Acute Stress Data-Based Fast Biometric System Using Contrastive Learning and Ultra-Short ECG Signal Segments

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ABSTRACT

This paper presents a novel approach of an ECG-based mental health biometric system that relies on ultra-short duration (2 seconds) of one-channel ECG signal segments from acute stress data for accurate user identification and authentication. The proposed method uses a simple framework for contrastive learning (SimCLR) to train the user identification and authentication models. The performance of the proposed ECG-based biometric system was evaluated for a single-session use case using an in-house dataset. The dataset consisted of ECG signals acquired during a study protocol designed to induce physical and mental stress. The proposed biometric system was able to achieve an accuracy of 98% for user identification and an equal error rate (EER) of 0.02 when trained and tested with a balanced condition with stress and baseline/recovery. Our proposed system was able to retain its accuracy to 95% and the EER to 0.05 even when the training size was significantly reduced.

CCS CONCEPTS

• **Computing methodologies → Unsupervised learning**; **Neural networks**.

KEYWORDS

Acute stress; Mental Health; Electrocardiogram (ECG); Contrastive Learning; Biometrics; Identification; Authentication

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1 INTRODUCTION

The integration of advanced wearable devices on the Internet of Things (IoT) has made continuous health monitoring easily accessible and ubiquitous. Enabling real-time monitoring and processing of important physiological signals such as electrocardiogram (ECG), electrodermal activity (EDA) and photoplethysmography (PPG) can enhance personal health monitoring and point-of-care diagnosis of key factors associated with mental health. Our recent work shows the potential of an ECG-based system for real-time acute stress type detection [3]. This method can be used to develop smart stress intervention and management systems which can alleviate mental health related problems. ECG signals also have the potential for use in biometric systems as ECG characteristics are unique to individuals, continuous in nature, and the acquisition does not require active engagement from the user [1].

ECG-based biometric systems have gathered a lot of interest among the research community and it is an active research area [2, 7]. The approaches adopted for ECG-based biometrics in the literature can be broadly classified into (i) fiducial feature-based approach, (ii) non-fiducial feature-based approach, and (iii) hybrid approach [4]. The evaluation protocols usually adopted for ECG biometrics are single-session evaluation and multi-session evaluation. In a single-session setup, data from the same session is used for training and testing, whereas, in a multi-session evaluation, data from separate sessions are used for training and testing. Biometric identification consists of user identification, that is, uniquely identifying a user from other users enrolled in the biometric system, and, user authentication, that is, authenticating the identity of a particular enrolled user. There are plenty of good literature reviews on the existing methods proposed by researchers for biometric identification, and hence, we will not go into details in this paper [2, 8].

Although there is a significant amount of work related to ECG-based biometric systems, there are several key areas of improvement that need to be considered for real-world implementation and acceptance. In this work, we identify and focus on two challenges that can be possible roadblocks to the real-time implementation of ECG-based biometric systems. Firstly, existing methods of creating an ECG template for user identification and authentication requires expert preprocessing of ECG signals such as heartbeat

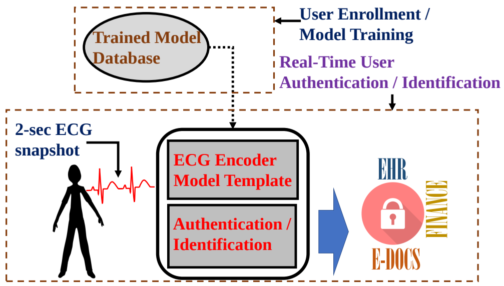

Figure 1: Visualization of the proposed approach for ECG based biometric system for real-time user authentication and identification

segmentation or extracting domain knowledge features [4]. These steps are greatly dependent on the quality of signals and can potentially be computationally expensive, both of which are highly likely in a real-world context. The second challenge is that ECG signals show variation even within a single user because of the changes associated with external mental and physical stimuli, and health conditions [4]. Hence, evaluating the effectiveness of ECG-based biometric systems under different physiological and psychological scenarios is important to increase their acceptability and reliability.

In this work, we propose a novel approach for ECG -based biometric identification and authentication and evaluate its effectiveness under rapidly alternating physical and mental stress scenarios. The proposed approach utilizes a 2-second snapshot of the ECG signal and does not require any preprocessing commonly used in this context and hence is suitable for developing real-time ECG biometric systems (see Fig. 1). The main contributions of our work are as follows:

- We use a novel framework for ECG representation learning in a self-supervised manner. The framework is based on simple framework for contrastive learning (SimCLR).
- We propose a novel method for user authentication and identification using ultra-short (2 seconds) raw ECG segments.
- We evaluate the effectiveness of the proposed approach under different stress scenarios such as baseline, anticipatory stress, physical stress, mental stress, and recovery.
- We evaluate the effectiveness of the proposed method using different sizes of training and testing splits for the single session authentication and identification use case.

