Error-Resistant RFID-Assisted Wireless Sensor Networks for Cardiac Tele-healthcare¹

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Abstract-Wireless transmission of a patient's electrocardiogram (ECG) signals can be used to reduce cardiac healthcare cost. However, wireless transmissions have high error rates due to radio interference. The ECG signal, where every second of data could mean abnormal patterns, cannot tolerate such losses. Due to this healthcare crisis, the ability for a device to remotely monitor a patient's medication intake and transmit accurate ECG readings, while being cost efficient, is a major innovation. In this research, we integrate a multi-hop wireless sensor network (WSN) with Radio Frequency Identification (RFID) readers. Our system has two distinct features: 1) remotely supervise patient medication intake via RFID technology, and 2) accurately and remotely transmitting a patient's ECG by adopting Extended Kalman Filter (EKF) for wireless error recovery.

Keywords – Medical Sensor networks, ECG, RFID, Extended Kalman Filter (EKF)

1. INTRODUCTION

According to the U.S. Bureau of the Census [1], the number of adults with ages from 65 to 84 is expected to double from 35 million to nearly 70 million by 2025 when the youngest Baby Boomers retire. A recent study found that almost one third of U.S. adults, most of whom held full-time jobs, were serving as informal caregivers – mostly to an elderly parent [2]. As this burden becomes too great and more elderly patients head to nursing homes, it will become very important to build a remote telehealth monitoring system that can continuously, automatically, accurately, and cost effectively monitor medical signals such as a patient's medication intake and ECG signal.

Telehealth monitoring can be defined as "mobile computing, medical sensor, and communications technologies for health-care." This represents the evolution of e-health systems from traditional desktop "telemedicine" platforms to wireless / mobile configurations [3]. While patient monitoring has conventionally been assigned to trained medical care personnel, putting some responsibility in the hands of the patient could alleviate a considerable amount of the staff's workload. This would free medical professionals from a tedious task and allow them to center their attention on more demanding medical emergencies.

Industry has taken notice of the need for remote medical monitoring and several companies have come out with products to remotely and wirelessly monitor a patient's ECG. Unfortunately, wireless transmissions have an error rate many times that of a traditional wired network. While there's a need to decrease the one-on-one time staff have with each patient, it must done safely. A loss in medical data typical of that seen in wireless transmissions cannot be tolerated - each piece of cardiac data could carry important medical information. For example, a sudden heart failure may produce an abnormal ECG signal that lasts for only a few seconds. The transmission error of such a segment of ECG data is disastrous to the capture of, and response to, sudden heart failure events.

Based on these motivations, remote medication and accurate ECG monitoring, there have been a number of attempts to develop medical systems similar to the proposed work in this research, but they have fallen short. While these systems monitor dispensing medication to patients using RFID, they do not oversee the actual application of the drugs by the patient. In addition, such systems employ an expensive communication infrastructure. For nursing homes that are regional areas, expensive cellular networks and wireless LANs should be avoided. Instead, a low-cost, short-distance telehealthcare system is preferred. Other handheld devices on the open market that use RFID to manage medication are not part of network and do not allow any monitoring by healthcare personnel, putting all the responsibility in the hands of the patient. Finally, in the systems that wirelessly monitor a patient's ECG, transmission errors are likely and cannot be tolerated.

This research designed a wearable medication monitoring platform which hosts an RFID reader and is capable of RF communication. The patient will be able to scan any of their medication bottles containing an RFID tag and wirelessly transmit the attempted drug application to a central workstation. The workstation queries a central database which contains the proper administration for the given medication. If for any reason the patient is improperly taking this drug, they will be alerted by a red LED toggle on their wearable device. Additionally, the healthcare employee manning the workstation will also receive a pop-up message indicating that a patient has attempted to improperly take a drug. It is then at their discretion whether to call the patient to follow-up or to physically check them.

¹ This project has been funded by NSF Cyber Trust 2007 program (CNS-0716455 and CNS- 0716211).

To avoid a high cost network while still attaining long range distance from the central workstation, the network employees multi-hop communication, using each patient's wearable sensor as a hop. By using patients as hops rather than statically placed sensors, the same affect can be achieved while making more efficient use of resources. Finally, in showcase the possibility of achieving more reliable ECG transmissions, the extended Kalman filter (EKF) is applied to real ECG signals (with simulated data losses) from a cardiac database. Although there have been many research efforts in both of the fields of medical asset monitoring and remote ECG monitoring, most of them stay theoretical at the best. This research marks an attempt to bridge the two research fields by providing a product that is realizable and would directly benefit the consumers in the medical field.

The rest of this paper is organized in the following way. Section 2 provides some background information on the topics of RFID, the Kalman filter, as well as others works supporting this work. Sections 3, 4, and 5 offer more insights regarding the implementation of the wearable platform with multi-hop communication, and using the extended Kalman filter to recover wireless ECG transmission losses. We conclude this paper in Section 6.

2. BACKGROUND

In this section, we briefly provide some foundational information on the subjects of RFID and its use in telehealthcare, the Kalman filter, wireless sensor networks, and the supporting work environment.

2.1 RFID

RFID is a method of storing and retrieving data, similar to the theory of the barcode. With RFID, the electromagnetic or electrostatic coupling in the RF portion of the electromagnetic spectrum is used to transmit signals. An RFID system consists of a reader and any number of tags. The reader contains an antenna and a transceiver, which both work to read the radio frequency and transfer the information to a processing device. The tag, or transponder, is an integrated circuit containing the RF circuitry and information to be transmitted. There are generally two types of tags, passive and active.

