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Gesture Based Home Automation for the Physically Disabled

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GESTURE BASED HOME AUTOMATION FOR THE PHYSICALLY DISABLED

GESTURE BASED HOME AUTOMATION FOR THE PHYSICALLY DISABLED

A thesis submitted in partial
fulfillment of the requirements for the degree of
Master of Science in Computer Engineering

By

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University of Arkansas
Bachelor of Science in Computer Engineering, 2012

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ABSTRACT

Paralysis and motor-impairments can greatly reduce the autonomy and quality of life of a patient while presenting a major recurring cost in home-healthcare. Augmented with a non-invasive wearable sensor system and home-automation equipment, the patient can regain a level of autonomy at a fraction of the cost of home nurses. A system which utilizes sensor fusion, low-power digital components, and smartphone cellular capabilities can extend the usefulness of such a system to allow greater adaptivity for patients with various needs. This thesis develops such a system as a Bluetooth enabled glove device which communicates with a remote web server to control smart-devices within the home. The power consumption of the system is considered as a major component to allow the system to operate while requiring little maintenance, allowing for greater patient autonomy. The system is evaluated in terms of power consumption and accuracy to prove its viability as a home accessibility tool.

This thesis is approved for recommendation
to the Graduate Council.

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I also thank my wife for her patience and support during this year-long endeavor, helping me to remain sane when various components refused to function no matter what I tried. I would also like to thank my parents who have provided for me and encouraged my continued pursuit of education for these many years.

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1. INTRODUCTION

1.1 Background and Problem

Physical disabilities, such as paraplegia, tetraplegia, and Parkinson's disease, can greatly limit the autonomy of patients with respect to home living[1]. In the United States, more than 270,000 patients suffer with paralysis with some form of spinal cord injury (SCI) which manifests itself in varied motor impairments [2]. Patients with SCI can suffer from any range of limb mobility impairment up to complete loss of movement. Additionally, severe SCI can culminate in the patient suffering from the loss of speech, loss of autonomous breathing, impaired organ function, and complete loss of sensation. Patients dealing with SCI face unique challenges performing day-to-day activities within the home and often require external help or even a transition to an assisted living facility. According to the National Spinal Cord Injury Statistical Center (NSCISC) approximately 86% of patients dealing with SCI are discharged to private homes while another 6.6% are discharged to assisted living facilities [2]. The cost of healthcare for patients dealing with SCI can create a significant economic and social burden on the patient and their families [3]. Patients sent to assisted living facilities can spend nearly \$177,000 per year in healthcare costs alone [4]. Many of the patients sent to private homes cannot live autonomously and require a caretaker (home nurse or family member) to assist the patient with various tasks throughout the home.

Computational gesture recognition is a field which has made significant technological advancement in the past few years. Techniques have been developed which use gesture recognition to assist patients with disabilities using systems including electrooculograph (EOG) sensors [5], gaming peripherals [6], and camera-based eye tracking [7] among other forms of

gesture input. These systems usually suffer from limitations with respect to their applicability to physical disabilities. First, the system may be physically intrusive as is the case with most human computer interaction (HCI) solutions. Second, these systems are generally expensive and require considerable external hardware in order to derive the gestures. Third, the systems generally assume a larger limb mobility range or accuracy than what may be provided by various physical disabilities. Finally, while these systems may exist as standalone gesture recognition sensors, systems which utilize gesture input as an end-to-end cyber-physical application are scarce.

Micro-harvesting from sources such as indoor light can enable a plethora of self-sustainable systems. This includes healthcare systems [5] and indoor home monitoring systems [8]. Self-sustainability is especially important in wearable devices for individuals with cognitive and physical impairments as any needed system maintenance reduces the effectiveness of such a system drastically. A wearable sensor that could operate perpetually from the energy gathered from indoor scavenged light would obviate the need to change batteries, leading to a more viable system [1] [4] [2].

1.2 Objective

This thesis presents the design, implementation, and evaluation of an end-to-end cyber-physical home automation system for physical disabilities. The system, a data glove, utilizes components of gesture recognition solving the issues of cost, intrusiveness, and accuracy while providing a framework for additions to the system. The system is evaluated in terms of its power consumption to assess the effectiveness and viability of a device which operates perpetually from indoor micro-harvested energy.

1.3 Approach

In order to create the system as described, a solution is presented as a hardware/software co-design using components of microcontroller and sensor systems, mobile development, cloud systems, and circuit design. The system was built iteratively, utilizing concepts of the minimum viable product followed by improvements and refinements to create an adaptive energy efficient solution to whole home automation for disabilities.

1.4 Organization of this Thesis

Chapter 2 discusses key concepts related to this field including gesture recognition, micro-harvesting, and sensor-systems, as well as presenting a literature review of related works.

Chapter 3 provides the architecture for the entire system at hardware and software levels, as well as the implementation details from device level to algorithmic approaches.

Chapter 4 presents empirical results of the system as functions of power consumption, accuracy, cost, latency, and program memory. The results are discussed with respect to the field in order to determine the impact and significance of the system as developed.

Chapter 5 summarizes the system, the results, the analysis, and concludes with the significance of the system. Future developments and potential additions to the system are presented and discussed.

2. BACKGROUND

2.1 Key Concepts

While this thesis is written so that the casual observer may understand the objective and the overall approach, it is beneficial to full comprehension of the details for the reader to have a working knowledge of the following topics.

2.1.1 Computational Gesture Recognition

Gesture recognition has been a significant branch of HCI dating back to the ‘Sayre’ Glove in 1977 [9]. Various gesture interpretation devices have been considered, including sensor aided glove devices and computer vision techniques. The Microsoft Kinect is a popular recent commercial release of a gesture recognition device, which uses depth sensors as well as high-definition cameras to create full models of the user as an input into games. Various other implementations have attempted to create sign-language interpretation devices as an accessibility tool for those with vocal or aural disabilities [10]. In a broad sense, gesture recognition can be used as another user interface (UI) peripheral (a mouse for example), with varying operational sets depending on the hardware implementation and the software intention.

2.1.2 Micro-Harvesting

Sensor systems are often implemented as very low power devices (microwatt range), and are therefore capable of sustaining themselves for years on a typical battery. Periodically having to replace these sensors, however, would become a constant maintenance issue as the number of sensors continues to expand. Micro-harvesting has been proposed as a solution to this issue by

providing power circuitry designed to draw power from the sensor's surroundings to maintain perpetual operation, and removing the maintenance as a necessary component for sensor systems [11].

2.1.3 Sensor System Development

Sensor systems are a branch of electronics which act as data aggregators for various sensor inputs. Systems are composed of a number of special purpose sensors and some external communication protocol to deliver data to a consumer. The processor of the system is application dependent, ranging from special purpose hardware meant for lowest absolute power point to general purpose microcontrollers and even standard processors over a serial interface. The goal of sensor systems is to model some information space numerically, the results of which are delivered to some data consumer which can use the information for any number of purposes.

2.2 Related Work

This system builds upon previous work in gesture recognition and wearable sensor devices as well as low power system development in order to create an end-to-end cyber-physical home automation system. A combination of renewable energy driven systems and energy-efficient design techniques is used to create an adaptable solution capable of long-term or always-on technology for easier adoption within the focus demographic.

2.2.1 Gesture Recognition

Gesture recognition techniques have long been used in assistive technologies for disabled and human computer interaction systems [6]. More specifically, hand gestures have been used as

a rich source of input patterns for assistive device implementations [12], including devices which utilize pressure sensors and 3D accelerometers [13] [14] [15] [16]. Similar systems are often computationally expensive, requiring advanced machine learning techniques in order to provide an expanded operational set for sign language interpretation or other goals. For this system to be useful in a day to day setting, the following features are paramount – low cost, high accuracy, low power consumption, and unobtrusiveness. This system utilizes gesture recognition, building on a large body of current work by extending its application to an always-on mobile solution to whole home automation.

