Patient Identity Verification based on Physiological Signal Fusion

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***Abstract*—Patient identification is crucial in providing proper care in hospitals or other care-facilities. Failure to correctly identify patients can result in a variety of problems such as medication errors, transfusion errors, testing errors, and duplication of EHR records. The current solutions for identifying patients in a hospital setting rely on confirming the patient's identity several times, the use of labels, bar-codes, and RFID tags. However, these solutions are not always sufficient and patient identification errors are common.**

In this paper we present a patient identity verification approach that can complement existing patient identification solutions in the event that they cannot be relied upon. Our approach works by fusing common physiological signals (vital signs) already collected from the patients. The idea is to fuse two physiological signals electrocardiogram (ECG) with arterial blood pressure (ABP) to identify an individual patient. Existing identification/authentication solutions based on cardiac signals have been primarily tested on healthy patients whose signals exhibit normative rhythm and morphology. However, in our context not all patients can be expected to have normative cardiac signals as many of them may be suffering from ailments that affect the cardiac process. The fusion of multiple ECG and ABP allows us to ensure patient identification even when the patients have ailments that affect their cardiac rhythms. An evaluation of our approach showed that it is over 97% accurate in identifying patients with non-normative cardiac rhythms and morphology with over 99% accuracy for patients whose cardiac rhythms are normative. Further, our approach can identify a patient in as little as 3 seconds, which makes it practical in real-world scenarios.

I. Introduction

Patient identification is crucial in providing proper care in hospitals or any care-facility. Failure to correctly identify patients can result in medication errors [1], transfusion errors [2], testing errors, wrong person procedures [3], duplication of EHR records [4], adverse drug events [5], and even discharging of infants to the wrong families [6]. The current solutions for identifying patients in a hospital setting rely on confirming the patient's identity several times during the course of a patient's stay/visit to the hospital and the use of wrist-band (bar-codes) and RFID tags. However, these solutions have not been sufficient and patient identification errors are common [1]. Errors in patient identification occur for a variety of reasons including: (1) human error, e.g., mistyping traditional patient identifiers, such as oral demographic data, social security numbers, and patients' addresses; (2) inability of the patients to provide the required identification, e.g., when the patient is brought in comatose to an ER; and (3) absence of required identifiers such as lost or damaged wrist-bands assigned to patients. Patient identification errors threaten to harm patient safety, impact hospital revenues and profit, and opens them up for law-suits.

One solution to address this problem is to perform patient identification using physiological signals-based biometrics. Such solutions can be used to complement the existing user identification approaches being used. Therefore, if during the course of a hospital visit, caregivers are not able to identify the patient due to some of the aforementioned reasons or need to verify/confirm the identify of a patient, they can rely on the use of physiological signals-based biometrics. It has been shown in the past that physiological signals collected from individuals can uniquely identify people (authenticate). Examples include electrocardiogram (ECG) [7], plethysmogram (PPG) [8], and electroencephalogram (EEG) [9]. The use of physiological signals for identification/authentication arose because they are difficult to spoof and do not require traditional input modalities, such as those based on based behavioral cues (e.g., voice, touch or gestures), input entry (e.g., passwords) or special hardware as with traditional biometrics (e.g., fingerprint/iris scan).

However, traditionally, identification/authentication solutions based on physiological signals are largely designed for and validated on a generally healthy patient population. It is not clear how well these solutions perform when the patient population has ailments that cause their physiological signals used in their identification to be "non-standard". In a hospital context, this assumption of patient "healthiness" is almost always wrong. Consequently, we need an identity verification solution that works for patients whose physiological signals are normative, as well as patients that suffer from ailments that result in the distortion of the physiological signal being used to verify their identity.

