# Poster Abstract: Detecting Malicious Morphological Alterations of ECG Signals in Body Sensor Networks

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## ABSTRACT

Body Sensor Network (BSN) – a network of body-worn wireless health monitoring sensors – have a tremendous potential to remove the space and time restrictions on health management. Given the importance of the data BSNs collect for improved health outcomes, securing the data from unauthorized tampering is essential. A compromised (or externally influenced) sensor in a BSN may generate erroneous patient data leading to, among other things, wrong diagnosis and treatment. In this paper, we present a novel approach to address the problem of detecting maliciously induced morphological alterations in the ECG signal (i.e., inducing changes to its shape). Our approach works by correlating the ECG signals with synchronously measured arterial blood pressure (ABP) signal measured using a distinct (and un-compromised) sensor. Initial analysis of our system demonstrates promising results, with 99.75% accuracy in detecting ECG signal morphological alterations for healthy patients with normal sinus rhythms.

## 1. INTRODUCTION

Body Sensor Networks have already demonstrated great potential in a broad range of applications w.r.t. healthcare and wellbeing. The fact that BSNs collect and act on sensitive data makes them attractive targets for tech-criminals to exploit. As BSNs become increasingly available, the threats posed to them by adversaries will also increase. One such threat is sensor compromise, where adversaries stealthily alter patient health data collected from the BSNs to something plausible but incorrect. This problem, though akin to the issues of detecting faulty sensors or lack/loss of sensor calibration, is a considerably tougher. The reason being, obvious/arbitrary modifications to the sensor data can be easily detected by the end-users of the data (i.e., clinicians, patients). The adversaries we consider in this work are advanced persistent, and therefore try to introduce subtle changes to the patient data which presents an incorrect picture of the patient's state over time.

In this regard, we focus on detecting ECG sensor compromise in a BSN. In general, compromising an ECG sensor in a BSN allows the adversary to alter its signal (i.e., data is measured) in two possible ways: (i) *temporal* alteration, which involves modifying the timing information of ECG complex (e.g., inter-beat-interval); (ii) *morphological* alteration, which involves modifying the shape of ECG complex. In our previous work [1], we focused on detecting temporal alterations in an ECG signal by correlating it with other signals that represent and influence the cardiac process, namely arterial blood pressure(ABP) and respiration signals. The advantage of the approach in [1] was that it did not require redundant ECG sensors or access to historical ECG data to detect current sensor misbehaviors. In this paper, we work on the complementary problem of detecting *morphological alterations* in the ECG signal using only the ABP signal as reference. Initial analysis of our system demonstrates promising results, with 99.75% accuracy in detecting morphological alterations for patients without cardiac issues.


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## 2. ECG MORPHOLOGY ALTERATION DETECTION

Our approach to detecting morphological alteration of ECG signal is to build a *portrait* of synchronously measured ECG and ABP signals. A portrait is an n-dimensional representation of the relationship of several time-series in a one multi-dimensional space. Once the portrait is created we extract specific features from it, which are then used to train a patient-specific model, which forms the basis for detecting morphological alterations to the ECG signal. The intuition being that if the ECG signal being tested has been modified then the portrait built for this altered ECG and synchronously measured reference ABP will not possess features similar to the portrait used to create the patient-specific model. We now describe each of the steps involved our approach in more detail.

**Portrait Creation:** To generate a portrait, first, we synchronously measure $w$ secs ABP signal and ECG signal and normalize. Normalization is needed as the magnitude and units of ECG and ABP signals are different. Let $a(t)$ and $e(t)$ be the normalized ABP and ECG signals at time $t$. We then create a 2-dimensional portrait $P = [a(t), e(t)]$, thus capturing the time-varying relationship between both the ECG and ABP (see Figure 1).

**Feature Generation:** Once a portrait is generated, the next step is to extract appropriate features from it. Based on the work in [3, 4], we extract a total of eight features.

*Matrix Features*: These features describe the distribution of points in the portrait which captures the shape of ECG signal with respect to the ABP signal. Matrix features are obtained by viewing the portrait under $n \times n$ grid and counting the number of points from the portrait that fall in each

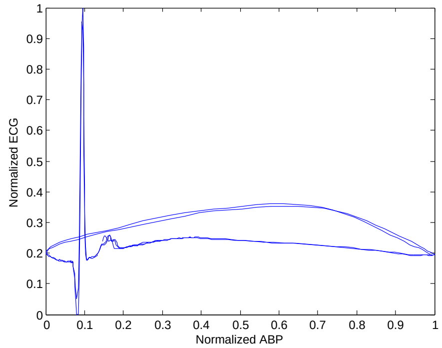


**Figure 1: A typical ECG and ABP Portrait**

cell in the grid. This information is stored in an $n \times n$ matrix $C$ where each element $c(i, j)$, where $i, j \leq n$, is the count of the number of points in the corresponding grid element $(i, j)$. From the matrix $C$, we extract three features: (i) spatial filling index, which represents the sum of the square of the fraction of points in each element of the matrix $C$; (ii) standard deviation of column averages of matrix $C$; and (iii) area under the curve formed by the column averages.