RFID has been used to replace Universal Product Code (UPC) in supply chain / object mobility monitoring applications in many organizations such as Wal-mart and the Depart of Defense [5]. Industry and telehealthcare corporations have seen the success and usefulness of RFID and are now beginning to incorporate it into healthcare scenarios to alleviate errors and to cut down costs. For examples, a Location-based Medicare Service (LBMS) was implemented in Taipei Medical University Hospital which used RFID tags to locate both patients and hospital assets with successful results [5]. Exavera's eSheperd uses RFID over a Wi-Fi network to track patients, staff, and supplies, including medication dispensed to patients by the staff [6].

En-Vision America has created a new way to provide prescription information to the user using RFID with ScripTalk [6]. When a patient using a ScripTalk reader submits a prescription, the pharmacy software prints and programs an auxiliary smart label using a dedicated, small-footprint printer. The smart label, which stores prescription information, is placed onto the prescription container by the pharmacist. In the home, the patient uses a hand-held ScripTalk Reader that speaks out the label information using speech synthesis technology.

Unfortunately, the first of these systems puts the actual medication intake into the hands of the patient; they all rely on staff dispensing. Additionally they require wireless LAN access points and an expensive infrastructure. While the last system mentioned does put medication administration into the hands of the patient, it is not part of a network and therefore cannot be supervised by staff.

The RFID based medication monitoring system proposed in this work does not require an expensive infrastructure. Instead it uses an ad-hoc network consisting of wireless sensors which host RFID readers. These sensors are worn by all patients and are used to scan their medication bottles containing RFID tags. The tag read is transmitted to a central work station which contains a central database. By referencing the database, it is determined if the medication should be taken or not. If the medication should not be taken, for any reason, the patient will be alerted with a red LED toggle on their sensor. Additionally a popup will appear on the central workstation citing the patient, the time of the incorrect application, and what the medication was. The sensors will utilize multi-hop communication so that they can communicate with the workstation even when out of transmission range. Staff members no longer need to make rounds to supervise patients taking their medication, it can be done remotely.

2.2 Error-resistant ECG Transmission

For our purposes, the wearable devices are assumed to be equipped with ECG sensors. It is also assumed that ECG interpretation software will be running on the central workstation where all data (medication intake and ECG signals) are being sent. Such a system is referred to as a Cardiac Sensor Network (CSN). Radio-based wireless networks are suitable to patients' mobility behavior. However, the wireless error rate is around $2\% \sim 10\%$ [8]. This is much higher than traditional wired networks, such as cable-based medical networks, which only have 10^{-9} error rate.

As mentioned earlier, many medical data errors cannot be tolerated because each piece of cardiac data could carry important medical information. There are several factors which can cause ECG data errors or even data

loss. They are hardware noise, wireless signal energy loss during propagation, and radio refection / diffraction / scattering. Hardware noise can occur with the ECG sensors due to the circuit interference among surface-mount parts and the limited amplifier capability. In a small ECG sensor, a tiny amplifier is used, making it difficult to enlarge signals to a satisfying level. Wireless signal energy loss during propagation can be attributed to the well-known fact that the received wireless signal strength decreases when distance from the sender increases. This can be seen from the following equation [8]:

$$P_{received} \propto 1/d^2$$

A radio wave could change its direction when hitting objects. Radio reflection / scattering can damage the wireless signals. An erroneous packet will be discarded by any receiver, which causes packet loss.

Fig. 1 shows one section of our collected ECG data series. It clearly shows the data missing (at 0.05-0.07 s) and possible data errors (at 0.09 - 0.11 s). Even though the ECG values are typically different at 0.01 s of time scale, 3 nearly



(1)

duplicate values at 0.09 s - 0.11 s are still seen, which indicates data errors.

Based on this knowledge it is clear an error recovery scheme must be implemented in order to obtain a reliable CSN. For this work the extended Kalman filter is chosen to recover wireless data loss. Before delving into the EKF, it would be sensible to describe its more simplified version, the Kalman filter.

The Kalman filter is named after Rudolph E. Kalman, who in 1960 published his famous paper describing a recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements. The Kalman filter is essentially a set of mathematical equations that implement a predictor-

corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance [9]. The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of noisy measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations [9].

For the Kalman filter, the system is assumed to be linear; if it is non-linear it should be linearized. While an ECG is a non-linear signal and therefore cannot use the standard Kalman filter, it can be linearized and have the extended Kalman filter applied to it. This enables us to predict what the lost pieces of wireless data where and to reconstruct the entire ECG signal. The differences in the standard Kalman filter and the EKF, as well as linearizing an ECG signal to be used with the EKF, will be covered in Section 5.

2.3 Wireless Sensor Networks

Wireless Sensor networks (WSNs) are highly distributed networks of small, lightweight wireless nodes. Each node consists of three subsystems: a sensor subsystem which senses the environment, a processing subsystem which performs local computations, and a communication subsystem. TinyOS is an open source operating system which targets WSNs. It was primarily developed by the University of California, Berkley in cooperation with Intel Research and is written in nesC. It is has a component-based architecture and is able to operate within the severe memory constraints imposed by a sensor network.

