An Energy Efficient Model for Monitoring and Detecting Atrial Fibrillation in Wearable Computing

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Abstract- **Current portable healthcare monitoring systems are small, battery-operated electrocardiograph devices that are used to record the heart's rhythm and activity. These on-body healthcare devices fall short on delivering real-time continuous monitoring of early detection of cardiac atrial fibrillation (A-Fib) when the symptoms last only a short period of time and require a long battery life. The focus of this paper is the design of an energy efficient model for real-time early detection of A-Fib in a wearable computing device. The design is realized by incorporating an A-Fib risk factor and a real-time A-Fib incidence-based detection algorithm. The results of the design show that the proposed energy efficient model performs better than a telemetry energy model. The design shows promising results in meeting the energy needs of real-time monitoring, detecting and reporting required in wearable computing healthcare applications.**

Keywords
Energy-aware model, wearable computing, real-time monitoring, real-time detection of cardiac atrial fibrillation, logistic regression model of atrial fibrillation

1. INTRODUCTION
Atrial fibrillation (A-Fib) is the most common cardiac arrhythmia [1] [2] [3]. The American College of Cardiology and the American Heart Association define A-Fib as a supraventricular tachyarrhythmia characterized by uncoordinated atrial activation accompanied by the deterioration of atrial mechanical function. A-Fib is responsible for approximately 15 percent of the strokes occurring in people with A-Fib. The cost to treat A-Fib in the United States exceeds $6.4 billion per year [4]. Small battery operated portable healthcare monitoring systems are used to monitor arrhythmia by recording the heart's rhythm and activities. The recorded data is eventually transmitted either to a physician's office or to a healthcare center for analysis and detection. Unfortunately, these on-body devices are plagued by energy constraints, process optimization problems, data security risks [5] [6] and interference, among others. They need to optimize energy consumption and implement energy management in order to balance innovative interfaces, network resources, continuous monitoring and apropos detection energy requirements.

The energy consumption must be efficiently allocated. Decisions of which various processes need to run, and when, must be made judiciously in order to deliver essential results in a critical device energy shortage. In addition, wearable healthcare computing devices need the ability to analyze and accurately detect arrhythmia and other medical ailments [7].
This paper presents the design of an incidence-based energy-aware model for real-time detection and reporting of atrial fibrillation in wearable computing devices. Section 1 briefly motivates the need for energy optimization in wearable computing healthcare devices. Section 2 highlights related work. Section 3 describes the required energy components in an A-Fib wearable computing system and defines the incidence, the diagnosis accuracy and the predictors of A-Fib. Section 4 presents the energy models to detect A-Fib, and compares the incidence-based energy-aware model to a telemetry energy model.

2. RELATED WORK
Wearable devices face high performance requirements in the middle of energy constraint challenges. Studies and research [8] [9] [10] [11] suggest various methods to minimize power consumption in mobile devices. The authors of [8] describe a framework that is used to reduce the energy consumption of sensors by temporarily turning them off. In study [9], the battery life is extended by as much as 30% through a collaborative relationship between the operating system and applications. In [10], the authors propose ways to enable systems to trade computational accuracy for resources by scaling down the data or feature set for use on a remote healthcare system. The study reports significant resource savings for small amounts of utility degradation, e.g., 33% of bandwidth saving for only a 1% of accuracy degradation. Study [11] suggests a trade-off between power saving and detection accuracy or performance, they show how power can be saved at the loss of a small amount of accuracy by applying different techniques using a low power real-time epilepsy seizure detection algorithm. In project [18], the battery life of a wireless healthcare system is optimized using a dynamic scheduling technique by efficiently assigning tasks to the available resources. The Framingham heart study [17] [20] developed a risk score to calculate an individual's risk of developing atrial fibrillation and a development framework for researcher. The research funded by the Health Technology Assessment Program addresses the accuracy of electrocardiogram (ECG) for the diagnosis of A-Fib and the potential risk of A-Fib misinterpretation errors[12] [13] [14]. Finally, a mobile medical device, dubbed HeartSaver [15] was developed to monitor the onset of atrial fibrillation and other cardiac pathologies. Our design extends battery life in a Risk Incidence-Based energy-aware model that may be applied in wearable computing devices to continuously monitor and detect the onset of A-Fib.