2 PROPOSED WORK

The overview of the analyses performed in the proposed work is visualized in Figure 2. The brown dotted box in Figure 2 represents the training of a CNN encoder and the user identification and authentication models. The CNN encoder is used to generate a representation of the 2 sec ECG segments in a self-supervised manner. The training of the CNN encoder and the model architectures are described in detail in our recent research [3]. The representation of the ECG segments in the training set is generated by the trained CNN encoder. Subsequently, the generated representations of the ECG signal are used to train and develop the identification and authentication models. A trained random forest classifier for a multi-class classification purpose is used to develop the identification model while the authentication models are developed by training a random forest classifier for one-vs-rest classification purposes.

The black solid box in Figure 2 represents the testing and performance evaluation of the identification and authentication models with various test splits. The splitting of the testing and training is discussed in section 2.1.

2.1 Data collection and signal processing

Data from 21 healthy young adults were used for this study. The study proposal was evaluated by the Ethics Committee in the Humanities and Social and Behavioural Sciences of the University of Helsinki. The whole study consisted of several tasks including the Maastricht acute stress test (MAST) [6] (Figure 3). The MAST protocol consists of physical stress tasks (cold pressor tasks) and mental stress (mental arithmetics) tasks. These stress tasks vary in duration (45 to 90 sec) with no recovery periods in between. During the cold pressor task, the participants were required to immerse their hands in cold water (temperature of 2°C). During the mental math task, the participants were required to perform verbal subtractions fast and accurately under time pressure. In addition to the MAST protocol, data from baseline, pre-stress, and post-stress phases were also included in the analyses. The pre-stress period is the task anticipation period where the participants are made aware of the upcoming tasks. The post-stress period is the recovery period where the participants are allowed to recover to their normal state without any external stimulus. The duration of the data from baseline, pre-stress, and post-stress periods are 120 sec, 60 sec, and 120 sec, respectively. More details on the experimental protocol and data collection are discussed in our previous work [5].

The ECG signal was acquired at a sampling rate of 1000 Hz using the NeurOne system (Bittium, Oulu, Finland) that employed a single lead ECG sensor between the left collarbone and right lower back. The sampling rate for ECG signal acquisition was high which is not usually the case in consumer-grade ECG sensors. Furthermore, a high sampling rate is not suitable for long-term signal acquisition and monitoring. Hence, we down-sampled the ECG signal to 250 Hz before further analyses. The down-sampled ECG signals were then filtered using a bandpass Butterworth filter in the frequency range of 2-30 Hz. Other than filtering, no other preprocessing is performed on the ECG signal. Subsequently, the ECG signals are segmented into 2-second lengths with an overlap of 1 sec for each stress task type, and the baseline, pre-stress, and post-stress periods (Figure 3). It is to be noted that, no overlapping signal segment was extracted in between the task types to avoid information leakage between the task types. Subsequently, the data from the different task types were split into training and test sets.

Three different splits, split-1, split-2, and split-3 were evaluated. Split-1 is created by selecting the last four alternating physical and mental tasks and the post-stress period (Figure 3). This split denotes a balanced condition with stress and baseline/recovery in both training and testing. The objective of the second split is to assess the performance of the models if they are trained with only one segment of each of the physical and mental stress tasks along with the baseline and pre-stress periods. Hence, in split-2,