3. Integration of RFID and Wearable Sensors

3.1 RFID via Mica2Dot

The RFID reader chosen for this work was SkyeTek's M1-Mini that is advertised as "the world's smallest, selfcontained multi-protocol 13.56 MHz" low power RFID reader [14] and sports a radius of a mere 12.7 mm. The reader requires an input voltage between 3.2 V and 6 V. Its current consumption is 60 mA when scanning a tag and 15 mA when being idle. ReaderWare, an open-architecture software suite residing on all SkyeTek's modules, provides intelligence for the RFID reader. It has an internal antenna which provides it with a read range of approximately 50.8 mm, but this also depends on the tag type. It has the ability to attach a standard 50 Ohm external antenna for improved read-range as well. It is capable of reading and writing to tags based on ISO 15693, ISO 14443A, AND ISO 18000-3 air-interface protocols. The effective read range for varying ISO 15693 tag types using the internal antenna, as done in this work, can be seen in Table 1 [14]. The WSN itself includes a number of node motes, Crossbow's Mica2Dot, which will be equipped with these RFID readers, and one base station mote. The Mica2Dot acts as the host system by sending the M1-Mini commands, as well as receiving and interpreting its response to the given command. The Mica2Dot has a 12.5 mm radius and a 433 MHz multi-channel radio transceiver for wireless communications. It requires an input voltage between 2.7 V and 3.3 V. These overlapping input voltages enable both reader and mote to run off the same power supply.

The M1-Mini was designed to interface directly with Crossbow's Mica2Dot mote. Both the M1-Mini reader and the Mica2Dot mote were run at a baud rate of 9600 bits per second, the default setting for the reader, in order to communicate. The mote was programmed with an individual node ID and continuously checked for a tag in the reader's

read range every 2000 ms via polling. The mote sent the instruction code for the SELECT_TAG command to the reader using SkyeTek's ASCII protocol, rather than the binary protocol. This command read the ID number of the RFID tag in the read range and delivered it to the mote.

Communication is the biggest expenditure of power in a WSN, and this should be minimized at all costs.

ISO 15693 Tag Dimensions	Effective Range for Internal Antenn		
48 mm x 76 mm	5.0 cm		
38 mm x 22.5 mm	3.5 cm		

Therefore, only when a successful response was received from the reader at the mote, indicating a tag ID was read, was the tag ID number sent to the awaiting base station, Crossbow's Mica2 mote. The RFID mote and base station mote had a communication range of approximately 150 m in an enclosed area.

Crossbow's *Mica2* mote serves as the *base station* for this work. The *base station*'s role was to receive and process the RFID tag ID sent by the Mica2Dot mote, as well as the mote's individual software programmed ID. Any Mica2 mote can function as a base station when it is connected to a standard PC interface or gateway board. The MIB510 provides a serial interface for both programming and data communication. Using the RFID tag ID and mote ID, the medical software written for this project was able to determine if that medication intake was appropriate for that patient. If it was an incorrect medication intake for the patient, the base station sends a command back to the original node mote to toggle its red LED.

3.2 Medical Software System

We have developed 2 software applications. The first is called RIT Medi-Write, while the second is called RIT Medi-View. Medi-Write allows a physician to program an RFID tag, while Medi-View alerts the physician and patient when an incorrect medication application was attempted. Both were created using Microsoft Visual C++ 6.0.

3.2.1 RIT Medi-Write

When using this application, the practitioner will use SkyeTek's M1 RFID reader, which follows the same protocol as the M1-Mini, but has native support for RS232 host interface and a supply voltage of 1.8 V to 5.0 V. As stated before, Medi-Write allows a practitioner to fill out all prescription information on an RFID tag, which is destined to be applied on a medication bottle. The tag will contain the patient's name, the name of the prescription, the quantity of medication in the bottle, the dose size, the doses needed per day, and the software programmed node (reader) ID, which would be printed on the unit if this system were to be manufactured.

The practitioner places the RFID tag over the reader, fills in all the fields with the previously mentioned information, and hits the "Write Tag" button. If they would like to check that all information was appropriately entered, all they need do is press the "Read Tag" button and the fields will be filled with the data they previously entered. If it is found that a mistake was made after reading the tag information back, the practitioner can simply correct the appropriate field and rewrite to the tag. The status box above the buttons informs the practitioner whether the read or write has failed or completed successfully.

3.2.2 MySQL Database

tagID	name	тх	QTY	doseSize	doseDay	doseToday	readerID
E005400001132A6C	Mary Woo	Prozac	36	2	2	0	3
E005400001132C43	Linda Doolittle	Zoloft	40	1 2	2	0	4
E005400001133032	Al Barr	Tylenol	40	1 2	2	I 0	2
E005400001132B72	Lou Smith	Aspirin	36	1 2	1 2	I 0	1 1
		+	·	•	+	•	

Fig. 3 Database screenshot

Behind the scenes, when the "Write Tag" button is pressed a new entry will be placed in the database with all the information supplied by the practitioner, plus the RFID tag's ID. The tag ID is stored under the database field name tagID.

There is also a field in the database, doseToday, for how many doses of that medication were taken for the current day. This is set to 0 when a new entry is added. A screenshot of the current database contents can be seen in Figure 3.

The correlation between the field names in Medi-Write and the database field names is shown in Table 2. Re-writing to the tag will erase the previous entry for it in the database and enter a new entry with the correct data. The database will never retain two entries for the same tag.