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3. PRELIMINARIES

This section describes the required energy components in an A-Fib wearable computing system and defines the incidence, the clinical diagnosis accuracy and the predictors of A-Fib.

3.1 Devices

Typically, a wearable computing device requires energy for signal sensing ($E_{ECGsense}$), for Bluetooth signal transmitting from the sensor to the GSM phone (E_{ECGTx}), for GSM phone signal receiving from the Bluetooth sensor (E_{ECGRx}), for GSM phone analysis and detection ($E_{classify}$), and for the GSM phone transmitting results (E_{Rep}) (see Figure 1). We compare the energy consumed by a Risk and Incidence Based A-Fib Detection Scheme to the energy consumed by a telemetry model. In this study, we use the two-lead ECG Alive Technologies Heart Monitoring Device A102D7 (650 mAh at 3.7 V) [16]. The device monitors and transmits ECG signals via Bluetooth to an Apple MacBook computer (see Figure 2). We assume that the telemetry model continuously monitors and transmits ECG signals during a 24-hour period.

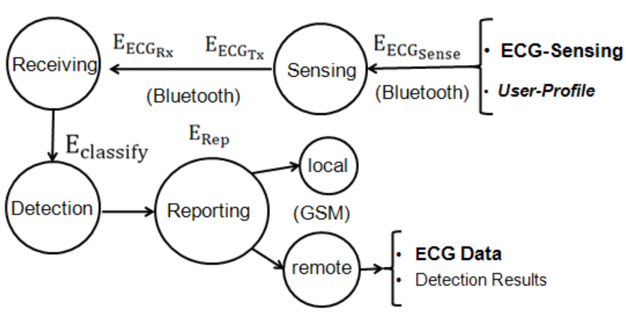

Figure 1: Wearable computing energy functional requirements

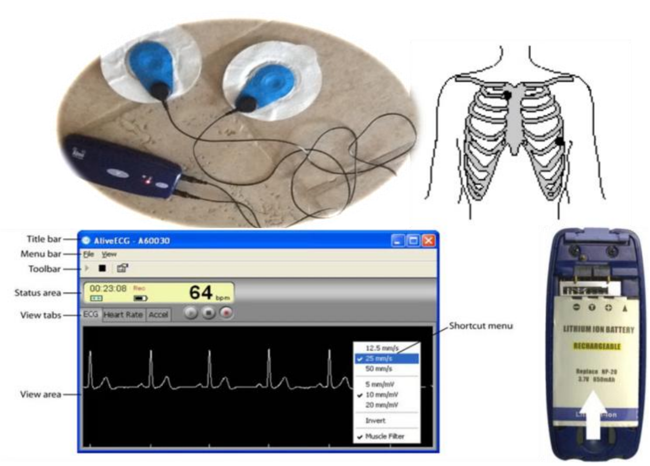

Figure 2: Alive Technologies Heart Monitoring Device A102D7

3.2 Understanding A-Fib

The following subsections define the incidence rate of A-Fib, the clinical diagnosis accuracy of the onset of A-Fib, and the predictors A-Fib.

3.2.1 Incidence Rate of A-Fib

Among all arrhythmia, A-Fib is the most frequently diagnosed and affects 2.5 million people in the United States, or close to 1% of the total population [4]. The Manitoba study [37] concluded that the incidence of A-Fib is 0.13 to 0.36 for people between 25 and 60 years old, 5.7 per 1,000 person-years after age 60, and 9.7 per 1,000 person-years after age 70. The Framingham Heart study [36] and other studies draw attention to the significance of the higher frequency of A-Fib with advancing age [19]. Patients with A-Fib have a 1.5-2 fold increase in mortality rate when compared with the general population as suggested by Framingham Heart study data [17] [20]. Early recognition of A-Fib is difficult because most people are not aware of this silent rhythm disturbance [21]. Today, frequent monitoring and screening of patients allow for early detection of arrhythmia.

