capacity over time. We measured that the hardware circuit consumes only 840 $\mu$Ws of power, while with the Bluetooth module switched on the system consumes 10 $m$W. This is because the micro-controller is in a deep sleep mode until a finger is flexed. Using the ADC to poll the sensors consumes close to 1.9 $m$W of power. The overall energy consumption is a function of the frequency of performing gestures. For example, the glove devices consumes only 990 $\mu$W of power if the frequency of gestures performed is once very minute. This implies that on a 1Ah rechargeable battery, the sensor would last for 42 days on a single charge. The headband device can last for 8 hours on a single charge of a 1Ah battery. The EOG headband has a higher energy consumption due to an always on Bluetooth module and an always-on low efficiency regulator, which we plan to replace in the next version of our design. The smartphone application, on the other hand consumes 2200 $m$W of power, when using the 4G-LTE connection to invoke the backend webservice. The result again illustrates the advantage of pushing the gesture recognition computation to edge devices.

**Micro-benchmarks:** Our software implementation consumes only 2190 bytes of program memory on the headband, and 2295 bytes of program memory on the glove module, which is a small fraction of the program memory available on the device. Moreover, our system, if manufactured in 10K quantities would cost less than $25 a piece for the sensors and less than $2000 for the home automation system hardware. While it cannot completely replace assistive care, it can lead to substantial cost savings.

**IV. Conclusion**

In this paper, we present a multi-sensor gesture recognition system for paralysis patients consisting of a glove device and a headband with textile-based EOG sensors that relays and analyzes data using a smartphone application. The system is used to control home appliances and we demonstrate that the system has good latency, accuracy, and energy consumption performance.

**References**