3.2.3 RIT Medi-View

The Medi-View application is the real software centerpiece. It is in charge of alerting the healthcare personnel member at the central workstation of an inappropriate medication application. Additionally, it must instruct the base station mote to send an alert to the original sending

patient mote. Since this application's only graphical requirement is to provide alerts to the personnel at the workstation, the program is comprised of a simple terminal window, which displays various status messages, and pop-up windows, which appear when an inappropriate medication application was attempted.

The terminal window displays status messages on the system. It relays to the user if it is successfully connected to the serial port and the database. Regardless of what the software is receiving over the serial port, it updates the database at the beginning of each new day, 12 AM. It must reset the *doseToday* field in the database to 0 for every database entry. When

this occurs, a message is also displayed in the terminal window. Finally, when the program does receive data via the serial port, it will display the tag and mote ID in the terminal window.

In addition to the pop-ups, there is an audible "beep" generated when inappropriate medication was attempted to be taken. The pop-ups and beeps are the only elements of the software the personnel truly need be concerned with, not the status messages in the terminal window. Once the base station mote has received a tag and mote ID, it sends it via serial communication, provided by the gateway MIB510 board, to the workstation. When the workstation has this information it can reference the database to ensure the patient is properly taking their medication. First, an account of the program's actions will be provided for a correctly taken medication. This will then be followed by the situations where the medication was taken inappropriately. It should be stated this program is continually polling to see if a tag and mote ID combo has been received. A state diagram of the program can be seen in Fig. 4.

In the event that a patient is correctly taking their medication, the database *doseToday* field will be incremented by 1, and the *QTY* field will be decremented by whatever the value of the *doseSize* field is. In this case, no information is



sent serially back to the base station. This is because an alert does not need to be sent to the patient.

There are several situations in which the patient and healthcare personnel will receive an alert, including the given medication not being in the database, a patient attempting to take medication that is not their own, if the patient is out of

and database field names					
Medi-Write Field Name	Database Field Name				
Full Name	Name				
Prescription	Rx				
Quantity	QTY				
Dose Size	doseSize				
Doses per Day	doseDay				
Reader ID	readerID				

pills, and finally, their taking not the required doses of that medication for the day. For each of these errors, a pop-up will be displayed containing a time stamp, the patient who is incorrectly taking their medication, and the reason the application was incorrect.



that is not their own, look up the tag ID in the database. If this entry doesn't have a value in the readerID field of the database that matches the patient's mote ID, the patient is attempting to take medication that is not his and an alert must be sent. It can easily be determined if a patient is out of pills by checking the QTY field in the database for the corresponding tag ID received. If the value in the OTY is 0, an alert should be sent so that the prescription may be refilled. Finally, perhaps most importantly is the check to ensure a patient is not about to overdose on their medication. The doseToday field in the database should be queried for the corresponding tag ID. If the value in this field is equal to the value in the doseDay field, the patient should not be taking anymore medication. If an attempt is made an alert must be sent to keep the patient from overdosing. An example pop-up message for each of the previously described situations can be seen in Figs. 5~8. This has detailed all the components of the RIT Medi-View. An illustrated overview of the entire system can be seen in Fig. 9. The entire physical system setup needed to run Medi-View can be seen in Fig. 10.



4. Enhanced System Design: RFID via Mica2 with Multi-hop

In this section, we will describe our enhanced system design. First, we will show our switching the wireless mote platform from the Mica2Dot over to the Mica2. This was done for several advantageous reasons. Next we will introduce our incorporation of "multi-hop" communication into our above system. Such a communication scheme allows the network to transmit over a regional area (such as a nursing home) while avoiding an expensive WLAN or cellular system. 4.1 Mica2 Advantages

The Mica2 and Mica2Dot represent the de facto standard platform for sensor networks, differing only in form factors and slightly different core resources. They come from the same family of Crossbow motes, but the Mica2Dot is from the MPR5x0 series, while the Mica2 comes from the MPR4x0 series. Both are third generation platforms and as such are relatively stable. While all platforms used operated using a 433 MHz transceiver, a 900 MHz version is also available. Table 3 below gives a side-by-side comparison of both platforms' radio properties.

By inspecting this table, it is clear that both motes possess the same physical radio. This is what allowed communication between the two motes, as described in Section 2. The differences between these two motes can be seen in the system core comparison, shown in Table 4. It is these differences, along with availability differences, which lead to the Mica2's superiority.

	Mica2		Mica2Dot	
Radio	CC10	00	CC1000	
Frequency 315-91		16 MHz	315-916 MHz	
Data Rate 38.4 kt		bps	os 38.4 kbps	
Setup Time <50 ms		isec	<50 msec	
TX Power	-/+ 10	dBm	-/+ 10 dBm	
Sensitivity	-101 d	Bm	-101 dBm	
Modulation	FSK		FSK	
Antenna	wire		wire	
Outdoor Range	150 m		150 m	
Channels 4			4	
Та	ble 4 Sy	stem core compa	rison	
			Mica2Dot	
Microcont	roller	ATmega1281	ATmega1281	
Architect	ture	8-Bit	8-Bit	
Speed		7.3728 MHz	4 MHz	
Program M	emory	128 kB	128 kB	
Data Mer	Data Memory		4 kB	
Storage Me	Storage Memory		512 kB	
External	External IO		18	
On-Board S	ensors	2	2	
UI Compo	nents	3 LEDs	1 LED	
Size	Size		492 mm ²	

