ABSTRACT

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/arbiter 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 Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
http://dx.doi.org/10.1145/2737095.2742930 ...$15.00.

Copyright 2015 ACM 978-1-4503-3475-4/15/04.

IPSN '15,
Copyright is held by the owner/author(s).
Permit third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
http://dx.doi.org/10.1145/2737095.2742930 ...$15.00.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
http://dx.doi.org/10.1145/2737095.2742930 ...$15.00.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
http://dx.doi.org/10.1145/2737095.2742930 ...$15.00.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
http://dx.doi.org/10.1145/2737095.2742930 ...$15.00.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
http://dx.doi.org/10.1145/2737095.2742930 ...$15.00.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s).

IPS '15, Apr 14-16, 2015, Seattle, WA, USA
Copyright 2015 ACM 978-1-4503-3475-4/15/04.
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

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