2.2.2 Wearable Sensors

Wearable sensors are widely used for health diagnostic applications. These include electrodes for EKG, EEG, EMG, and EOG monitoring [17], vests for full body monitoring [8], and sensors in items of day to day use such as hats and under garments [18] [19]. A primary goal of these sensors is to detect body temperature, heart rate, brain waves, as well as pulse rate and blood pressure [20].

Recently, there is an effort to design micro-mote platforms for health diagnostics and wearable sensing [21]. While research efforts exist on gesture recognition, the focus on comfort and multi-sensor gesture recognition for paralysis patients is scarce. Moreover, end-to-end cyber-physical systems for practical applications such as home automation are few. This system fills the gap using comfortable wearable sensors for gesture recognition. The system is used to control home appliances for paralysis patients.

2.2.3 Renewable Energy Driven Systems

Most of the related work in renewable energy driven devices has focused on outdoor solar panel driven systems. Energy harvesting systems have been developed for applications such as tracking [22] [23], environmental sensing [24], and networking [25]. Indoor-light driven motion sensing has been explored as a potential renewable sensing platform [26]. This body of work extends the underlying ideas of renewable energy driven systems to ultra-low power sustainable gesture recognition. The given system can have applications for assisted living facilities to aid patients with various motor impairments.

This research is related to the modeling and profiling of battery-driven systems [23] [27]. Contrary to out-of-band techniques leveraged in many devices, this system uses a simple in-band mechanism of leveraging the analog-to-digital converter as a known load to measure the voltage drop across the batteries, therefore being able to estimate the residual battery capacity.

2.2.4 Energy-Efficient Techniques

Energy management is an important component of computing; especially in mobile, embedded, and consumer driven systems. Energy management typically explores tradeoffs of design parameters with respect to power consumption and performance. Classical approaches include voltage and frequency scaling [28], turning off components [29] [30], and using low-power modes on radios and other peripheral devices [31]. Recently, studies have shown that these techniques do not remove some non-reducible power draws of the system. This has led to a recent body of work on multi-tiered systems using hardware and software techniques for task sharing between platforms in combination with duty cycling of higher tiers [32] [33] [34]. These systems have been focused on medium scale sensors and PC systems.

3. ARCHITECTURE

The goal of this system is to apply the multi-tiered approach to always-on and renewable energy driven devices. An application-specific hardware circuit, general purpose microcontroller, and Bluetooth device is used to create an adaptive system that can perform gesture recognition for home automation.

3.1 High Level Design - Hardware

The overarching system developed is an end-to-end cyper-physical system of multiple wearable sensor inputs designed with data fusion in mind to create an accurate and widely accessible home automation system for the physically disabled. The subsystem developed within is a glove device which utilizes a 3D accelerometer and five flex sensors to model hand gestures. The glove device is paired with an EOG based headband [35] to extend the accessibility to extreme tetraplegia and Smartphone system support to expand the viability of the system beyond the borders of the home. As such, the glove subsystem was developed with modularity in mind and includes gesture confidence intervals to provide a platform for sensor fusion control.

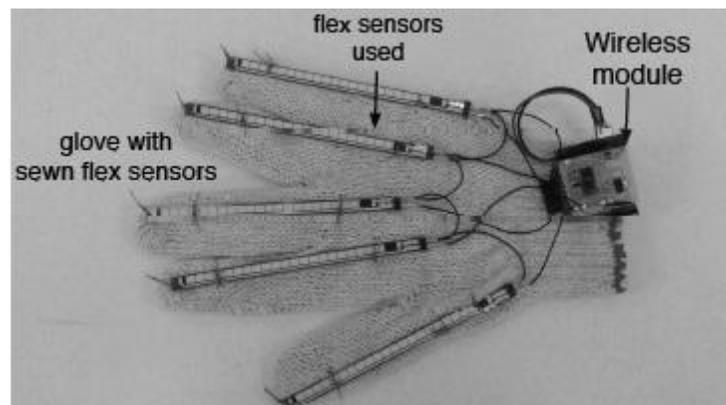


Figure 1: Glove Device

The glove device is composed of a TI MSP430 microcontroller with various sensors as inputs, reporting its results over a Bluetooth transceiver. These results are received by a Smartphone which can act as a UI for controlling various menu systems or as a relay to control specific objects. The Smartphone sends the request via Wi-Fi or its mobile connection to a remote server which parses the request and maps it to an action. The remote server then passes the action to the home server which controls all the smart appliances in the home [36].

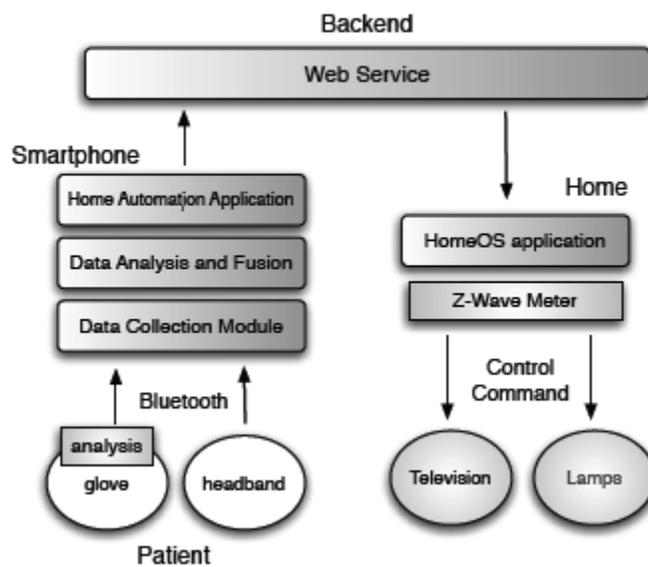


Figure 2: Abstract System Specification

The power-aware glove system was developed as an extension to the original system, utilizing similar hardware with a coprocessor interrupt circuit aimed at allowing the main system to duty cycle during periods of in operation (Figure 3). The hardware wakeup circuit was developed to provide a digital interrupt signal whenever any sensor inputs change significantly. In order for the system to adapt to any light condition, the sensors and even the hardware wakeup circuit is also duty cycled using a timer approach to allow the system to maintain an extremely low power point, capable of storing energy from indirect indoor light

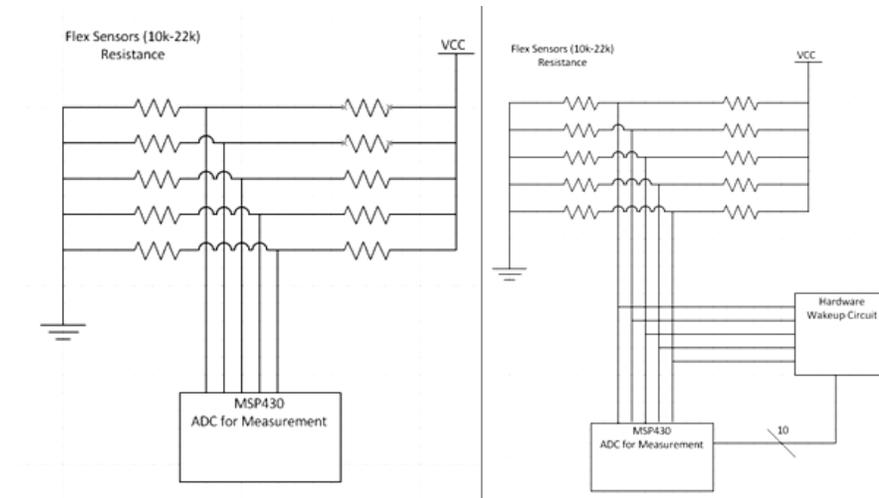


Figure 3: Glove and Flex Circuit (Left) – Glove with Wake-Up Circuit (Right)

3.2 High Level Design - Software

The MSP430's were programmed using Code Composer Studio, a TI variant of the popular Eclipse debugging platform. The code itself is written in C, with TI providing macros and variables to easily access special purpose registers and on board peripherals. The workflow of the two devices is shown in figure 4.