Referring to Table 4, one of the noted differences between the motes is their number of user interface (UI) components. The Mica2Dot only comes equipped with one red LED. This means its one light must be reserved for alerts to the patient that medication is being incorrectly taken. Ideally, the system should be able to give the patient confirmation that a tag read was sent. Without this, a level of confidence is removed from the system, as the patient can't be sure that their medication intake was actually sent to the base station mote. On the other hand, the Mica2 is equipped with three LEDs, one green, one yellow, and one red. For this platform, it was decided that the node mote's vellow LED should toggle when it is sending to the base station. This allows the patient to confirm that their intake was sent, as well as receive notification in the event they incorrectly administered a drug. There is one light left over which could be used during additional development.

Another noted difference is the Mica2Dot's diminished capacity for peripherals when compared to

the Mica2. While the Mica2Dot only has 18 input / output (IO) pins, the Mica2 has 51. While the system implemented in this work did not require more IO pins than that provided by the Mica2Dot, it is envisioned that this wearable device will have many more requirements other than RFID medication supervision. As mentioned previously, the system should at the very least also possess an ECG sensor, though which was not implemented here. This additional sensor would of course require additional IO pins on the mote. It is also likely that, due to further development, a designer would like to add a sensor to measure a patient's breathing rate. This again would require the availability of more IO pins on the mote. Clearly as more functionality is added to the system more IO pins need to be made available. The Mica2 is far more extendable, making it a better choice for this system.

While both motes have an external power supply range of 2.7 V - 3.3 V, the battery packs for each require different batteries. The Mica2Dot requires a 3 V CR2032 coin cell battery, while the Mica2 requires 2 AA batteries. From the incurred costs of this work, on average a single coin cell battery costs as much as 4 AA batteries. This means for the same cost, double the amount of Mica2's could be powered when compared to the Mica2Dot. Additionally, AA batteries have a lifetime of approximately 2700 mA-hours, while coin cell CR2032 batteries only have a lifetime of approximately 225 mA-hours. Since the considerations for this work include minimizing costs for the already expensive healthcare industry, the Mica2 is a more economical choice.

While the Mica2Dot's CPU only runs at 4 MHz, the Mica2's CPU runs at almost double, 7.3728 MHz. This means the Mica2's processing time is shorter and faster compared to the Mica2Dot for the same task. Therefore, in applications where the mote is required to perform computations, the Mica2 is a better choice. In Section 4.3 we will discusses multi-hop communication. This requires each node to find a path to the base station if it cannot communicate with it directly. The algorithm required for path establishment and discovery demands a high CPU clock cycle if it is to be done quickly. For multi-hop communication, the Mica2 is clearly the better choice.

4.2 Mote-Reader Interface

Unlike the Mica2Dot, the M1-Mini was not created to directly interface with the Mica2. Instead, additional hardware needed to be purchased to break out the Mica2's IO pins. This work utilized Crossbow's MDA100CB digital acquisition (DAC) board, which connected to the Mica2 via its mezzanine connector. The MDA100 series sensor boards have a precision thermistor, a light sensor/photocell, and general prototyping area.

The prototyping area supports connection to all eight channels of the mote's analog to digital converter (ADC0–7), both USART serial ports and the I2C digital communications bus. The prototyping area also has a series of 45 unconnected solder holes that are used for breadboard of circuitry to connect other sensors and devices to the mote. The M1-Mini has been connected to the MDA100CB. Power and ground were also connected between the MDA100CB and M1-Mini. A picture of the two connected can be seen in Fig. 12.

4.3 Multi-hop Communication

As previously stated, the indoor communication range for the Mica2 is approximately 150 m. The application setting in



which this system should be applied, a nursing home, is clearly more spacious than this distance. Therefore, a method of communicating information between the base station mote and a patient must exist even when they are separated by more than 150 m. This can be achieved by using a hop-to-hop, or in this case patient-to-patient, communication scheme where information from patient A, outside the base station's range, is routed through patient B, who is within both patient A's and the base station's range. An illustration of this can be seen in Fig.13. It assumed that all patients will not be 150 m away from the base station mote at the same time and that each patient will never be more than 150 m away from another patient.

Before discussing multi-hop communication, it is important to

understand how *single hop* communication occurs under TinyOS. This occurs through active messages, the TinyOS networking primitive.

The primitive, active messages, is a simple message-based networking abstraction. Depending on the platform, the abstraction differs to work with the specific networking stack. This work utilized the Mica2 platform, so it will be featured here. The default media access used for all radio communication is Carrier Sensed Multiple Access (CSMA).

The TinyOS-1.1 release and later include library components that provide ad-hoc multi-hop routing for sensor-to-sensor network applications. The implementation uses a



shortest-path-first algorithm with a single destination node, the base station, and active two-way link estimation. The multi-hop communication scheme used in this work was based on this pre-existing configuration, known as *MultiHopRouter*, which is further explained below.

The *MultiHopRouter* protocol is founded on tree-based routing. Tree based routing is primarily based on two pieces of information: a parent node identifier and a hop-count (the parent's hop-count plus one). A routing tree is built via local broadcasts from the root, in this case the base station node, followed by selective retransmission from its descendents. A node routes a packet by transmitting it with the parents as the designated recipient. The parent does the same to its parent, until the packet reaches the root of the tree, the base station node.

