# Automated Home Monitoring of Atrial Fibrillation in Heart Failure Patients

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## Abstract

*Atrial fibrillation (AF) is a major cause of cardiovascular complications. AF is likely to occur in heart failure (HF) patients and may precipitate episodes of worsening HF. AF is often underdiagnosed or detected late using traditional diagnostic tools. The increasing use of home telemonitoring (HTM) in the long-term management of chronic HF may facilitate the detection of incident and recurrent AF. Many HTM solutions for HF include devices that allow patients to take and transmit their daily heart rate along with other vital signs. Software-based processing of the cardiac signal underlying the heart rate assessment may reveal the presence of AF. In this study, we investigated the feasibility of detecting AF from the raw signal of a HTM device. The device records a short, non-conventional ECG to determine average heart rate. An algorithm based on Markov modelling of inter-beat-intervals (IBI) was used to distinguish AF from other heart rhythms. The approach was evaluated using daily self-assessments (n=3831) transmitted by HF patients over the course of one year. Implantable devices and patients' medical records served as a reference. On this dataset, the algorithm obtained a sensitivity of 94% and a specificity of 99% in discriminating AF from non-AF rhythms. Further studies should investigate the contribution of AF monitoring to the early detection of HF worsening.*

## 1. Introduction

Atrial fibrillation (AF) and heart failure (HF) are common in the elderly population and may present as co-morbidities that adversely affect each other. Due to their increasing prevalence and the associated risk of cardiovascular complications they have become major public health issues over the last decades.

HF is a chronic condition characterized by cardiac dysfunction which impairs the patients' quality of life and leads to reduced life expectancy. It is often a consequence of myocardial infarction or long term hypertension. The prevalence of HF is estimated at 1% in the general population, 3% in the age group 65-75 and 7-10% in those above 75 years [1]. Chronic HF is marked by frequent episodes of worsening signs and symptoms which require unplanned hospitalizations or doctor's visits. Each of these episodes contributes to the progression of the disease. Because HF is generally irreversible, medical treatment focuses on controlling symptoms by keeping patients in a stable range of physiologic parameters. To this aim, home telemonitoring (HTM) is increasingly used in the management of chronic HF. HTM enables patients to perform and transmit daily self-assessments of vital signs and symptoms to their healthcare provider. Monitoring these data for changes indicative of worsening HF, allows the clinical team to intervene in a timely manner (e.g. by titrating therapy), thereby potentially preventing impending hospitalizations. Vital signs measured by most HTM systems for HF include weight, blood pressure, heart rate and oxygen saturation.

AF is the most common life-threatening cardiac arrhythmia which affects 1% of the general population. The prevalence of AF increases with age, reaching 10% in patients older than 80 years. HF patients are more prone to developing cardiac arrhythmias than the general population and 25% of them have AF [2]. The characteristic of AF is a chaotic electrical activity in the atria which leads to irregular contractions of the ventricles. AF decreases the heart's ability to pump blood efficiently and facilitates the formation of blood clots. Therefore, patients with AF have an increased risk of stroke. Over long periods of time, AF can weaken the heart. In patients with HF, AF may precipitate episodes of worsening HF. Therapeutic targets in AF are stroke prevention through blood thinning medication and reduction of strain on the heart muscle through rhythm or rate control. Despite the availability of therapeutic options, diagnosing AF remains challenging. Traditional diagnostic tools including 12-lead ECG or long term ambulatory Holters allow for limited monitoring durations and are prescribed only when patients report symptoms of AF. Due to the episodic and frequently

asymptomatic nature of the AF, many cases remain undiagnosed.

In view of the increasing number of HF patients who use HTM over extended periods of time, we hypothesize that the abundant data generated through intermittent self-assessments of heart rate may provide an effective means to passively monitor for AF in this high-risk population. A variety of devices used in HTM for measurements of heart rate rely on short recordings of electrical, optical or other pulsatile signals of cardiac origin. The analysis of inter-beat interval (IBI) series obtained from these signals may reveal the presence of an irregular heart rhythm characteristic to AF.