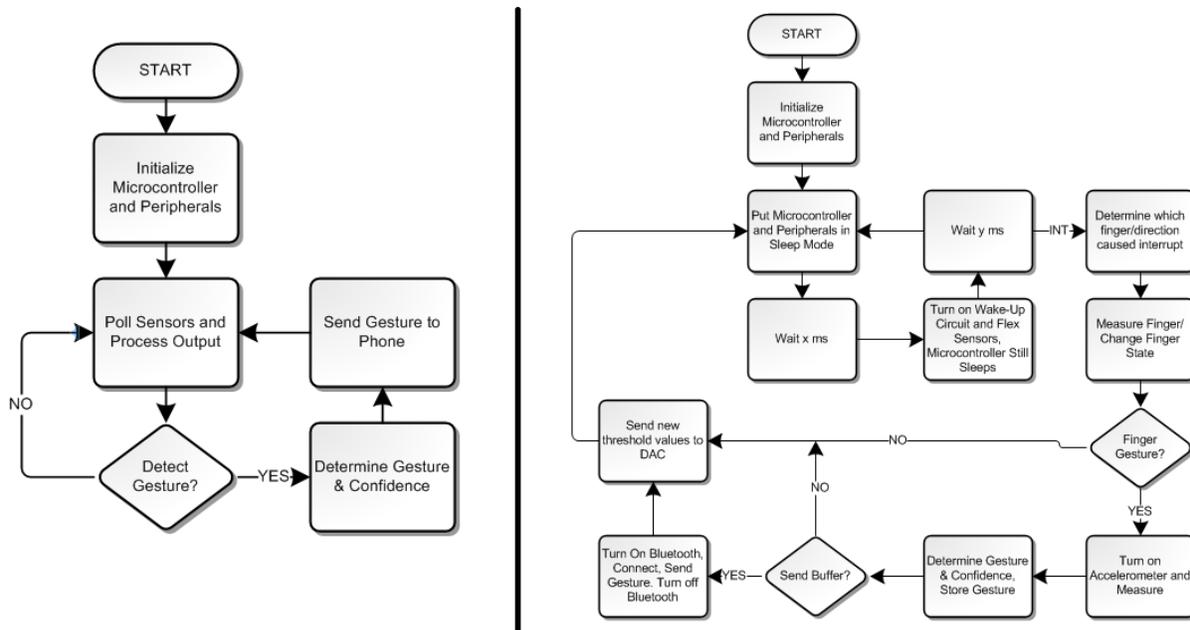


Figure 4: Standard Glove Workflow (Left) – Power Aware Glove Workflow (Right)

The standard glove maintains a straightforward poll and report workflow. The sensor values are all stored on-chip until a gesture is detected based on the algorithms to be discussed in section 3.4. To save processing power, an optional duty cycling stage can be added at the beginning of the polling stage. During this time, any gestures performed will be ignored as each finger is individually measured by the on-board analog-to-digital converter (ADC) and the accelerometer must be polled on a regular basis to determine consecutive rotational positions when looking for a turn, so it is necessary to maintain a short duty cycling period for this system.

The power-aware glove maintains two different duty cycling stages, x and y. During duty cycle stage x, all devices are in sleep modes and any gesture input will be missed. This stage, therefore, should be relatively small and is only included for indirect indoor light scenarios where the power draw of the wake-up system consumes more power than the solar panels can supply. Duty cycle stage y, however, maintains power to the flex sensors, the comparators, and the DAC so that the interrupt signals can be sent if any threshold is broken. If no interrupt signal

is generated, the system will move back into a deep sleep mode and continue with the cycle. If an interrupt signal is generated, the microcontroller wakes into active mode and determines the correct operation to perform. The new threshold values for the DAC must then be set via a serial interface from the microcontroller. The largest power savings from this system comes from the Bluetooth duty cycling. Leaving the Bluetooth module on in idle mode consumes nearly an order of magnitude more than the rest of the system combined. However, in order for the Bluetooth system to power on, establish a connection, send a packet, and go back into sleep mode requires 5 seconds, which eliminated the possibility of a live updating UI. Therefore, gestures can be batched based on user preference to save power on non-time critical tasks. The queuing algorithm is discussed in greater detail in section 3.4.3.

The power aware system utilizes its on-board ADC to measure the voltage drop across the batteries as a method for estimating the residual battery capacity, and therefore being able to make intelligent decisions in wake-up frequency, batching, and duty cycling percentages. This technique allows for system checkpointing if the battery capacity drops below a certain percentage of its operating range. This serves a dual purpose of allowing requests to persist in total system power-loss while protecting the batteries from over-discharge.

3.3 Implementation – Hardware

As shown in figure 1, the original glove device is composed of the following components: a MSP430 microcontroller, five flex sensors, a 3D accelerometer, a Bluetooth module, and a battery. The power aware glove extends this functionality with ten nano-power comparators, a digital to analog converter, solar panels, and a power management circuit. Each is explained in detail here:

3.3.1 MSP430

The microcontroller used for this system is a MSP430F1611. This chip has two on board serial interfaces, an 8-port by 12-bit ADC, and 5 low power-modes. The entire system is run from a 3.3V battery, but is tolerant between 3.7V and 2.7V. The microcontroller itself is a 16-bit device which is capable of running at up to 8MHz, but can be scaled to reduce power consumption.

3.3.2 Flex Sensor Circuit

The flex sensors are 4-inch long devices that act as a variable resistance. The sensors provide 10k ohms resistance when straight, up to nearly 23k ohms when fully flexed. In order to determine the amount that each sensor is flexed, a resistance divider is created by placing a pull-up resistor between one terminal and VCC, with the other terminal going to GND, The contact point for voltage detection is between the pull-down resistor and the flex sensor terminal.

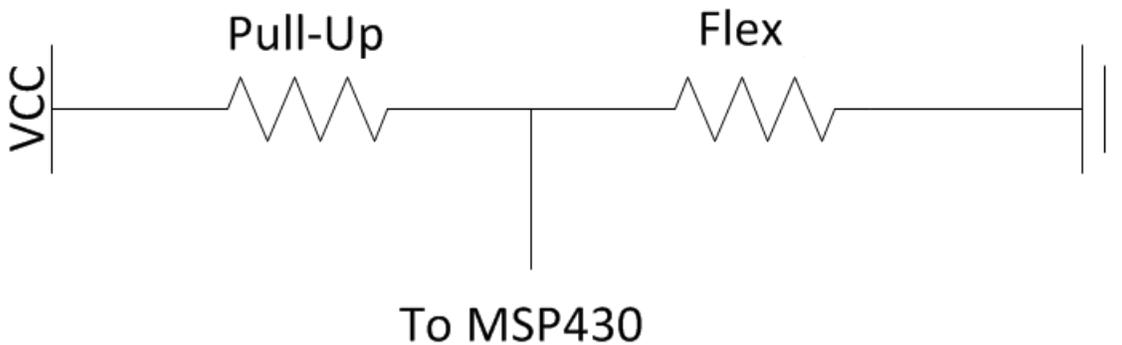


Figure 5: Flex Sensor Circuit

The size of the pull-down resistance is determined by a tradeoff of two factors: power consumption and swing voltage. A larger swing voltage allows for more accurate measurements of the flexion, but consumes more power as can be found from the formulas $P = VI$ and $V = IR$.

Our system uses 200k ohm pull-up resistors, allowing for voltages at the contact point between 0.187V and 0.340V with power consumption between 51.5uW and 48.8uW per sensor. The 12-bit ADC can recognize approximately 250 different positions when using GND and the internal 2.5 reference voltage as the rails.