3.2.2 Clinical Diagnosis Accuracy of A-Fib

At least one-third of the A-Fib episodes go undetected because either people do not get screened often, or A-Fib diagnosis is missed by a general practitioner or practice nurse [23]. Few studies have addressed the misdiagnosis of A-Fib from an electrocardiogram (ECG) and the potential risk of A-Fib misinterpretation errors. Knight et al. [13] concluded that A-Fib is more often misdiagnosed by internists than cardiology fellows and cardiologists. Mant et al. [23] discovered that general practitioners correctly detected A-Fib 80% (true positive) of the time when interpreting 12-lead ECG data and misinterpreted 8% (false positive) of sinus rhythm cases as A-Fib. One of the major misdiagnosis confuses A-Fib with atrial flutter [13] [24].

3.2.3 Predictors of A-Fib

A-Fib is the most prevalent arrhythmia in the United States and accounts for more than 750,000 strokes per year [25]. According to classification guidelines used by cardiologists and electro-physiologists, for the management of patients with A-Fib [26], after the first A-Fib is detected, there are mainly four types of A-Fib: Paroxysmal, persistent, longstanding persistent, and permanent. A-Fib is termed progressive, as once a patient is diagnosed with a paroxysmal A-Fib, he or she will eventually migrate to persistent A-Fib. Similarly, a patient diagnosed with persistent A-Fib, will drift to longstanding persistent A-Fib and in time to permanent A-Fib [27].

Some of the ECG waves and intervals in figure 3 are used to derive our A-Fib detection algorithm. The latter plays an integral part in the Risk Incidence-Based energy model. The QRS interval is the duration of the ventricular muscle depolarization. The P wave is a record of the electrical activity or the sequential activation (depolarization) through the right and left atria. The PR interval is the time interval measured from the beginning of the P wave (atrial depolarization) to the onset of the QRS complex (ventricular depolarization). The RR interval is the duration of the ventricular cardiac cycle; it is an indicator of the ventricular rate. The PP interval is the duration of the atrial cycle; it is an indicator of the atrial rate.

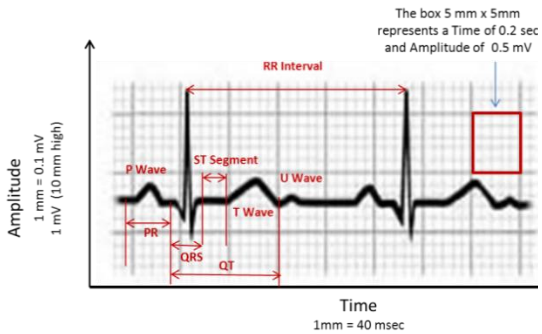

Figure 3: Typical ECG wave and intervals

During A-Fib, the electrical signal begins in a different part of the atria instead of the SA node. The abnormal signal causes the atria to quiver rapidly instead of contracting normally. The atria do not pump blood efficiently into the ventricles causing the blood to pool in the atria where clots can form. Blood clots may travel from the heart to the brain resulting in strokes (Figure 4 describes the path of the electrical signals during an A-Fib episode).

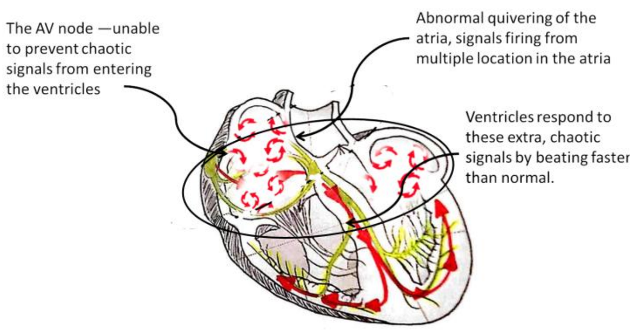

Figure 4: Describing A-Fib chaotic electrical signals

We acknowledge detecting A-Fib is difficult and requires a more intense research, however one of the strong indicators of A-Fib presence is the absence of P waves on the ECG plot and an erratic noise-like activity in their place combined with irregular R-R intervals [28][25][27]. Sometimes when the heart rate is too fast, irregular RR intervals may be difficult to determine [19]. Wide QRS complexes may be present with rapid ventricular response.