In our previous work, we proposed an approach that fuses characteristics of two commonly measured physiological signals, ECG and arterial blood pressure (ABP) to authenticate (uniquely identify) patients in a health-context independent manner [10]. However, our approach had one major disadvantage. In order to be able to build an authentication model for a patient, it relied on extracting characteristic features from the ECG and ABP signals, such as, the location and magnitude of the R peaks and systolic peaks, respectively. For patients with normative ECG and ABP, we were able to utilize standard peak detection algorithms such as [11], [12]. For patients with physiological signals that were non-normative, however, there are no good ways to capture the characteristic features that we needed. Consequently, we had to rely on annotations in the dataset to identify the characteristics features. The availability

of such annotations however, is not realistic and we need to find a way to capture the characteristics of the ECG and ABP signals without relying on locating such characteristic features.

Consequently, in this work, our approach removes the need of detecting any characteristic features in the ECG and ABP signals by viewing these signals as images. We basically create two different classes of images that captures: (1) the inter-relationship between ECG and ABP signals from a patient for whom we are building the model; (2) the inter-relationship between ECG and ABP signals from several other patients. We then build an image reconstruction-based classifier that can classify these two classes of images by leveraging the Principal Component Analysis (PCA) technique. The use of PCA allows us to leverage the unsupervised learning of the ECG and ABP shapes rather than relying on the locating the characteristics features in the signals.

An analysis of our approach based on a dataset of 36 patients from the MIT PhysioBank Fantasia and MGH databases [13] shows that we achieve similar results to our previous work, with over 97% accuracy in verifying the identity of patients with non-normative cardiac rhythms and morphology, and over 99% accuracy for patients whose cardiac rhythms are normative. Even though the results are no objectively better than our previous work, the fact that we do not rely on mechanisms for identifying characteristic features in the physiological signals makes this work much more practical in real-world scenarios.

The rest of the paper is organized as follows. Section II presents the related work. Section III presents the problem statement and the system model. Section IV presents the approach, followed by Section V which describes the parametrization of the the models we developed in the approach. Section VI then presents the performance evaluation of our approach and finally Section VII concludes the paper.

II. Related Works

Physiological signals have often been used for patient identification purposes in the recent past. Approaches have been proposed that utilize electrocardiogram (ECG) [7], [14], [15], [16], [17], photoplethysmogram (PPG) [8], bioimpedence [18], heart-rate [19], and electroencephalogram (EEG) [9] for identification. Most of these efforts have focused on creating a template for an individual based on characteristic points in the signal waveforms followed by statistical or machine learning approaches for authenticating (i.e., one-versus-all identifying) the individual. Work has also been done where more than one physiological signals have been used to authenticate patients. These approaches are usually an extension of the single signal identification solutions, in that, they perform identification based on a primary signal while using the rest of the signals for artifact removal. For example in [20] the authors combine ECG with EEG signals for improving the ECG-based identification in the presence of artifacts such as movements [21], [22].

None of these solutions have been shown to work for individuals whose ailments affects the very physiological signal that is being used for identification. In [23], [24], the authors attempt to consider individuals with normative and non-normative physiological signals to evaluate their identification approach. However, these approaches produce relatively low accuracy and high false negative rates. In our own previous work [10], we developed an approach to identify individuals based on the fusion of ECG and ABP signals. Unlike the multi-signal approaches of the past, our approach looks at both ECG and ABP signals in tandem and depends on fusing both signal features together to perform identification. Our approach achieves high accuracy rate irrespective of the current state of the individual's physiological signal. This approach depends on knowing where certain characteristic features (i.e., peaks) of ECG and ABP signals lie along with their inter-relationship. However, locating these characteristic features on the physiological signals, in general, is a difficult problem. Often finding the characteristic features for individuals, whose physiological signals vary dramatically from the norm, is very error prone. This makes our previous effort not very practical. In this work we remove the need of having to find characteristic features when using ECG and ABP signals in tandem for identification of individuals.

III. System Model and Problem Statement

Our *system model* consists of a scenario where a patient arrives at a hospital/care-facility and we want to be able to identify them. Such patients are assumed to be hooked on to vital signs monitors that collect a variety of physiological signals from them including ECG and ABP. These vital signs monitors can be bed-side patient monitoring or using wearable medical systems such as [25]. The data collected from the ECG and ABP devices is sent to a medical cloud for analysis and user identification. We assume the data transfer from the medical devices to the cloud is secure.