3.3.3 Accelerometer

The 3-D accelerometer used in the system is the ADXL345. It is capable of 10-bit resolution at +/- 2G. Data values are requested and sent over a 3-wire SPI interface. The angle of the accelerometer can be determined by generating the G-force values for each axis, and performing trigonometric transformations to convert to angle between each axis. For instance, assuming the accelerometer reports a force vector of $\langle 0.268, 0.268, 0.464 \rangle$, then the orientation can be determined as the difference from vertical by $\arctan(x/z)$ and $\arctan(y/z)$. This would show that the x-z angle is 30 degrees rotation positively around the y-axis, and the y-z angle is 30 degrees positively along the x-axis.

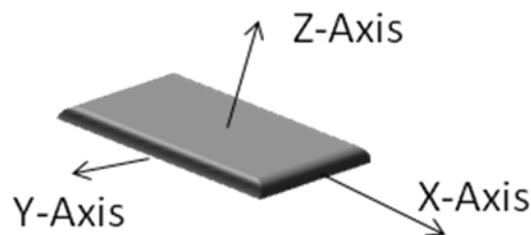


Figure 6: Orientation of ADXL345 axes

3.3.4 Bluetooth Module

The Bluetooth Module is a SPBT3632C2A.AT2, a chip that is capable of a data rate of 1.5Mbps, and can communicate over several different serial protocols. For our purposes, we

have gated the serial clock to 9600 so that the peripheral can be controlled by an external 32.768k Hz oscillator. The module itself exposes an API which makes connecting and communicating with the Bluetooth stack straightforward. While a relatively low power Bluetooth module, consuming 16.7mA current average during transmission, this chip represents the largest power draw of the system by over an order of magnitude. Therefore, maintaining it in idle mode (~4.9mA), sleep mode (~70uA with external oscillator), or turning the chip off is a necessity for any effective power management. The chip will consume approximately 4.9 mA when idle. Reducing the internal clock to 2 MHz drops the active consumption to approximately 9 mA on average.

3.3.5 Battery

The system is powered by a 3.7V Li-ion battery rated at 1700mAh, similar to what is found in many Smartphone devices. The battery is regulated to 3.3 V so that performance is unaffected as the battery is drained or charged.

3.3.6 Hardware Wake-Up Circuit

The Hardware Wake-Up Circuit was designed to take advantage of the large number of pins exposed by the MSP430, the low-power sleep modes, and its efficient wake-up times. Ten nano-power comparators are used along with a low-power Digital-to-Analog converter (Figure 7) to create positive and negative thresholds around each individual flex sensor, which will trigger an interrupt signal to the MSP if broken. The hardware interrupt circuit can be implemented with each of the comparators output tied together as a single interrupt signal (1-wire), each individual finger having its own interrupt signal (5-wire), or each individual

comparator having its own signal (10-wire). The advantage of maintaining more interrupt signals is in the amount of processing required for the MSP to determine the correct operation to perform before going back to duty-cycle mode. There is relatively little power disadvantage as the pull-up resistors between the input and power are rather large (2.1M Ω) and the largest power dissipation is a result of allowing the pins on the microcontroller to be driven externally. The disadvantage of a larger number of interrupt signals is in the space required to route traces to the microcontroller and the number of pins used on the MSP430. A full power comparison of this system can be found in section 4.2

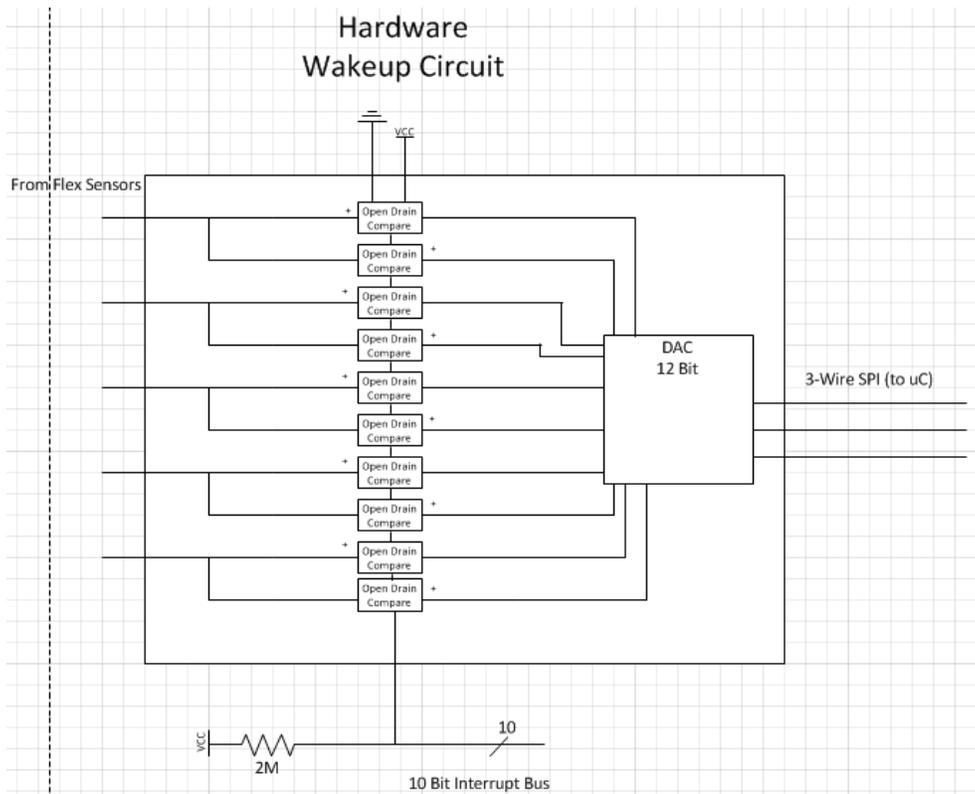


Figure 7: Hardware Wake-Up Circuit

This wake-up circuit can be used in place of the ADC in the standard glove system with some design tradeoffs. These trade-offs are explored in section 4.3.

3.3.7 Solar Panels and Power Management System

The solar cells used in the power-aware system were a combination of mono-crystalline and amorphous silicon solar cells in order to maximize energy harvesting among various light conditions. The power management unit (PMU) is a MAX17710 IC, a special purpose chip meant for low-power harvesting circuits with a selectable output voltage. This combination of circuitry allows for maximum energy harvesting in changing light conditions as might be experienced in a wearable system.

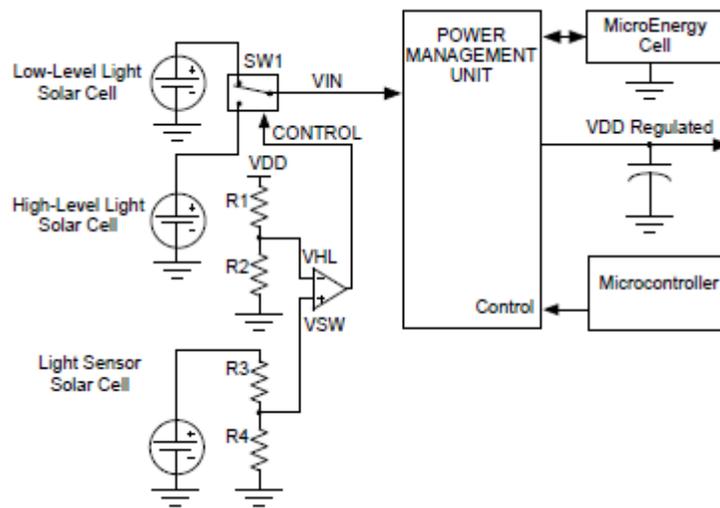


Figure 8: Solar Array and Power Management

The solar cells were profiled for power harvesting capabilities, and those results are reported in section 4.2. The mono-crystalline solar panels were measured to be more efficient in direct light (approximately 23 times in direct incandescent light), where the amorphous silicon panels were more efficient in indirect or ambient light (approximately 4 times in ambient incandescent light). The circuitry switches which panel is being harvested from based on the output of the light sensor.