4. ENERGY MODELS TO DETECT A-FIB

Today, portable healthcare monitoring devices such as Holter monitors, event monitors, and telemetry devices are small battery operated electrocardiograph (ECG) devices, which are used to monitor a patient's heart activity for periods of time ranging from days to weeks. Sensed or recorded ECG data is sent to a doctor or a care center for analysis and reporting. Unfortunately these on-body devices are not energy efficient; they drain batteries quickly and necessitate patients to replace batteries sometimes daily [29]. This weakness in wearable computing devices runs the risk of missing the first 30 seconds of A-Fib or might not be possible if the user is incapacitated. They also fall short on delivering real-time detection; the patient waits for the eventually transmitted recorded data to be analyzed and results fed back to him. Telemetry and wearable healthcare computing systems are concerned with three main components: monitoring, detection, and reporting. In an energy-aware environment, the different components must run sensibly in order to extend battery life.

4.1 Telemetry Energy Model

When prescribed by a physician, telemetry may be applied continuously for few days in the hope of capturing episodes of A-Fib. Telemetry may also be user-triggered by the patient as soon as he or she feels symptoms of A-Fib (such as heart palpitations). We assume that telemetry ECG interpretations are conducted by a cardiologist or a cardio-physiologist who is a trained expert at ECG readings thus, all judgments of what constitutes A-Fib are going to be assumed to be as accurate as possible. The total energy consumed is the sum of the energies that are required for sensing ECG signals, transmitting to the cell phone via Bluetooth, receiving ECG record, and reporting ECG record for a period of 24 hours.

$$\mathrm{E_{telemetry}} = \mathrm{E_{ECG_{Sense}}} + \mathrm{E_{ECG_{Tx}}} + \mathrm{E_{ECG_{Rx}}} + \mathrm{E_{Rep}} \quad (1)$$

The telemetry report includes all positive and negative results. False positive outcomes are usually interpreted as false alarms; they contribute to wasted or needless energy spent in transmitting inaccurate information. In a 24-hour period, such a telemetry system would use approximately 50% of the capacity of the Heart Monitoring Device battery. Typical monitoring and detection healthcare wearable body network devices have limited energy and therefore limited monitoring duration.

4.2 Risk and Incindence Based Energy Model

The implementation of a risk and incidence based A-Fib detection model in A-Fib monitoring devices alleviates the aforementioned challenges in telemetry[30] [31]. For instance, knowing the A-Fib risk factor of a patient allows one to prescribe an A-Fib monitoring and detection schedule. A high A-Fib risk factor may suggest more frequent monitoring compared to a low A-Fib risk factor. Because A-Fib is not a common occurrence [23], we want to report a result only when there is an actual occurrence of A-Fib. We adopt an A-Fib logistic regression model to detect the first episode of A-Fib, that is the first 30 seconds of continuous A-Fib. After the first $_{30}$ seconds of A-Fib is detected, monitoring may proceed beyond 24 hours to detect paroxysmal, persistent, long-standing persistent and permanent A-Fib. Monitoring may be prescribed for days or weeks.