The *problem* we are addressing in this work is to use the fusion of ECG and ABP signal features for identification in a manner that makes no assumption regarding the normative nature of the physiological signal. In this regard, we want to be: (1) accurate with low false positive and false negatives, and (2) quick to identify the patient.

IV. Approach

In this section, we introduce our approach for identifying a patient using electrocardiogram (ECG) and arterial blood pressure (ABP) signals. The goal is to build a system that complements existing patient identification solutions deployed in hospitals and care-facilities, such that, we can rely on it in case existing patient identification process fails or if it cannot be trusted. That is, our approach can be used to confirm the identity of a patient.

Fig 1 shows our system setup. It works in two stages: enrollment stage and identity verification stage. In the *enrollment stage*, we first build a patient-specific model that captures their physiological uniqueness. We do this by creating two classes of images that capture: (a) the inter-relationship between synchronously measured ECG and ABP measurements from a particular patient; and (b) the inter-relationship between synchronously measured ECG and ABP measurements from several other patients. We then perform Principal Component Analysis (PCA) on the two classes of images to generate two sets of principal components (PCs). Based on the two sets of PCs, we create a patient-specific, image reconstruction-based classifier (i.e., a decision function). During the *identity verification stage*, we collect a short snippets of current ECG and ABP signals from an unknown patient we are trying to

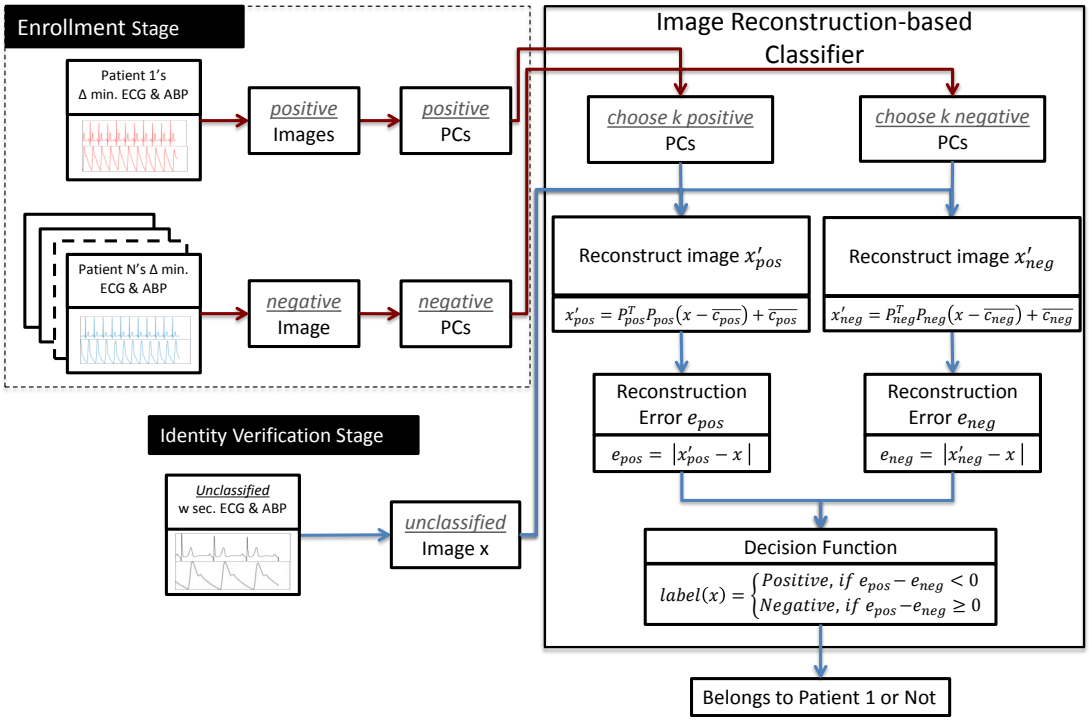


Fig. 1: **The ECG and ABP based Identity Verification Approach**

identify. We create an image that captures the inter-relationship between the two signal snippets and feed it into the patient-specific model. The model then produces a label for this new image which allows us to confirm the identify of the patient (see Figure 1). We describe the two steps in detail below.