3.4 Implementation - Algorithms

This section discusses the gesture detection and confidence value determination in each system as shown in Figure 4. The two systems share the same detection algorithm for the accelerometer but use different techniques for sensing finger flexion. While related gesture detection systems use computationally intensive neural-network approaches, this system uses intentionally light detection algorithms capable of running in real time on the microcontroller to prevent having to off-load data to the Smartphone which would generate large power overhead through the Bluetooth module.

3.4.1 Flex Gesture Detection Algorithms

The standard glove uses a poll and report workflow, processing the results from each new value to determine gestures. Values for each finger are determined by using the on-board ADC which reports back a 12-bit integer representation of the voltage across each resistive divider. These values are stored in an integer array of width five, and then used for comparison using a three-point linear differencing algorithm ($d(s_n - s_{n-2})$) in combination with thresholds determined by preprocessing using supervised clustering algorithms on labeled gestures.

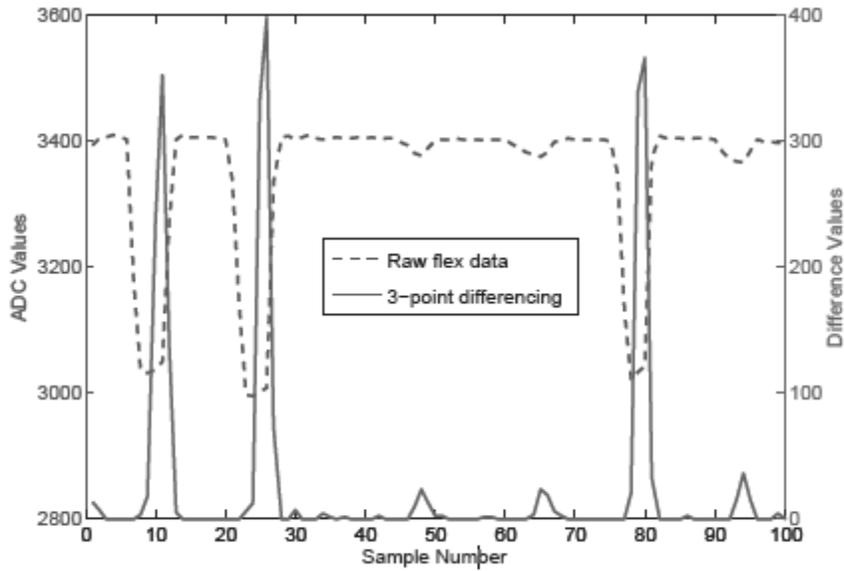


Figure 9: Three-Point Differencing Algorithm

The power-aware glove uses the event driven algorithm, and therefore cannot perform a three-point differencing algorithm as each data point is not updated until an interrupt is triggered. Therefore, the external hardware interrupt is used to determine finger flexion. As shown in figure 10, the Wake-Up circuit will trigger an interrupt on the MSP430 when a threshold changes state. The thresholds (V_{THigh} and V_{TLow}) are adjusted to be centered around the current state of the finger after every interrupt in order to maintain continuity when duty cycling the wake-up circuit.

Once an interrupt is triggered from one of the fingers, the system updates the current state of the fingers, updates the thresholds presented to that finger, and then checks to see if the current state of the system represents a gesture. At this point, an optional post-processing stage can be implemented to increase the confidence of the gesture. This can include querying the state of the accelerometer, requiring a mandatory “hold” time for the gesture, or measuring the exact voltages across the dividers. Each of these options trades off power consumption and delay for confidence in gestures. However, the consequences of a false-positive gesture is at the very least

an unnecessary Bluetooth packet, and could extend up to multiple compensatory Bluetooth packets as the user attempts to correct the state of the system.

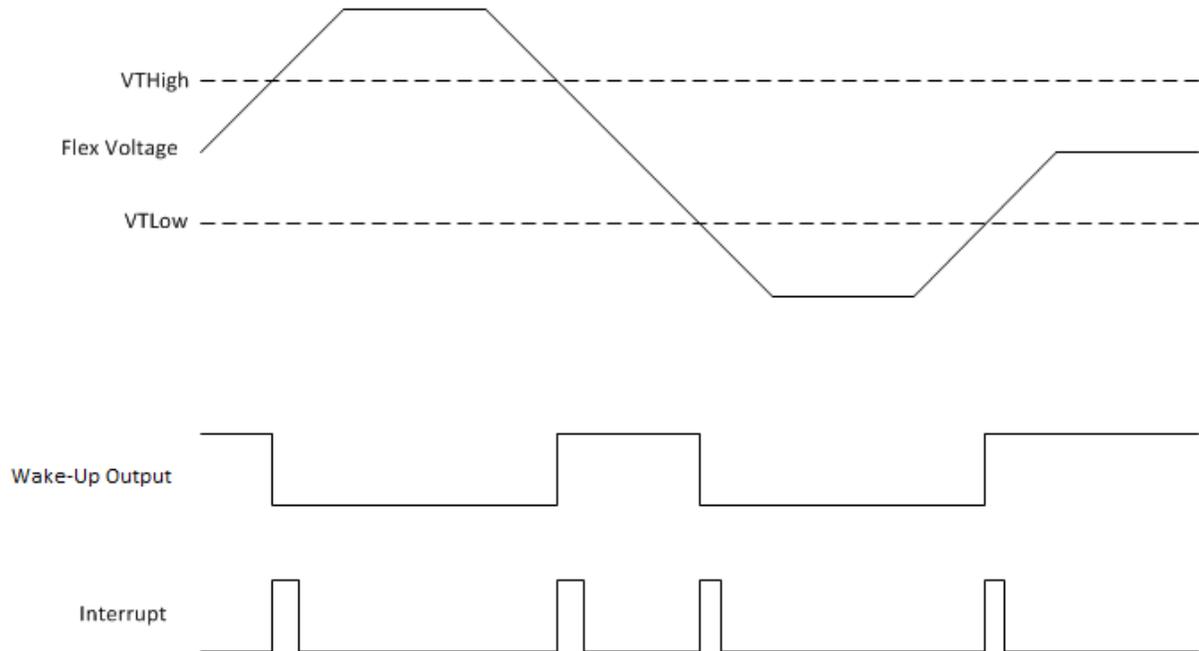


Figure 10: Hardware Wake-Up Interrupt Waveform (5-Wire)

3.4.2 Accelerometer State Detection Algorithm

The accelerometer (ADXL345) represents its orientation as a 10-bit representation of G-Force scaled from -2G to +2G in each x, y, and z directions. Assuming the accelerometer is experiencing very little external force, the sum of the total force experienced should be 1G (gravity pointing in the direction of the ground). The orientation of the accelerometer can be derived from this assumption by calculating the offset from vertical as equal to $\arctan(x/z)$ and $\arctan(y/z)$. Precalculating these values for various angle offsets allows for simple determination

of approximate state (categorized into histogram like “bins”) with very little data processing on chip.

The orientation is determined by an averaging of these predetermined bins over a variable sized window. The confidence in that orientation is related to the variance from that orientation over that window. For instance, if the average orientation is a 60° rotation to the right, with a standard deviation of 10 degrees or less, we can report a high confidence that there was a turn to the right during that window. However, if the average orientation is a 60° rotation to the right with a standard deviation of 45 or more, then the data is noisy and will be reported with a very low confidence interval.

3.4.3 Low-Power Gesture Queuing Algorithm

Given that the power consumption of the Bluetooth module is the largest component by an order of magnitude, it is essential that the Bluetooth module be duty-cycled almost entirely. In order to allow for maximal sleep time, some tasks may be queued and sent as batch operations based on given deadlines. However, some tasks, such as turning on lights, must be performed almost immediately in order for the system to be viable. Therefore, a set of priorities allow for variable send times based on user-preference.