*Geometric Features*: Geometric features are another way of describing the relationship between ECG signal w.r.t. ABP signal through the capture of the absolute and relative location of certain *characteristic points* in the signals. The characteristic points represent important peaks and troughs in the signal, such as P, Q, R, S and T points in the ECG signal, systolic (C) and diastolic (D) points in the ABP signal. In this preliminary work, we only consider the R and the C peaks in the ECG and ABP signals, respectively as characteristic points of interest. To identify where the characteristic points lie on the portrait, for each $w$ secs of ECG and ABP signals, we first perform peak detection for both R peak and C peak and label them. Note that, depending upon duration of $w$, a portrait can have multiple characteristic points from ECG and ABP in it. We extract five geometric features based on these labeled characteristic points in the portrait: (i) the average of the angles (w.r.t. x-axis) for the ECG's characteristic points; (ii) the average of the angles (w.r.t. x-axis) for the ABP's characteristic points; (iii) average distance between ECG's characteristic points from the origin; (iv) average distance between ABP's characteristic points from the origin; and (v) average distance between the ECG's characteristic point and its corresponding ABP characteristic point.

**Model Training and Evaluation:** In order to account for the individual variation in the physiological processes, we build a *patient-specific* model for each patient. Figure 2 illustrates the training and evaluation process. It has four main steps. (1) Generate positive examples for the model by building $w$ second portraits (from a larger $\Delta$ second snippets of synchronously measured ECG and ABP signals from the same patient) and extracting the aforementioned features from them. (2) Similarly, use the patient's ABP snippets and other patients' ECG snippets during feature generation to generate negative examples for our model. (3) Use Naive Bayes classifier to train the model. (4) Use the trained model for the patient to decide if any newly received ECG signal snippet has been altered or not.

**Preliminary Results:** In this preliminary work, we selected 12 healthy patients with normal sinus rhythm from MIT PhysioBank Fantasia database [2]. The data set consists of data from 5 males and 7 females with average age at

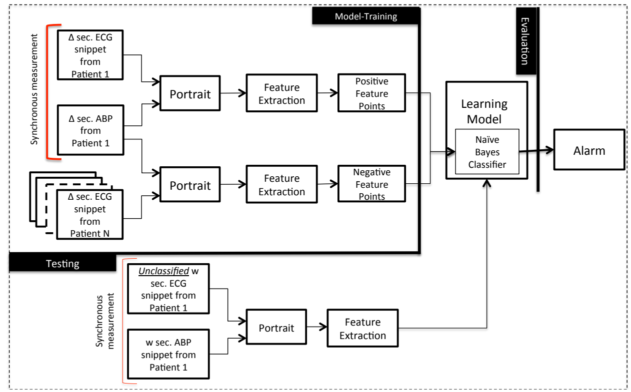


**Figure 2: Morphological Alteration Detection**

46.5 years. We collected ECG and ABP signals for $\Delta = 480$ seconds, chose $w = 3$ seconds sliding window size and $n = 50$ for the grid size, thus generating 160 positive examples and 1760 negative examples for each patient. We trained a patient-specific model for each of the 12 patients using the Naive Bayes classifier, and used 10-fold cross validation to test each patient's model. Our preliminary results show an average accuracy of 99.75% with false positive 1.3% and false negative 0.16%. We define false positive as the case where an unaltered ECG snippet is classified as altered. False negative is the case where an altered ECG data is classified as unaltered.

# 3. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a novel approach to detect malicious morphological alterations of ECG signals in a BSN using data from synchronously measured ABP signal. We plan to continue our work in following directions: (1) consider the rest of characteristic points for the feature generation process to capture the morphology alteration with higher fidelity, and (2) test the approach on patients with cardiac issues whose morphological variations are much more non-uniform compared to patients with normal sinus rhythms.

# 4. REFERENCES

[1] H. Cai and K. K. Venkatasubramanian. Sift: Multi physiological signal feature correlation-based sensor compromise detection in body sensor networks. Technical Report WPI-CS-TR-14-04, Worcester Polytechnic Institute - Computer Sciences Department, July 2014.

[2] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley. Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals. *Circulation*, 101(23):e215–e220, 2000.

[3] O. Malgina, J. Milenkovic, E. Plesnik, M. Zajc, and J. F. Tasic. Ecg signal feature extraction and classification based on r peaks detection in the phase space. In *GCC Conference and Exhibition (GCC), 2011 IEEE*, pages 381–384. IEEE, 2011.

[4] T. Rocha, S. Paredes, P. de Carvalho, J. Henriques, and M. Antunes. Phase space reconstruction approach for ventricular arrhythmias characterization. In *Engineering in Medicine and Biology Society, 2008. 30th Annual International Conference of the IEEE*, pages 5470–5473. IEEE, 2008.