The *MultiHopRouter* protocol is based on the shortest-path algorithm that forms a spanning tree so that the path from any mote in the sensor field to the sink uses the least number of hops. Route control messages are periodically broadcast from each node in the network to estimate the routing cost and monitor link quality. *MultiHopRouter* uses the least number of hops as the primary metric with link quality as a tiebreaker. It provides support for retransmission and output queuing.

For building route information, a spanning tree is built with the base station at the root of the tree. Every 5 seconds, the node broadcasts a packet, including hop count to the base station and its node ID. Once the neighbor node gets the packets, it chooses the parent based on the minimal hop count and link quality.

If a source wants to send a message to the base station, it should use the Send.getBuffer command to get a pointer to the data region of a packet. Afterward, the Send.send command should be called in order to send packet to the next hop. Upon the reception of a message, the active message component signals the Receive interface if the destination is the local node or Intercept interface if otherwise. If the node is not the base station, it should use Send.send to forward the packet.

While MultiHopRouter ensured that packets would be successfully delivered to the base station, a method of sending alerts from the base station to the correct patient needed to be constructed. The first step is to have the patient node send its mote ID, a 16-bit unsigned integer, along with the RFID tag ID, an 8-bit unsigned integer array of length 16, as its message payload. When this is received at the base station, the appropriate processing takes place to determine if the medication is being taken properly. In the event there was an incorrect application, the base station sends a message off with node ID, also a 16-bit unsigned integer, as its payload. By examining this value the patient node can determine if the message it received was intended for it. If so the red LED on the mote will turn on, if not that node will forward the packet on, until it gets to the appropriate mote.

In this work one base station node was used along with 3 RFID nodes. Multi-hop communication was tested inside an enclosed building, with 2 of the RFID nodes only being able to see one RFID node, while the third being able to see one RFID node and the base station. The nodes were separated by approximately 150 m each. It was found that from mote power-up to route discovery the delay was approximately 90 seconds.

5. Error-resistant ECG Data Collection through the Extended Kalman Filter

A Kalman filter that linearizes about the current mean and covariance is referred to as an Extended Kalman Filter (EKF). We will use EKF to recover the damaged ECG data. To use EKF, an ECG stream must be modeled with governing equations to be supplied to the filter.

5.1 Discrete Kalman Filter Alterations [9]

For the EKF, the state estimate is now governed by the non-linear difference equation. Here, f represents the non-linear function that relates the state at the previous time step, k - 1, to the state at the current time step, k. An optional driving function may be included as u_{k-1} , and w represents the zero-mean Gaussian process noise. The measurement equation has also changed to equation (3). Similarly, h is the non-linear function that related x_k to the measurement z_k and v_k is the measurement noise. Since individual noise values, w_k and v_k are not known at each time step, instead the estimated state and measurement can be replaced with equation (4) and (5), respectively. In both, \hat{x}_k is some *a posteriori* estimate of the state from a previous time step k.

$$\begin{aligned} x_{k} &= f(x_{k-1}, u_{k-1}, w_{k-1}) & (2) \\ z_{k} &= h(x_{k}, v_{k}) & (3) \\ \widetilde{x}_{k} &= f(\hat{x}_{k-1}, u_{k-1}, 0) & (4) \\ \widetilde{z}_{k} &= h(\hat{x}_{k}, 0) & (0) \end{aligned}$$

New linearizing equations are needed to estimate a process with non-linear relationships. The governing equations seen in (6) and (7) linearize about (4) and (5), respectively. The equations for the matrices A, W, H, and V, seen in these equations can be seen in (8) through (11), respectively. For simplicity, the time subscript k is not used in the notation for these matrices even though they are in fact different at each time step. The information in Table 5 details what each variable represents.

$$\begin{aligned} x_k &\approx \widetilde{x}_k + A(x_{k-1} - \hat{x}_{k-1}) + W w_{k-1} \\ z_k &\approx \widetilde{z}_k + H(x_k - \widetilde{x}_k) + V v_k \end{aligned} \tag{6}$$

$$A_{[i,j]} = \frac{\partial f_{[i]}}{\partial x_{[j]}} (\hat{x}_{k-1}, u_{k-1}, 0)$$
(8)

$$W_{[i,j]} = \frac{\partial f_{[i]}}{\partial w_{[j]}} (\hat{x}_{k-1}, u_{k-1}, 0)$$
(9)

$$H_{[i,j]} = \frac{\partial h_{[i]}}{\partial x_{[j]}} \left(\widetilde{x}_k, 0 \right)$$
(10)

$$V_{[i,j]} = \frac{\partial h_{[i]}}{\partial v_{[j]}} \left(\widetilde{x}_k, 0 \right)$$
(11)

Variable	Meaning		
x_k	Actual state vector		
Z_k	Actual measurement vector		
\widetilde{x}_k	Approximate state vector from 5.3		
\widetilde{Z}_k	Approximate measurement vector from 5.4		
\hat{x}_k	An <i>a posteriori</i> state estimate at time <i>k</i>		
W_k	Random variable representing process noise		
v_k	Random variable representing measurement noise		
A	The Jacobian matrix of partial derivatives of f with respect to .		
W	the Jacobian matrix of partial derivatives of f with respect to v		
Н	The Jacobian matrix of partial derivatives of h with respect to		
V	The Jacobian matrix of partial derivatives of h with respect to		