Gestures are placed into a data structure containing the gesture type, associated deadline, and priority. Deadlines are monitored and updated as the microcontroller wakes to change duty-cycling modes. Once a deadline for a gesture is hit, all gestures are batched by priority. The batch operation is sent by turning on the power to the Bluetooth, initiating a connection, sending the batch message, and then immediately shutting off power to the Bluetooth module.

4. RESULTS AND ANALYSIS

The two systems described are evaluated in regards to the following metrics: power consumption, accuracy, system latency, and program size. The gesture set as defined here is a reduced set for sensor fusion with the more limited EOG headband. This set acts as proof of concept and can be expanded to a much larger set to individually control devices if using the glove as a standalone system.

4.1 Methodology

In order to measure power consumption, each of the systems is measured and logged for current using a Fluke or Agilent multimeter, which is multiplied by the voltage of the system to achieve the power. System latency is measured using a DigiView DV-100 digital analyzer for any processes performed on chip. The Code Composer Studio programming tool reports compiled program size at runtime. Accuracy of the systems is measured by having external test subjects perform a predetermined set of gestures, recording both the actions they actually perform and the gestures reported by the system. Inaccuracies are reported both as a false-positive and a false-negative rate over the totality of the tests.

4.2 Results

The results from each of the following sections are reported as empirically determined data from multiple tests across several devices or test subjects. The results are representative of the average of the given metric.

4.2.1 Power Consumption

The micro benchmarks reported for each component of the system are standard for both gloves. The total power consumption of the system, therefore, is measured as average power consumption of each system over a given time as a function of gestures per minute.

Sub-System	Average Power (uW)
Accelerometer (Read Time)	420
Accelerometer (Idle)	0.3
Analog to Digital Converter (On-Board, Measure Mode)	1250
Bluetooth Module (Transmit)	29,700
Bluetooth Module (Idle)	16,170
Flex Sensors	225
Microcontroller (Active)	600
Microcontroller (Sleep)	13.2
Wake-Up Circuit (Active)	1200
Wake-Up Circuit (Sleep)	55

Table 1: Power Micro-Benchmarks

The standard system has no power harvesting capabilities, and therefore its power consumption is solely a function of the usage of the various components listed above. With no duty cycling, the Bluetooth module in idle mode, sampling the flex sensors at a constant 15 Hz, and sending no gestures the system will average a 7.01 mA current draw, which will last approximately 10.1 days with the provided 1700 mAh battery. Figure 11 shows the power consumption of the system in a time series, alternating gestures every 2 seconds. Figure 12

demonstrates the relative power consumption of each device over a 5 minute period performing an average of 10 gestures per minute.

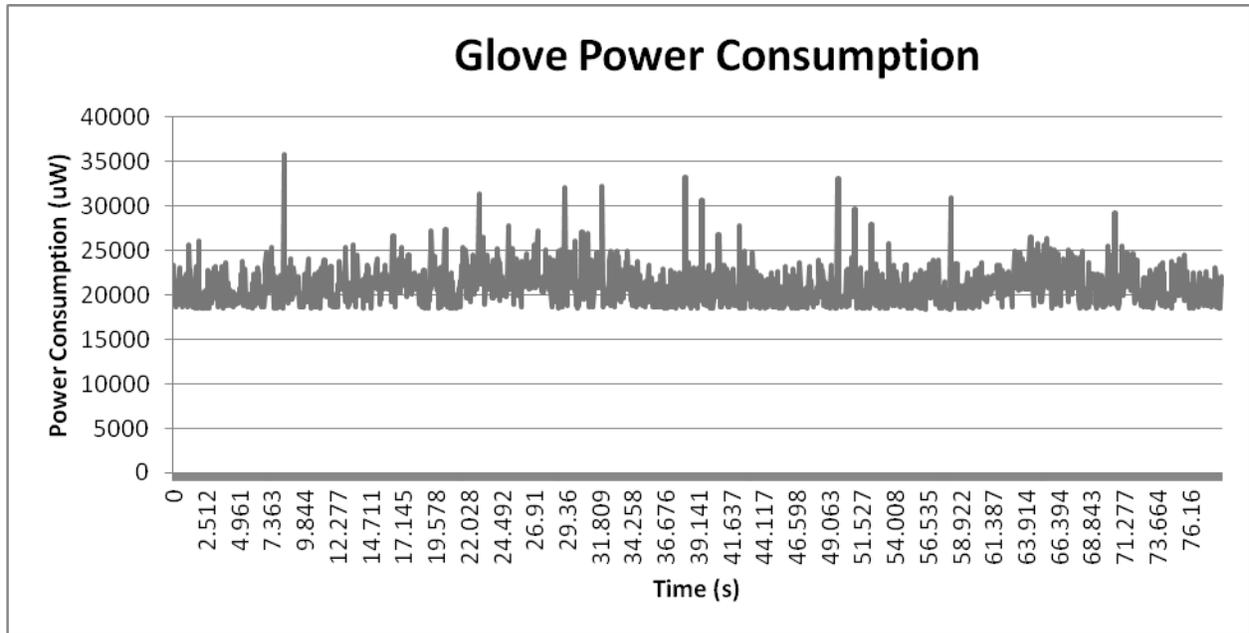


Figure 11: Power Consumption, Standard Glove System

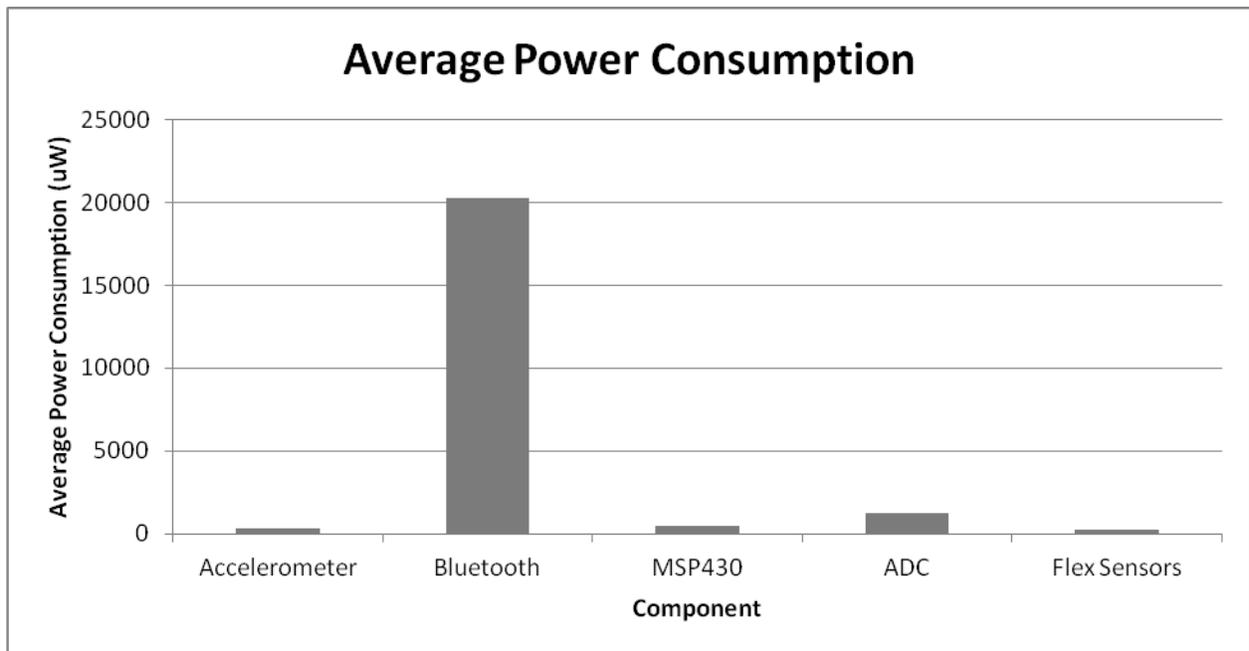


Figure 12: Relative Power Consumption of each Device

The solar panels were profiled for power density in various lighting conditions. These results are reported in figure 13. These results led to the circuitry shown in figure 8 for switching between panels.