4.2.1 *Assessing the A-Fib Risk Factor*

The Cox proportional-hazards regression [32] is used to analyze the effect of risk factors on survival. The probability of the onset of A-Fib is called the hazard. The following covariates and their corresponding coefficients responsible for predicting A-Fib risk in people aged between 45 and 95 years old are extracted from the Framingham Heart Study [17] [20]: Age, Age^2, Gender, Body Mass Index (BMI), Systolic Blood Pressure (SBP), Treatment for Hypertension (TH), Significant Heart Murmur (SHM), Prevalent Heart Failure (PHF), $\mathrm{Gender*age}^2$, and Age*PHF, PR Interval ($\mathrm{PR_{interval}}$). We can express the hazard or risk of getting A-Fib at time *t* as:

$$H(t) = H_0(t) * e^{\sum_{i=1}^{k} \beta_i X_i} \quad (2)$$

Where H_0 (10) = 0.96337 is the 10 year baseline survival or cumulative hazard function at time t = 10 years extracted from the Framingham Heart study [17] [20].

$$\sum_{i=1}^{k} \beta_i X_i = 1.994060\,Gender + 0.150520Age + 0.019300\,BMI + 0.006150\,SBP + 0.424100\,TH + 3.795860\,SHM + 9.428330\,PHF - 0.000380Age^2 - 0.000280\,Gender * Age^2 - 0.042380\,Age * SHM - 0.123070\,Age * PHF + 0.070650\,PR_{Interval} \quad (3)$$

For example, the predicted Risk Factor for a male person, who is 70 years old, who weighs 70 kg, with a body mass index of 22.96, a systolic blood pressure (SBP) of 130, no hypertension, a PR interval measuring of 16 ms, no significant heart murmur, and no previous heart failure, is 0.0863. This is compared to the risk for a person of the same age and gender, with BMI 20 to 24.9, a normal SBP (120 to 129), no treatment for hypertension, a PR Interval of 16, no significant murmur or prevalent heart failure.

4.2.2 Implementing A-Fib Detection

The dataset used in our analysis was extracted from the Machine Learning Repository at University of California, Irvine [33], MIT-BIH Atrial Fibrillation database [34] and from data donated and corroborated by a cardiologist. The dataset describes the attributes for diagnosing cardiac A-Fib where each instance or patient is classified into two categories: presence of cardiac A-Fib and absence of cardiac A-Fib. The resulting dataset contains 304 records including 80 A-Fib cases, 224 non-A-Fib cases, seven attributes and two classes (A-Fib Present, A-Fib Absent). The cardiologist's classification is used as a reference (see Figure 5).

	Variable	Description	Value
1	age	Age in years , linear	real
2	Age^2	Age^2 in $years^2$	real
3	Gender	Gender (0 = male; 1 = female) , nominal	{0, 1}
4	BMI	Kg/m^2, Linear	real
5	QRSduration	Average of QRS duration in msec., linear	real
6	PRinterval	Average duration between onset of P and Q waves in msec., linear	real
7	heartrate	Number of heart beats per min, linear	real
	class	{A-Fib present, A-Fib absent}	binary

Figure 5: A-Fib attributes.

Logistic regression determines the relative effect of independent variables x_i on the dependent variable Y or class and their statistical significance. This effect is usually explained in terms of odds ratios where the odds of an event x occurring with probability p is defined as: odds (p) = p / (1-p) where p is the probability of the presence of the disease. The logit transformation is defined as the natural log of odds,

$$logit(p) = \ln\left(\frac{p}{1-p}\right) \quad (4)$$

$$p(Y = 1|x) = \frac{1}{1 + e^{-logit(p)}} \quad (5)$$

$$logit(p) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i \quad (6)$$

$x_i = (x_1, x_2, \ldots, x_k)$ is the covariate vector and β_i $(i = 1,2, \ldots, k)$ denotes the coefficients of the k predictors. Fitting a logistic regression model to a given data implies deriving estimates of the coefficients β_i that maximize the likelihood of the model. The outcomes of the Logistic Regression include all True Positive and False Positive results. They may be triggered at A-Fib incidence rates reported in the Manitoba studies [37] where the incidence of A-Fib is 0.13 to 0.36 for people between 25 and 60 years old, 5.7 per 1,000 person-years after age 60, and 9.7 per 1,000 person-years after age 70 .