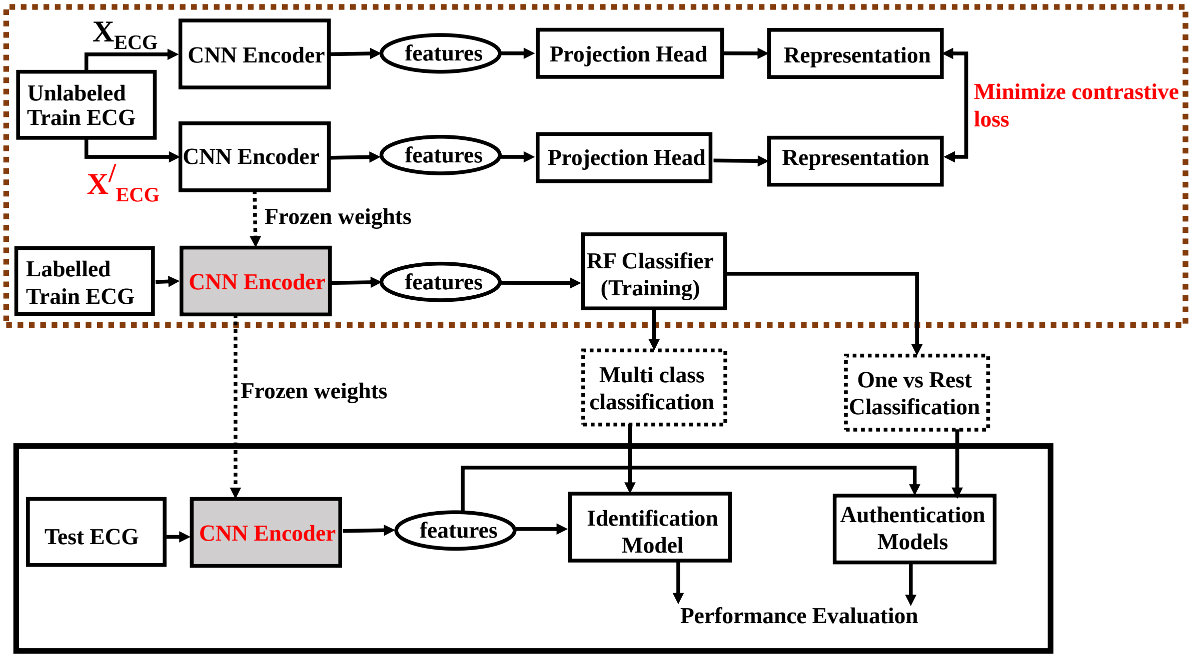

Figure 2: Overview of the proposed work. The brown dotted box represents the SimCLR framework for self-supervised learning of ECG features (upstream task) and the supervised training of the random forest classifier (RF) during the downstream task. The black solid box represents the testing of the identification model and authentication model on different test splits

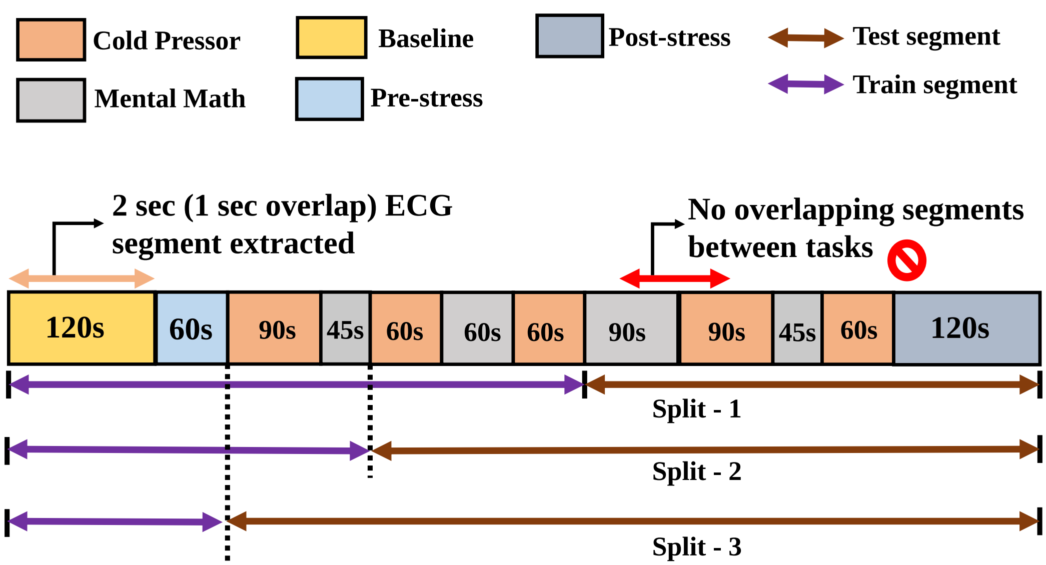

Figure 3: Visualization of the study protocol and the three different splits used for performance evaluation. Pre-stress is the task anticipatory period and post-stress is the post-task recovery period.

the training set consisted of four task types and the remaining 8 task types belonged to the test set (Table 1). Finally, in split-3 no stress task type was included in the training set and hence, the training set consisted of only the baseline and pre-stress period and the remaining task types belonged to the test set (Table 1).