Panels	Max Power Density ($\mu\text{W}/\text{cm}^2$)		
	Direct (Incandescent, 14K Lux)	Direct (Fluorescent, 15K Lux)	Ambient (400 lux)
KXOB 22-04X3 (Mono.)	8105	338	3.3
SLMD 600 H10L (Mono.)	7673	411	3.8
Sanyo AM-1417 (Amor.)	348	240	11.9
ECS300 1607 (Amor.)	242	123	4.5
ECS300 2505 (Amor.)	205	74	8.0

Figure 13: Power Density of Solar Panels

Given the solar array used for the glove with these power densities, the chart in Figure 14 demonstrates the total energy harvested in given light conditions.

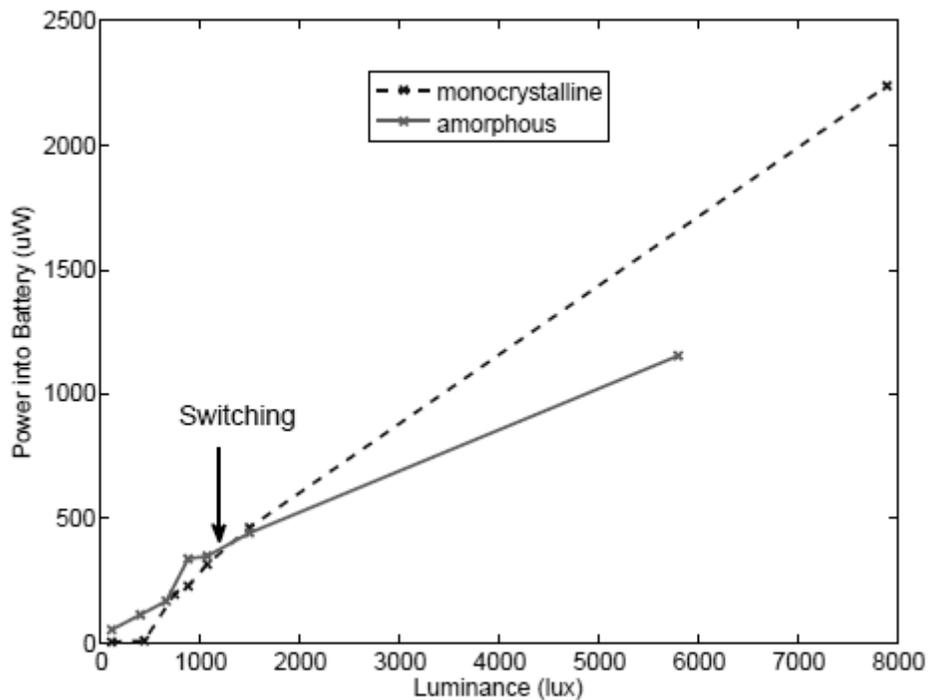


Figure 14: Power Harvested by Solar Array

The system draws directly from energy harvested into the battery by the solar panel. The software implementation seeks to maintain the Bluetooth module in a sleep mode almost

constantly. The rest of the system is duty cycled such that the microcontroller is active for approximately 5 ms in a given cycle (cycle time varies between 100-500 ms depending on system sensitivity). The wake-up circuit is also heavily duty cycled, being turned on long enough for the DAC voltages to stabilize and having the opportunity to trigger an interrupt to the microcontroller before being placed back into sleep mode. The accelerometer is only sampled during an active gesture. This implementation represents an average power draw of between 0.2mA and 0.3mA when batching Bluetooth requests. The median power draw of this implementation is shown in Figure 15.

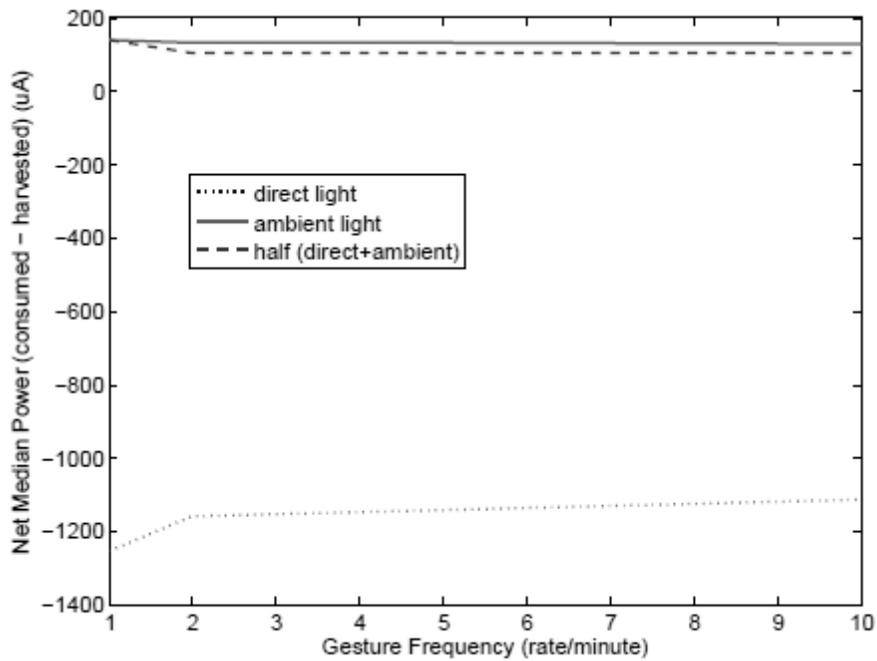


Figure 15: Power Consumption/Harvested, Power-Aware Glove

4.2.2 Accuracy

The following results are reported as system accuracy results for the glove alone, as well as sensor fusion with the headband for the totality of the tests. The accuracy tests were measured using the hardware wake-up circuit for the flex sensors instead of the ADC. The thresholds are similar and should be representative of the polling mechanism given a similar duty cycle rate.

The glove correctly identifies the gesture approximately 92.7% of the time, with a 3.1% false positive (FP) rate and 4.1% false negative (FN) rate. Using sensor fusion with the headband drops the accuracy to 85.5%, with 8.9% FP and 5.5 % FN while opening up accessibility to more users.

These results show that gestures are correctly identified more than 90% of the time, and that 57% of the error results in a missed gesture while 43% of the errors result in an erroneous gesture. Adjusting thresholds by person and slower rotations increases this accuracy to more than 95% for the glove. The sensor fusion accuracy is reduced based on inaccuracy of the headband creating conflicting gestures.

4.2.3 Latency

Latency results are average time to report results as measured by a DigiView digital analyzer. Micro benchmarks are included:

Device/System	Delay (ms)
Accelerometer - 6 samples	200
ADC - All Flex Sensors	27.8
MSP Wake-Up Time	< 0.001
Standard System to Gesture Recognition (w/Rotate)	274 (474)
Gesture Recognition to Phone:	< 1
Power-Aware System to Phone:	Variable (Queuing)
Phone to Device	2400
Phone to Device w/ Sensor Fusion	3700

Table 2: Latency Results

These results show that on average, the phone will receive a gesture request between a quarter and a half of a second after the gesture is performed. There is another two and a half second delay between the phone and the device response over a 3G network. This timing is likely reduced on a WiFi network depending on the given user's connection. This response time is within the tolerance range of the average user, but could be reduced with local caching for in-home use.

4.2.4 Program Memory

The standard system consumes 7,736 bytes of program memory while the power-aware system consumes 10,345 bytes.