Given all this information, a new prediction error and measurement residual can be defined. Recall the measurement residual reflects the discrepancy between the predicted measurement, z_k , and the actual measurement, \tilde{z}_k . These can be seen in (12) and (13), respectively.

$$\widetilde{e}_{x_k} \equiv x_k - \widetilde{x}_k$$

$$\widetilde{e}_{z_k} \equiv z_k - \widetilde{z}_k$$
(12)
(13)

Unfortunately, in practice one does not have access to x_k in (12), since it is the actual state vector attempting to be estimated. One does have access to z_k in 5.12 though, since it is the actual measurement that one is using to make an estimate. By utilizing (12) and (13), approximate linear governing equations for an error process can be written. These can be seen in (14) and (15). It should be noted ε_k and η_k represent new independent random variables having zero mean and

covariance matrices WQ_kW^T and VR_kV^T . Recall Q and R are the process noise covariance and measurement noise covariance matrices, respectively. Additionally, \tilde{e}_{x_k} has a covariance matrix of $E[\tilde{e}_{x_k}\tilde{e}_{x_k}^T]$.

$$\widetilde{e}_{x_k} \approx A(x_{k-1} - \hat{x}_{k-1}) + \varepsilon_k$$

$$\widetilde{e}_{z_k} \approx H\widetilde{e}_{x_k} + \eta_k$$
(14)
(15)

It can be seen that (14) and (15) are linear, and resemble the original discrete Kalman filter cases. This suggests there is a better way to estimate the error prediction of (15). This new estimate of \tilde{e}_{x_k} , called \hat{e} , can be found by using (13) and a second hypothetical Kalman filter. The Kalman filter equation used for this estimate can be seen in (16).

$$\hat{e}_k = K_k \tilde{e}_{z_k} \tag{16}$$

Once (16) is attained, it can be used in (17) to obtain an *a posteriori* state estimate for the original non-linear process. By substituting (16) into (17), the equation in (18) is obtained. Finally, by substituting (13) into (18), the equation which will be used for the measurement update in the extended Kalman filter is achieved. Note that \tilde{x}_k and \tilde{z}_k come from (2)

and (3), with the appropriate substitution for the measurement error covariance.

$$\begin{aligned} \hat{x}_k &= \hat{x}_k + \hat{e}_k \tag{17} \\ \hat{x}_k &= \tilde{x}_k + K_k \tilde{e}_{z_k} \tag{18} \end{aligned}$$

$$\hat{x}_k = \tilde{x}_k + K_k \left(z_k - \tilde{z}_k \right) \tag{19}$$

The complete set of EKF equations can be seen in Table 6 and Table 7. The tables separately group those equations used for time updates and those for measurement updates, respectively. Additionally, the appropriate subscript has been attached to the matrices A, W, H, and V to reinforce the notion that they are different at each time step, and therefore must be recomputed each time. Just as with the discrete Kalman filter, the time update equations in (1) project the state and covariance estimates from the previous time, k - 1, to the current time, k. An important feature of the EKF is that H_k in the equation for the Kalman gain, K_k , serves to correctly emphasize or magnify only the relevant component of the measurement information. H_k affects the Kalman gain so that it only

magnifies the portion of the residual, $z_k - h(\hat{x}_k, 0)$, that does affect the state.

5.2 ECG Modeling

With the EKF modifications made, we need to determine the equation which governs an ECG and apply it to the filter. Produced by an ECG, the signal is constructed by measuring electrical potentials

between various points of the body using a galvanometer. Fig. 14 shows an example of a normal ECG trace, which consists of a P wave, a QRS complex and a T wave.



While this work mainly focuses on using the EKF to recover wireless transmission errors, it can simultaneously be used to correct baseline wander of the ECG. The baseline is the resting potential of the ECG between the P, QRS, and T waves. Baseline wander occurs whether the ECG is sent wirelessly or not, as it is due to slipping or even moist electrodes on the body when collecting the ECG. Since the baseline of an ECG is used to diagnose many different cardiac diseases, it is important to receive an accurate portrayal of this part of the signal. For instance an ST segment below the baseline implies shortage of blood flow and oxygen.

McSharry et al. have proposed a synthetic ECG generator, which is based on a nonlinear dynamic model [19]. This model has several parameters, P, Q, R, S, and T, which come from the ECG and makes it adaptable to many normal and abnormal signals. The dynamic model consists of a three dimensional state equation, which generates a trajectory with the coordinate (x,y,z). These equations may be seen in (20) through (22). The variables α , $\Delta\theta_i$, and θ are

given in (23) through (25). Note that (25) is the four quadrant arctangent of the real parts of the elements of x and y, with the bounds given in (26). The variable ω is the angular velocity of the trajectory as it moves around the limit cycle. The baseline wander of the ECG signal has been modeled with z_0 .