A. Enrollment Stage: Creating Positive and Negative Images

Before introducing the idea of an image that captures the inter-relationship between ECG and ABP signals, we first introduce the notion of a *portrait*, based on which we create our images. A portrait allows us to specify the instantaneous state of the the two signals over time [26]. Let $abp(t)$ and $ecg(t)$ be the normalized ABP and ECG signals at time t, where $1 \leq t \leq w$, where w is the length of both ECG and ABP snippets. Then, the portrait P can be calculated using the function $f(t) = (abp(t), ecg(t))$. Figure 2a and 2b show an example of creating a portrait from the ECG and ABP snippet.

Once a portrait P is created, we create an image I by taking a graphical view of portrait at a certain resolution. This image depicts the trajectory formed by ECG and ABP signals in the two-dimensional space. We first view portrait as an $n \times n$ grid, where each element of the grid records whether there are any points from the portrait that fall into it. Then based on this grid, we can create a binary matrix with size of $n \times n$, where the element $I(x, y)$ of the matrix equals to 1 or 0, indicating there is at least one point that falls into the corresponding grid element (x, y), or no points that fall into the corresponding grid element (x, y). In this work, we chose n = 50 for generating the matrix, as it allows us to capture the required inter-signal relationship without overly increasing the complexity of resulting image. This binary image matrix with $n \times n$ elements is what we refer to as image I. Figure 2b and 2c show an example of creating an image based on the portrait of ECG and ABP signals.

During the enrollment stage, we create two classes of images: (1) the *positive class* images, which are created by sliding window of size $w < \Delta$, over the synchronously measured ECG and ABP signals from the patient whose classifier we are training; (2) the *negative class* images, which are created by sliding window of size $w < \Delta$ minutes synchronously measured ECG and ABP signals belonging to several other different patients. Each w-sized window of data produces one portrait and therefore one image. Consequently, both negative and positive classes have a series of images.

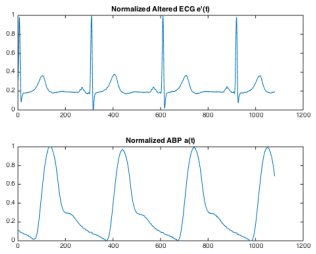
B. Enrollment Stage: Learning an Image Reconstruction-based Classifier

Inspired by [27], we build a classifier for identifying patient. In this regard, we perform Principal Component Analysis (PCA) on the series of images in both classes to obtain two different sets of principal components (PCs). The set of PCs generated from the images in a class will preserve important characteristics of that class. Let each column vector c_i with a length of n^2 to represent each image in a class. Then, a covariance matrix Cov can be generated as follows:

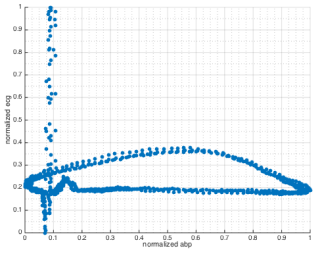
$$Cov = \sum_{i=1}^{m} (c_i - \bar{c})(c_i - \bar{c})^T, \tag{1}$$

where m is the total number of images in a class, and $\bar{c}$ is the mean of the column vectors of these images in that class.

The set of PCs are then generated by finding the first k eigenvectors of the covariance matrix Cov, which then forms a *projection matrix* P, where each row of P is an eigenvector. In this work, we set $k = 10$ as we tried different numbers and it works best for us. Therefore, from two classes of images we generate two covariance matrices, two sets of PCs and two projection matrices, which capture all the major variations observed in the images of each class.