4.3 Analysis

The results for the standard system present a viable device capable of lasting approximately 10.1 days without any usage on a standard 1700mAh Li-Ion battery. Infrequent usage (less than five gestures per hour) does not greatly impact the power consumption of the system. The system operation time is lower bounded by every device in constant operation, a cost of nearly 16.2 mA constant draw, resulting in operation time of approximately 4.4 days. For total patient autonomy, the power aware system needs to be harvesting slightly more power into the battery than it consumes. This cannot be done with the current system for anything besides direct light. However, the Bluetooth Low Energy Stack (BLE) released earlier this year will greatly reduce the time that the Bluetooth module must be active [37]. This innovation combined with more efficient solar panels, a more efficient charging circuit, and a higher duty cycling ratio creates a system capable of perpetual operation.

The system shows a high accuracy and low cost and can be considered as a viable option for paralysis patients looking for a non-invasive solution for whole-home automation pending a more thorough study using patients with varying degrees of paralysis or motor impairment. Further, it proves that a platform of renewable energy driven wearable sensor-systems is a potential field for further study and analysis. The system, if manufactured in quantities of greater than 10,000 would cost less than \$25 per standard glove device (power aware system is bounded to the cost and efficiency of solar technology) and less than \$2,000 for the home automation system hardware. The use of this system could lead to substantial cost savings by minimizing dependence on assistive care facilities.

4.3.1 Use of Hardware Wake-Up Circuit in Standard Glove System

The Hardware Wake-Up Circuit can be used in place of the standard glove system given a few tradeoffs. First, the hardware wake up circuit reduces the necessity of maintaining the flex sensor circuit constant power draw. The power consumption of the two measuring capabilities are comparable, with an instantaneous consumption differing only 50uW, and both requiring a set-up time for reference voltages (approximately 18ms for the ADC, approximately 60us for the AD8804 DAC). Polling the ADC will consume slightly more power as the microcontroller must remain in active mode (~600uW) during measurement mode, and the actual module must be on during this additional time as well. The measurements take no more than 180us to process so this overhead does not translate into much power consumption. Therefore, assuming an identical duty cycle time, the two systems should result in comparable power. The overhead comes from maintaining the flex resistors and the internal reference voltage and maintaining the microcontroller during measurement modes. The power consumption of the systems is modeled here:

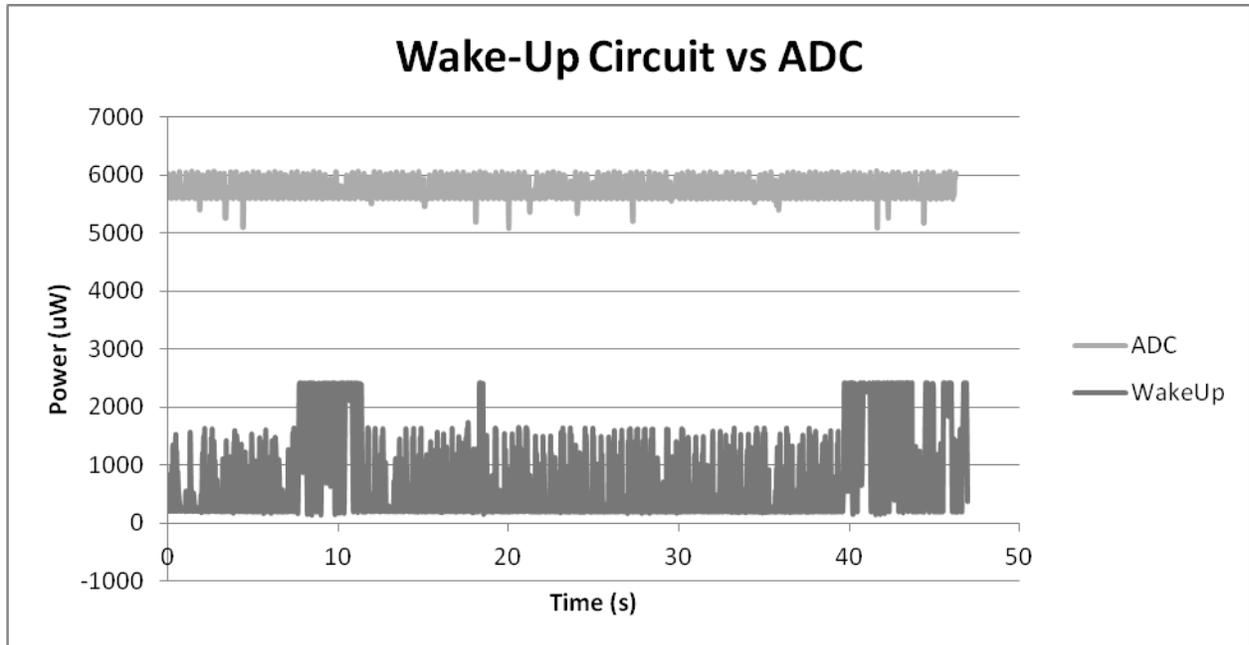


Figure 16: Power Comparison of Wake-Up Circuit and ADC

The hardware wake-up circuit consumes approximately 5mW on average less than the standard flex circuit. The power consumption of the ADC is mainly based on maintaining a constant 2.5V internal reference. This can be mitigated by shutting off the reference voltage between readings, but this produces an 18ms settling time for each measurement. This power consumption reduction comes at the price of a significant increase in chip area, doubling the total surface area of the board. The system complexity is slightly higher as multiple SPI devices must be individually controlled and external references must be managed as they change. The cost of the system does not increase by much given large quantities.

5. CONCLUSIONS

5.1 Summary

Two versions of a wearable computing solution to whole-home automation for paralysis patients were developed. Each system utilizes a combination of flex sensors used as variable resistance to calculate the bending angle of each finger with an accelerometer to create a simplistic model of the human hand. This model is used for low-level gesture recognition capable of live calculation on the microcontroller while maintaining a high duty cycling rate.

The two systems explore tradeoffs in system latency and power consumption. The first system utilizes the on-board ADC and a polling mechanism to monitor the status of the sensors to determine a gesture while maintaining an active Bluetooth connection for live updating of a Smartphone UI. This approach is higher power ($\sim 8\text{mA}$ constant) but much lower latency ($\sim 200\text{ms}$). The second system adds an external hardware wake-up circuit and a solar panel array in order to create a perpetually operating system while maintaining the Bluetooth module and accelerometer in off states unless prompted by gesture input to be utilized. This system is much lower power ($\sim 200\mu\text{A}$ in ambient light, charging the battery at 1.8mA in direct light) but requires a Bluetooth reconnect sequence during communication, greatly increasing the latency (> 4 seconds average from microcontroller to phone) and decreasing the accuracy of the system due to Bluetooth instability.

Each of the systems is described from a high-level, and the implementation of each is described such that a similar solution could be developed by a person with knowledge of the field. The two systems are evaluated as functions of power consumption, accuracy, latency, cost, and program memory, and are shown to be viable solutions.

5.2 Contributions

If productized, the systems as described could be implemented as whole-home automation for paralysis and motor-impaired patients at a fraction of the cost of home healthcare, while providing a patient with a broader range of autonomy that could positively impact the patient's quality of life.

The power-aware system contributes to the field of wearable computing by presenting a system that in its current state is nearly perpetual. A similar branch of wearable sensor systems could be developed to augment users with sensors more computationally expensive than current health monitors.

5.3 Future Work

This thesis provides a basic framework for a gesture set capable of whole-home automation, but does not explore extending this gesture set beyond a minimalist structure. The system is capable of creating a gesture set expanding to at least the American Sign Language (ASL) alphabet, with similar solutions modeling 203 words of ASL [38].

A further implementation of the power-aware glove using the Bluetooth Low Energy stack and more efficient components could be putting energy back into the battery on average. Instrumenting similar wearable sensors for perpetual operation could enable a human computing interface augmentation capable of providing a wide-range of data to a user.

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