Table 6 EKF time update equations				
$\hat{x}_k^{-} = f(\hat{x}_{k-1}, u_{k-1}, 0)$				
$P_{k}^{-} = A_{k} P_{k-1} A_{k}^{T} + W_{k} Q_{k-1} W_{k}^{T}$				

+	Table 7 EKF measurement update equations						
ι	$K_{k} = P_{k}^{-}H_{k}^{T} \left(H_{k}P_{k}^{-}H_{k}^{T} + V_{k}R_{k}V_{k}^{T}\right)^{-1}$						
	$\hat{x}_{k}^{-}=\hat{x}_{k}^{-}+K_{k}^{-}ig(z_{k}^{-}-hig(\hat{x}_{k}^{-},0ig)ig)$						
	$P_{k} = (I - K_{k}H_{k})P_{k}^{-}(I - K_{k}H_{k})^{T} + K_{k}R_{k}K_{k}^{T}$						
1							
2							



$$x' = \alpha x - \omega y$$
(20)
$$y' = \alpha y + \omega x$$
(21)
$$z' = -\sum_{i \in \{P, Q, R, S, T\}} a_i \Delta \theta_i \exp\left(-\frac{\Delta \theta_i^2}{2b_i^2}\right) - (z - z_0)$$
(22)
$$\alpha = 1 - \sqrt{x^2 + y^2}$$
(23)

$$\Delta \theta_i = (\theta - \theta_i) \operatorname{mod}(2\pi) \tag{24}$$

$$\theta = \arctan 2(y, x) \tag{25}$$

$$-\pi \le \arctan(y, x) \le \pi$$

Some typical parameters for the synthetic ECG model can be seen in Table 8. The three dimensional trajectory which is generated consists of a circular limit cycle which is pushed up and down when it approaches one of the *P*, *Q*, *R*, *S* or *T* points. In fact, each of the components of the ECG waveform has been modeled with a Gaussian function, which is located at a specific angle. This can be seen in (20) through (22) by neglecting the baseline wander term, $z - z_0$, and integrating the man the provide size a synthetic ECC size of

z' equation. The projection of the three dimensional trajectory on the z axis gives a synthetic ECG signal.

Index (i)	P	Q	Ŕ	S	Т
Time (Sec.)	-0.2	-0.05	0	0.05	0.3
θ_i (rads.)	- π/3	- π/12	0	$\pi/12$	$\pi/2$
a_i	1.2	-5.0	30.0	-7.5	0.75
bi	0.25	0.1	0.1	0.1	0.4

5.3 Implementation

With the changes necessary for the EKF documented and a modeling equation for the ECG completed, these two elements simply need to be put together to filter a noisy wireless signal. From here this work utilized the accomplishments of Sameni et al., who were able to linearize the ECG model and apply the EKF to it in Matlab [20]. Their usage was noninvasive fetal ECG extraction. This same work can applied in a completely different area, wireless data recovery.

The actual ECG data came from the Physionet.org PhysioBank database of physiological signals [21]. A sample of one of these normal ECG signals can be seen in Fig. 15. While the signal does have the baseline wander typical of all ECG signals, since it wasn't transmitted wirelessly there are no missing pieces of data. Therefore, the work of Sameni et al. had to be modified to remove data points from these real ECG signals in order to simulate wireless data loss.

As stated in Section 2, the error rate of wireless transmissions is in the range of 2% - 10%. For this work it was decided to simulate the amount data lost to be 10%.

The normal ECG signal filtered by the EKF can be seen in Fig. 16. It can be seen the final filtered signal, seen in green, is centered at 0 and its simulated wireless data loss has been recovered. The baseline wander removal was performed in the signal seen in red. The filtered abnormal ECG signals can be seen in Fig. 17 where the patient had an arrhythmia. Cardiac arrhythmia is any of a group of conditions in which the electrical activity of the heart is irregular or is faster or slower than normal.By analyzing all three filtered wave forms, it can be seen that whether the ECG is categorized as normal or abnormal, the wireless data loss can be recovered. This is all due to the parameterized software, which allows

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the P, QRS, and T waves to be specified individually. Hardware related to ECG reading, interpretation, and recovery was not implemented in this work. Clearly though, it can be seen that this method of using the EKF to recover data lost due to a wireless transmission proved successful.

6. Conclusion

The objective of this research was to reduce health care costs by creating a means to remotely monitor medication



intake of nursing home patients. Our system is composed of two major components. First, based on wireless sensor network technology, there are the wearable mobile platforms distributed to patients. These mobile platforms are responsible for gathering patient medication intake using an RFID monitoring system. The second part of the system is based on TinyOS's multi-hop communication protocol, *MultiHopRouter*. This allows patient nodes to communicate with the base station even if they are out of its transmission range. For a regional area like a nursing home, the target environment for this application, expensive cellular or WLAN infrastructures should be avoided. By utilizing multi-hop communication, a large transmission range can be achieved without sacrificing cost minimization.

In addition to these functionalities, a simulation was provided to ensure accuracy and reliability when remotely monitoring ECG signals. The data contained in an ECG is highly sensitive, since every second of information is so meaningful. A disastrous event like heart failure could begin to occur in mere seconds. This information cannot be lost due to its wireless transmission. It is imperative a remote ECG monitoring system employ a means for error recovery. The error recovery technique implemented here is the extended Kalman filter, which is designed for non-linear applications, such as an ECG signal.

Although there have been many research efforts in both of the fields of medical asset monitoring and remote ECG monitoring, most of them stay theoretical at the best. This research marks an attempt to bridge the two research fields by providing a product that is realizable and would directly benefit the consumers in the medical field.

Acknowledgement

The work is partially supported by the US National Science Foundation (NSF) under grants CNS-0716455 and CNS-0716211.

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