A-Fib is predicted present if probability p (A-Fib is Present | age, age^2, gender, BMI, QRSduration, PRinterval, heartrate) > 0.5
Otherwise, A-Fib is absent. (7)

$$logit(p) = -41.175 + 0.820\,age - 0.006\,age^2 + 4.737\,Gender - 0.047\,BMI + 0.098\,QRSduration - 0.178\,PRinterval + 0.066Heartrate \quad (8)$$

and $p = 1 / (1 + e^{-logit(p)})$ (9)

Figure 6 describes a possible daily monitoring and detection of episodes of A-Fib according to a logistic regression model.

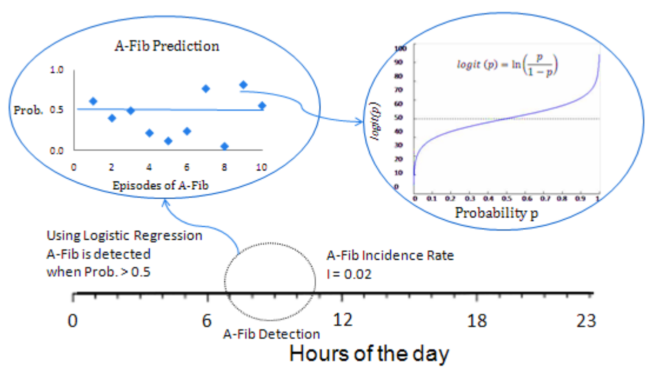

Figure 6: A-Fib Episodes

4.2.2.1 Evaluating Classifier Performance

Given an ECG record, a binary classification has four possible outcomes or rates: True negative (TN), False Positive (FP), True Positive (TP), and False Negative (FN). Detection rates are measured in terms of sensitivity and specificity [26]. Both the overall classification accuracy and the overall classification error defined below may be used to evaluate the performance of the classifier:

$$\text{Overall Error rate} = \frac{FP+FN}{TP+TN+FP+FN} = 2.63\% \quad (10)$$

$$\text{Overall Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = 97.37\% \quad (11)$$

However, when the cost of misclassifications of the different classes is uneven, this measure may be unacceptable. In order to take into account the unevenness of misclassification costs when evaluating a classifier, area under the Receiver Operating Characteristic (or ROC) curve is explored. ROC curves have been used in biomedical informatics [7] to express the sensitivity versus specificity of classifiers.

The ROC curve plot displays the False Positive rate on the X-axis (1- Specificity) and the True Positive rate (Sensitivity) on the Y-axis. Each point on the ROC curve represents a sensitivity / (1-specificity) pair corresponding to a particular decision threshold. The area under the ROC curve measures how well a particular parameter can distinguish between two diagnostic groups (such as presence of a disease/ absence of A-Fib). The bigger the area is and the closest to 1, the better the classifier performance. The area under the ROC curve for the derived logistic regression model is 0.986.

The A-Fib detection algorithm is triggered by the onset of A-Fib. Suggested studies [24] reveal that clinical measurement of sensitivity (True Positive rate) of 80% and specificity (True Negative rate) of 92% when internists and general practitioners instead of cardiologists diagnose A-Fib. Our logistic regression classification of A-Fib has a measurement of sensitivity of 98.8% and specificity of 96.9%. The false positive results, usually interpreted as false alarms, contribute to wasted or needless energy spent in transmitting inaccurate information.

4.3 Applying Risk and Incidence Based Energy Model to A-Fib Detection

A-Fib monitoring devices may become impractical when they run out of battery energy. Typical monitoring and detection healthcare wearable body network devices have limited energy and therefore limited monitoring duration. The implementation of a risk and incidence based A-Fib detection in such devices helps extends a monitoring device battery life. For instance, A-Fib risk factors may be classified in three categories made up of risk ranges such as $k < 0.05$, $0.05 < k < 0.15$, $k > 0.15$. Knowing the A-Fib risk factor of a patient allows one to prescribe an A-Fib monitoring and detection schedule (see Figures 7). A high A-Fib risk factor may suggest more frequent monitoring compared to a low A-Fib risk factor.