(a) Normalized ECG $e(t)$ & Normalized ABP $a(t)$



(b) A Portrait G

(c) An Image I

Fig. 2: **An Example of Portrait and Image Created by Using ECG and ABP Snippets**

The next step is to build a *decision function* for classifying which class a newly received image x, obtained from yet unseen ECG and ABP snippet, belongs to. This decision function essentially assigns the label of the image x by comparing which set of PCs (from a class) can reconstruct the image x the best.

To reconstruct an image using PCs obtained from the images of a given class, we first project the image x on the eigenspace as:

$$p = P(x - \bar{c}). \tag{2}$$

We then try to recover the original image from this projection as follows:

$$x' = P^T p + \bar{c} = P^T P(x - \bar{c}) + \bar{c}, \tag{3}$$

where x' is the reconstructed image based on the set of PCs from a class.

As we have two sets of PCs, we obtain two reconstructed images x'_{pos} and x'_{neg}. Then, we compute the *reconstruction error*, by calculating the Euclidean distance between the reconstructed image (using the set of PCs of a given class) and the original one. We represent the reconstruction error as e_{pos} and e_{neg}, which can be calculated as follows:

$$\begin{aligned} e_{pos} &= \left| x'_{pos} - x \right| \\ e_{neg} &= \left| x'_{neg} - x \right| \end{aligned} \tag{4}$$

Finally, based on these two reconstruction errors, we build our *decision function* which outputs the label of this image x as either positive or negative:

$$label(x) = \begin{cases} \text{Positive}, & if \quad e_{pos} - e_{neg} < 0 \\ \text{Negative}, & if \quad e_{pos} - e_{neg} \geq 0 \end{cases} \tag{5}$$

The two sets of PCs and the decision function thus form our image reconstruction-based classifier. This classifier is patient-specific and needs to be generated for each patient individually. Consequently, it is not efficient to use our approach to identify a patient from all the others but rather confirm the identify of a patient.

C. Identity verification Stage

In the ***identity verification stage***, the trained patient-specific classifier will be used to decide whether the newly received snippet of the ECG and ABP measurements belong to a particular patient or not. In this regard, we collect w time-unit of newly measured ECG and ABP signals from the patient, and then create a *test image*. We feed this test image into patient-specific, image construction-based classifier. As we have a classifier for each patient in the system, which classifier we feed our test image to will depend on who we suspect the patient to be. In this regard, we first computes two reconstructed images from this input test image using the two projection matrices and the two means of the column vectors (obtained using the series of images from two classes during the enrollment stage). By comparing the input test image with its two reconstructed images respectively, two reconstruction errors are generated. Based on these two reconstruction errors, our model uses its decision function to decide the label of the test image as either positive or negative. If the test image is deemed to be positive, then we have verified the identity of the patient otherwise not.

V. Parameter Selection

In this section, we illustrate how we select the two most important parameters of our identity verification approach: (1) Δ, the amount of the data needed to train the model (i.e., *training time*), and (2) w, the amount of data needed to be able to make an identity verification decision. We begin with an introduction of the dataset we used, followed by performance metrics used to choose the two parameters. Finally, we discuss the parameter selection process itself.

Dataset: In this work, we collected data belonging to 36 subjects (i.e., patients) from the MIT PhysioBank Fantasia and MGH/MF databases [13]. We chose these particular subjects from these databases because the availability of both ECG and ABP signals for them. Furthermore, the Fantasia database is made up of subjects who exhibit normative ECG and ABP, while the MGH/MF database mainly contains data from subjects with specific cardiac conditions that affect their ECG and ABP signals (such as sinus tachycardia, atrial fibrillation and etc.). Table I shows the statistics on the patient population we used to train and test our ECG plus ABP identification system. We categorized the patients in the dataset into two types based on their ECG signals: (1) *Normative subject type*, which only includes subjects who did not suffer from any ailments that affect their cardiac rhythm; (2) *Non-normative subject type*, which only includes subjects who are suffering from the cardiac diseases and thus may have non-normative ECG and ABP signals. For each of the 36 subjects we had on average about 40 minutes of usable ECG and ABP data for our experiments.