In this study we investigated the feasibility to automatically detect AF in HF patients using short series of IBIs extracted from daily measurements with a HTM device. To this aim, we retrospectively applied real-time AF detection to raw device data collected during the MyHeart HTM study. In the following sections we present the device used for data collection, the real-time method for detecting AF, the validation steps, and results. We conclude by discussing strengths and limitations of our approach.

## 2. Materials and methods

### 2.1. HTM device

The investigational device used to collect data for this study is a fluid accumulation vest (FAV) designed for self-assessments of thoracic fluid status. The FAV measures trans-thoracic bioimpedance using four textile electrode pads integrated into a vest (Figure 1). Patients can use the FAV as part of a HTM solution to quickly check and transmit their daily thoracic bioimpedance. The routine is comparable to taking and transmitting other vital sign measurements e.g. blood pressure or weight every morning. In the background, an automated alerting algorithm monitors the trend of bioimpedance time series to detect thoracic fluid accumulation as an early indicator of worsening HF.

A secondary parameter determined by the FAV is the patient's average heart rate during a self-assessment. The parameter is derived from a single-lead ECG signal recorded throughout the bioimpedance measurement between two of the electrodes located on either sides of the vest (Figure 1) [3]. In this study, we used this non-conventional ECG lead to monitor for AF.

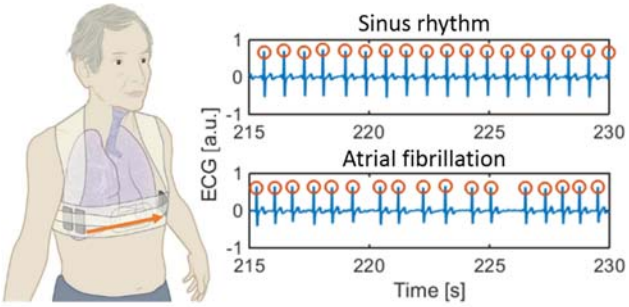


Figure 1. Left: Fluid accumulation vest (FAV). Two pairs of textile electrode pads (dark gray) are located on either side of the chest. Two of the electrodes detect a non-conventional ECG lead on the frontal axis indicated by the arrow. Right: ECG waveforms recorded with the FAV during sinus rhythm (top) and atrial fibrillation (bottom). Circles mark the position of the R-peaks.

### 2.2. AF detection

A strong discriminator of AF is its corresponding irregular heart rhythm [4]. The two series of IBIs in Figure 2 illustrate the visible difference between a normal sinus rhythm and an irregular AF rhythm. To detect this characteristic of AF in ECG signals from the FAV, with low computational cost, we employed real-time ECG processing and a subsequent analysis of IBIs.

Real-time ECG processing involves signal conditioning, beat detection, and beat classification. A full review of these steps is out of scope of this manuscript. In this study, we used the ST/AR algorithm (Philips Healthcare, Andover, MA, USA) to detect and classify normal beats in a single ECG lead. Using the best single lead of the MIT-BIH arrhythmia database [5], ST/AR yields a sensitivity and positive predictive value of 99.1% and 99.9%, respectively. The algorithm's sensitivity and positive predictive value in detecting

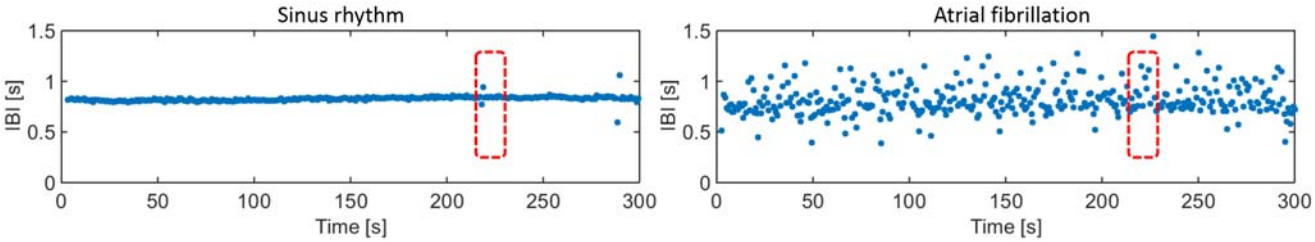


Figure 2. Inter-beat interval (IBI) series for 5-minute recordings with the fluid accumulation vest (FAV): sinus rhythm at 73 beats/min (left) and atrial fibrillation at 76 beats/min (right). IBIs in the dashed rectangles (red) correspond to the ECG strips in Figure 1.

premature ventricular complexes on the same database are 94.8% and 96.4%, respectively.