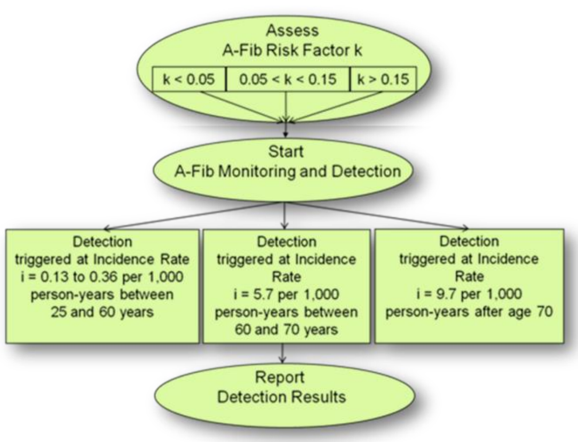

Figure 7: Overview of an efficient wearable computing device

We design an A-Fib detection energy model by adopting an A-Fib risk factor assessment algorithm from [20] and a logistic regression model. We consider an incidence rate equal to 2% for illustration purposes. The total energy consumed during a 24-hour period is the sum of the following energies, $E_{ECGsense}$ for continuously sensing ECG signals, E_{ECGTx} for transmitting ECG signals to the cell phone via Bluetooth, E_{ECGRx} for receiving ECG signals, $E_{classify}$ for classifying the received data, and E_{Rep} for reporting when there is an episode of A-Fib suggested by the detection algorithm output at the positive rate r_p.

$$E_{RPclassification} = E_{ECG_{Sense}} + E_{ECG_{Tx}} + E_{ECG_{Rx}} + E_{classify} + r_p * E_{Rep} \quad (12)$$

Figures 1 and 8 illustrate the major components in the A-Fib detection energy model.

Ideally, when there are no A-Fib episodes, r_p is equal to 0 that is, the model spends its time in a monitoring state. On the other hand, when the model continuously monitors, and continuously transmits, r_p is equal 1. False positive outcomes result in wasted energy that is needlessly spent transmitting inaccurate information. In a 24-hour period, such a detection system would necessitate 31.1% of the capacity of the Heart Monitoring Device battery. This is equivalent to 61.8% of the energy consumed by a telemetry energy model.

The authors plan to implement a risk and incidence based atrial fibrillation detection scheme in a wearable device and further validate the results in a clinical setting.

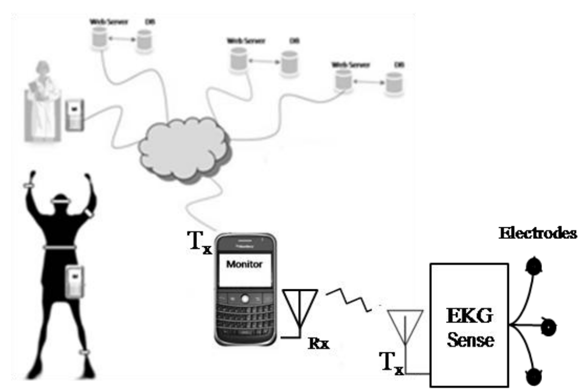

Figure 8: Overview of a wearable A-Fib detection system

Figure 9 illustrates the energy consumption as the positive detection rate varies with respect to the clinical incidence rate.