Metrics: In this work, we formulated the problem of identification as an instance of a binary classification task. To evaluate the classification performance, the metrics are based on the notion of false positive rate (FPR), false negative rate (FNR), true positive rate (TPR) and true negative rate (TNR).

TABLE I: **Subject Data Summary**

Type	Total #	Male	Female	Avg. Age (years)	Std. Age (years)
Normative	12	5	7	46.5	24.4
Non-Normative	24	16	8	64.4	18.7

In our case, *TPR* refers to the fraction of the cases in which an unseen ECG and ABP snippet belonging to a particular patient X is identified as such. Similarly, *TNR* refers to the fraction of the cases where an unseen ECG and ABP snippet belonging to other patients, is identified as such. *FPR* refers to the fraction of the cases in which an unseen ECG and ABP snippet belonging to other patients is identified as belonging to patient X. Finally, *FNR* refers to the fraction of the cases in which an unseen ECG and ABP snippet belonging to patient X is identified as belonging to other patients. We usually combine TPR and TNR into an accuracy rate as follows $\frac{1}{2} * (\frac{TPR}{TPR+FPR} + \frac{TNR}{TNR+FNR})$.

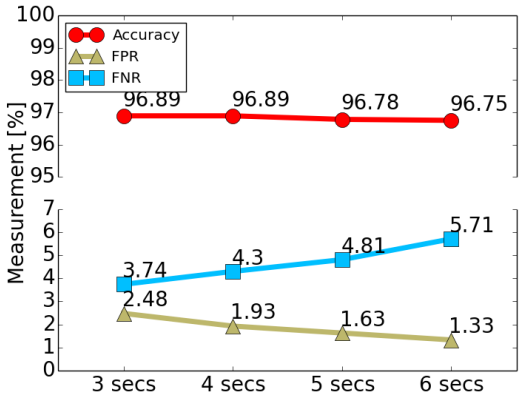


Fig. 3: **Average Accuracy, FPR and FNR for Different** w

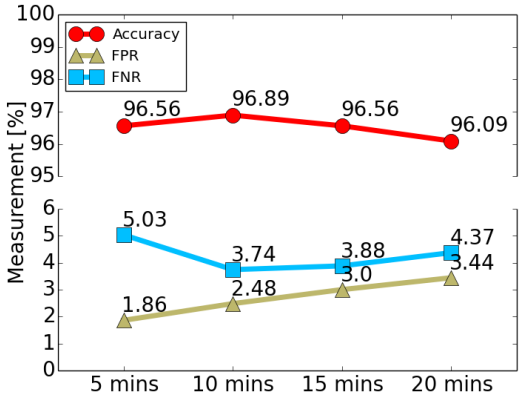


Fig. 4: **Average Accuracy, FPR and FNR for Different** Δ

Selecting Δ **and** w**:** To select w, we tried several window sizes w with a fixed Δ of 10 minutes and evaluated our identity verification approach (i.e., cross-validated the machine learning model). Figure 3 shows the average accuracy rate, FPR and FNR for different window size w. We can see that the average accuracy rates of the patient-specific models for 4 different window size w are all considerably high. We chose window size $w = 3$ seconds, as it provided us with the best performance and responsiveness for our identity verification system. Once the value of w was set to 3 seconds, we tried several Δ sizes and evaluated our identity verification approach. Figure 4 shows the average accuracy rate, FPR and FNR for different values of Δ. Similarly, we can see that the accuracy rate for 4 different training time Δ are all considerably high with only a small deviation. Further, the more data we have the better models we were able to create overall. Therefore, we set $\Delta = 20$ minutes as the training time for our model. Even though our training time is quite large, it needs to be noted that it is a one-time cost. The fact that we have a window size of just 3 seconds means that once the identity verification system is deployed, we can quickly verify the patient's identity. Further, if time is of essence, we can reduce the size of Δ without losing much in accuracy.