Markov process modeling of IBIs bounded by R-peaks of normal QRS complexes was used to discriminate between AF and non-AF rhythms [6]. This method assumes that a sequence of IBIs is controlled by a stationary first-order Markov process characterized by a transition probability matrix. The matrix captures the probability of an IBI to transition from one state to another. The low values among the elements of the matrix represent transitions that are more likely to occur in AF than non-AF. The calculated Markov score reflects the relative likelihood of observing a certain sequence of IBIs during AF versus making the same observation outside of an AF episode. Our AF classifier compares the Markov score to a discriminatory threshold to detect the AF rhythm. The transition probability matrix and the discriminatory threshold were determined using on a database of ambulatory Holter recordings (n = 633) annotated by expert readers [4].

## 2.3. Validation

This analysis was performed on a dataset collected during the MyHeart study, an observational HTM study of HF patients. The study aimed to identify early predictors of HF decompensation based on traditional and innovative measurements of vital signs as well as patient reported symptoms. MyHeart enrolled 148 HF patients with and without an implantable cardiac resynchronization therapy (CRT) device. During a 12-month home monitoring period, patients performed and transmitted daily self-assessments with the FAV and with other HTM devices. The CRT devices were interrogated during regular follow-up visits.

The ECG signals available from the FAV were automatically analyzed to detect AF. Each recording had a duration of 5-minutes and was classified as AF (*test positive*) if the Markov score exceeded the discriminatory threshold at least half of the recording time and as non-AF (*test negative*) otherwise. By applying this duration-based rule we ignored the unlikely event of an AF episode to start and/or end during the short daily recording.

We evaluated the AF classification on a subset of FAV ECGs for which the reference rhythm could be retrieved from implantable CRT devices and the patients' medical records. The AF burden per day (cumulative duration of AF episodes) was available for patients with CRT devices. All recordings on days with logged AF burden <2 minutes were included in the evaluation dataset as non-AF (*condition negative*). Recordings on days with AF burden >2 minutes were not included in the evaluation dataset because, based on the available information, it could not be determined whether the AF episodes were ongoing at the exact time of the FAV self-assessment. Furthermore, we did not include recordings on days when the CRT device interfered with the natural ventricular rhythm of the patient e.g. by overriding a slow or irregular rhythm. All FAV recordings of patients with a diagnosis of longstanding persistent AF or permanent AF and no CRT device were included in the evaluation dataset as AF (*condition positive*).

## 3. Results

A total of 3831 measurements from 19 patients met the criteria for inclusion in the evaluation dataset. On this dataset of 2003 condition positive and 1828 condition negative measurements our AF detection algorithm achieved a sensitivity of 94%, a specificity of 99% and an accuracy of 96%.

## 4. Discussion

At-home patient devices dedicated to heart rhythm monitoring have not reached wide-spread use in HTM of HF patients, partly because they required time-consuming manual review of a large number of rhythm strips transmitted by patients. Our approach is to automatically detect AF using short signals recorded by other at-home devices during assessments of heart rate. Previous studies have shown that AF can be detected accurately in long-term ECG recordings by analyzing IBI sequences [4,6]. In this study we investigated the feasibility to automatically detect the characteristic rhythm of AF in short series of IBIs obtained from HF patients through daily self-assessments with a HTM device (FAV). The AF detection performance on this dataset was slightly superior to previous studies of long IBI series obtained from diagnostic grade medical devices[4,6]. It is noteworthy to point out the differences and limitations of our evaluation dataset. The reference AF annotations for each FAV recording were obtained from log files of implantable CRT devices or patient's medical records, and were not confirmed by an expert reader. The evaluation dataset did not include AF and non-AF recordings of the same patients.