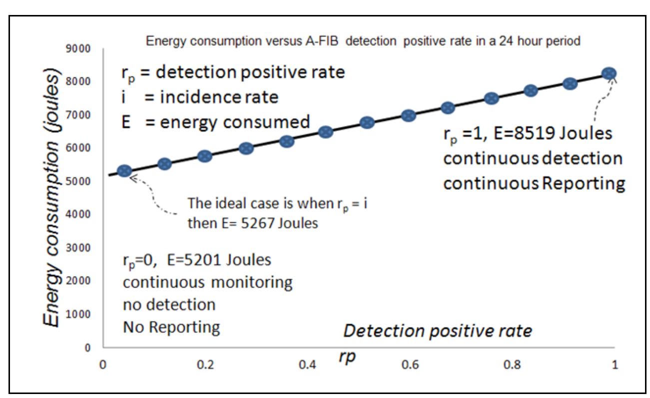

Figure 9: Energy consumption versus A-Fib positive rate r_p

Figure 10 suggests that the ideal detection case is when the logistic regression positive rate r_p is equal to cardiologist referenced A-Fib incidence rate i. The worst case is when the positive rate equals 1, which corresponds to a telemetry energy model.

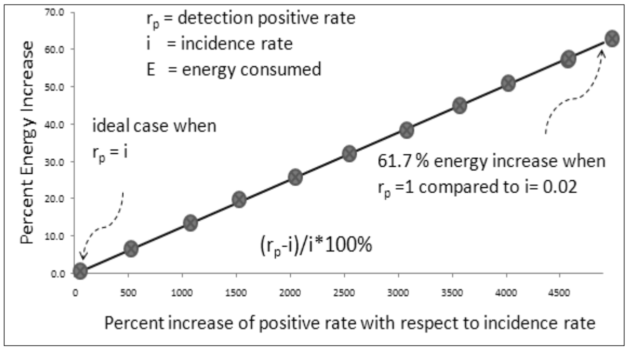

Figure 10: Energy required as positive rate varies with respect to incidence rate

4.4 A-Fib Energy Model Versus Telemetry

Telemetry is ubiquitous in health care monitoring. Unfortunately, it places high demand on energy consumption necessitating daily replacement of batteries in the telemetry monitoring device. If the positive rate r_p is equal to the incidence rate i then if the classification detection algorithm correctly classifies 100% of the episodes of A-Fib, one may conclude that the general classification energy-aware model combined with an incidence rate delivers better results in energy consumption than the telemetry model.

$$E_{telemetry} = E_{ECG_{Sense}} + E_{ECG_{Tx}} + E_{ECG_{Rx}} + E_{Rep} \qquad (13)$$

$$E_{IncidenceRate} = E_{ECG_{Sense}} + E_{ECG_{Tx}} + E_{ECG_{Rx}} + E_{classify} + 0.02 * E_{Rep} \qquad (14)$$

Figure 11 depicts how the risk factor and incidence based energy efficient model combined with an A-Fib incidence rate of 2% consumes approximately 38% less energy than the telemetry model.

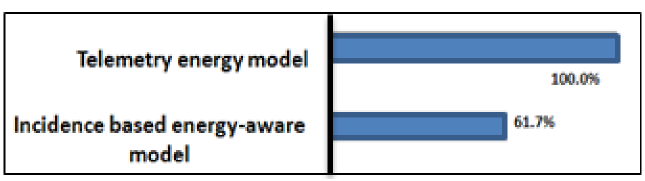

Figure 11: Comparing energy-aware model to telemetry energy model

5. CONCLUSION

Early recognition of A-Fib is difficult because most people are not aware of this silent rhythm disturbance [19]. A-Fib is typically diagnosed, or misdiagnosed, during a routine screening visit or during a yearly scheduled check-up, by a general practitioner or a referred cardiologist. Current cardiac A-Fib telemetry devices do not deliver continuous real-time monitoring and require a long battery life. Furthermore, because some of these solutions require patient interaction and device activation, they may become impractical when the patient is incapacitated during symptomatic periods. In this paper we design an energy efficient model for real-time monitoring and detection of cardiac A-Fib using A-Fib risk factor assessment and A-Fib incidence rate. Though our energy-aware model depends on detection accuracy, the wearable computing detection model shows promising results in meeting the energy needs of real-time monitoring, detecting and reporting required in wearable computing healthcare applications.

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