VI. Security Analysis

In previous section, we selected the parameter for the identity verification approach and build the patient-specific model at the enrollment phase. In this section, we address the viability of our approach with respect to two cases: (1) correctly identify a patient, and (2) correctly reject a patient. Before delving into details, we introduce two key notations used in this section. We define T_{learn} as a time interval for which we collected ECG and ABP data from a patient to build their patient-specific models. The duration of T_{learn} is same as the training time Δ, i.e., 20 minutes. T_{curr} is the current time interval when we are testing our identification model. *It is to be noted, that the signals in the* T_{curr} *time-interval are new and have never been seen by the patient specific-model in enrollment phase.*

We first tested our identity verification approach to see if it can correctly identify a particular patient. For each of our subject-specific model, we have exactly one acceptable patient. Therefore, we divided his $T_{curr} = 15$ minutes of synchronously measured ECG and ABP signals into 300, 3-second intervals (windows), each of which produced an image. These images were then input into the patient-specific model, which then labeled as positive or negative. Ideally, we should get all positive labels for the images and accept them all, as they are all from the particular patient.

We then tested our model to see if it can correctly reject ECG and ABP snippets from patients other than the one whose model we are evaluating. Therefore, for each trained model, we obtained $T_{curr} = 15$ minutes of synchronously measured ECG and ABP signals from every other patient in our dataset. We randomly select 37, 3-second intervals from every other subject in our dataset (we have a total of 35 such subjects), each of which produced an image. These 35×37 images were then input into the patient-specific model, which then labeled as positive or negative. Ideally, we should get all negative labels.

Overall with a Δ set to 20 minutes and w of 3 seconds, our approach produced an average accuracy of 97.36%, with FPR of 4.49% and FNR of 0.80%. Table II shows how our approach fares in comparison to other approaches that uses both normative and non-normative signals to evaluate their identification approach. We can see that we perform considerably better than these previous efforts. Table III compares our current approach with our previous works [10] that relied on locating characteristic features for identification. We can see that our current approach has a relatively higher identification accuracy for the normative case and a similar identification accuracy for non-normative cases. Most importantly, this performance

TABLE II: **Performance Comparison**

Approach	Accuracy	FPR	Enrollment Time	identification Time
Singh et. al [24]	82%	7%	1/2 record	1/2 record
Arteaga-Falconi et al. [23]	84.93%	1.29%	30 seconds	4 seconds
Our current approach	97.36%	4.49%	20 minutes	3 seconds

TABLE III: **Comparison with Our Previous Work**

	Subject Group	Accuracy	FPR	FNR	Peak Detection Algorithm
Our Previous Work[10]	Normative	98.96%	0.98%	1.09%	Required
	Non-Normative	96.66%	1.31%	5.37%	
Current Approach	Normative	99.66%	0.61%	0.08%	Not Required
	Non-Normative	96.21%	6.43%	1.16%	

is achieved without requiring any characteristic feature (peaks) detection. On the other hand, our previous work [10] relies on the presence of peak detection algorithms or annotation files for locating the characteristics features. In the absence of such annotations or peak detection algorithms, the performance of our previous approach will definitely collapse.

VII. Conclusions

Patient identification is crucial in providing proper care in hospitals or other care-facilities. Existing identification solutions are not always sufficient and patient identification errors are common. In this paper we present a patient identity verification approach that can complement existing patient identification solutions in the event that they cannot be relied upon. Our approach, based on ECG and ABP fusion, achieves over 97% accurate in identifying the user on whom the system is deployed with just 3 seconds. In the future we plan to work on several issues to improve this work. (1) we plan to reduce the amount of time it takes to train the model which is considerable, and (2) we plan to expand our data source to include a larger and even more diverse patient population to provide extensive validation of the idea in this work.

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