Analyzing IBI series is an attractive approach for automatically detecting AF in patient self-measurements performed in the context of HTM. This approach differs from the standard for diagnosing AF which takes into account the presence or absence of P-waves in a conventional 12-lead ECG. It is known that analyzing P-waves in addition to IBIs may improve the results of automated AF detection [4]. However, detecting the P-wave in a non-conventional single-lead ECG signal such as the one recorded by the FAV (Figure 1) is often not possible. IBI series, on the contrary, can be extracted robustly even from noisy ECG signals or from PPG signals recorded by patients.

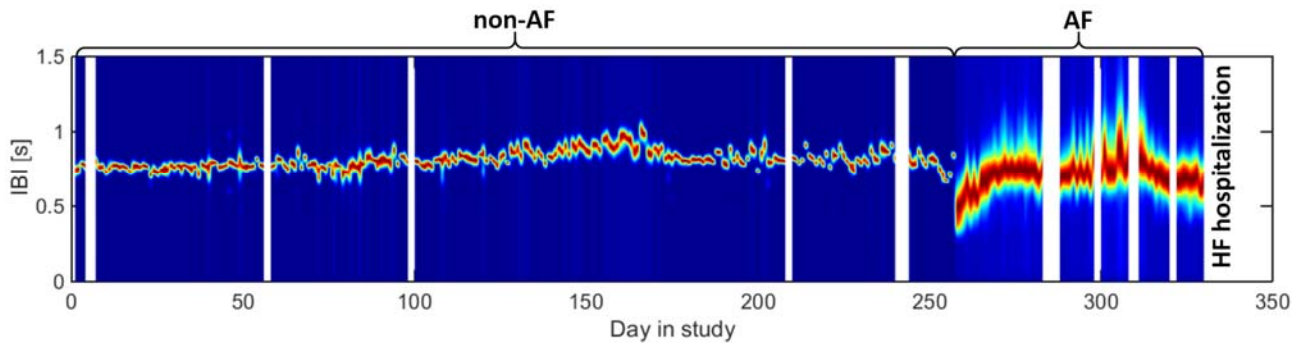


Figure 3. Inter-beat interval (IBI) densities in daily measurements transmitted by a patient over a 12-month monitoring period. Gaps (white) are days when the patient did not perform measurements. Daily monitoring ended when the patient was hospitalized for worsening HF. At admission, the patient was first diagnosed with AF. Measurements from the beginning of the monitoring period until day 257 contain IBIs visibly concentrated within a narrow band and were classified by the algorithm as non-AF. The following measurements until the hospitalization have a wider-band IBI distribution and were classified by the algorithm as AF.

The IBI series available for our study had a duration of 5 minutes and were used in full-length. However, the AF detection algorithm is also applicable to shorter IBI series, which has the potential to reduce the duration of the measurement. Further studies may investigate the minimum length of an IBI series necessary for accurate detection of AF.

The application proposed in this work is directed towards HF patients who use HTM as part of their daily routine. Short measurements with an at-home device performed over several months enable monitoring of AF over longer periods compared to traditional tools for detecting AF such as office-based 12-lead ECGs or ambulatory Holters. The approach is likely to detect AF episodes with a duration of 24 hours or longer and may benefit patients with incident or recurrent AF who do not experience symptoms. Figure 3 illustrates the incidence of AF based on FAV recordings of a patient from the MyHeart study. The patient was first diagnosed with AF only at the end of the monitoring period when hospitalized for worsening HF. Our retrospective automated analysis of IBIs from the FAV ECGs detected the onset of the AF episode 2.5 months in advance.

Further HTM studies may investigate the contribution of AF detection to multi-parametric algorithms for the early detection of worsening HF.

## 5. Conclusions

Using the FAV non-conventional ECG, our IBI-based AF monitoring algorithm detected the presence of AF in HF patients. Detecting AF in patients monitored with the FAV is feasible and may be valuable for those at risk of incident and recurrent AF.

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