Table 1: Details on the number of tasks and number of 2-sec ECG samples in the training and test set for each splits

	Train		Test	
Splits	No. of Tasks	ECG Samples	No. of Tasks	ECG Samples
Split-1	7	10101	5	8295
Split-2	4	6447	8	11949
Split-3	2	3696	10	14700

2.2 Training and Testing

The number of estimators and the maximum depth of the random forest classifier were 100 and 15 for the user authentication models. Due to the multi-class setting, these were set to 150 and 20 for user identification. For performance evaluation, various classification metrics such as accuracy, f1 score, sensitivity, and specificity were estimated for user identification, and additionally, an equal error rate (EER) was also computed for user authentication models.

3 RESULTS

In this section we present the results on the performance of the user identification and authentication models.

3.1 Performance of user identification model

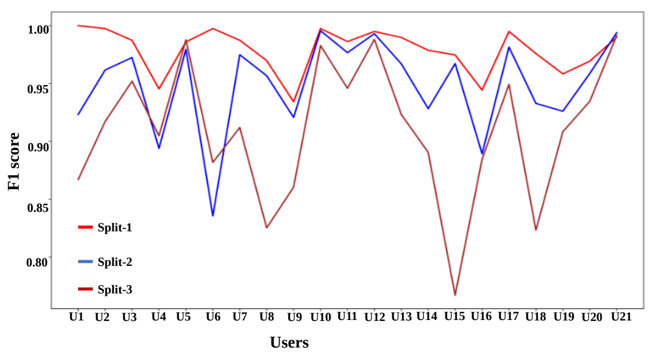

Figure 4: F1 scores for the 21 users for split-1, split-2, and split-3 represented by red, blue, and brown lines respectively of the user identification model.

The multi-class classification accuracy of users for the identification model using split-1, split-2, and split-3 were 98%, 95%, and 91%, respectively. The degradation in performance is not surprising because of the differences in the training and test sizes. However, analyzing the identification performance of individual users leads to interesting observations. The F1 scores of identifying each user for the three splits are shown in Figure 4. The F1 scores of all users were highest for split-1, and split-2 was mostly higher than split-3, apart from users 4, 5, and 6. Even though there was a significant difference between the training and testing set in split-1 and split-2, there is not much difference between the F1-score between the splits for most of the users. However, the difference was more prominent for some users such as U4, U6, U14, and U16. This difference was even higher for some users when tested with split-3 despite several users still retaining similar F1 scores as of split-1 and split-2. The fact that several users still retained similar performance regardless of the splits used can mean that the reason for performance degradation in split-2 and split-3 could also be linked with the reduction/exclusion of stress-type segments from the training splits. If we consider users U7, U8, U9, and U15, we observe that their F1 scores are close to each other for split-1 and split-2. A huge degradation in the F1 score is observed for those users in split-3 even though the difference between the training and testing size of split-1 and split-2 is larger than that between split-2 and split-3. This could mean that so long as at least some stress-type segments are included in the training data, the performance degradation is not as prominent as compared to when there were no stress-type segments in the training split.

3.2 Performance of user authentication models

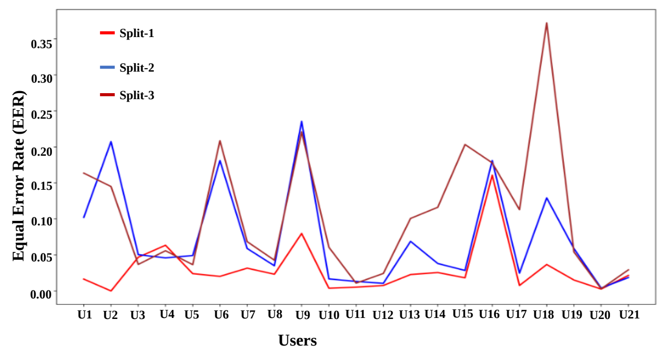

Figure 5: Equal error rate (EER) for the 21 users for split-1, split-2, and split-3 represented by red, blue, and brown lines respectively with the user authentication model.

The equal error rate (EER) of the 21 authentication models trained for the authentication of each of the 21 users is shown in Figure 5. The median EERs for split-1, split-2, and split-3 were 0.02, 0.05, and 0.07. Overall, the trend of user authentication EER across the three splits and between the users is the same as that observed for user identification F1 score. For example, a similar exception is seen between split-2 and split-3, where the EER of split-3 is slightly lower than that of split-2 for users 2, 3, 5, and 9. In general, for most users, the authentication model performed poorly on split-2 and split-3 with EER above 0.05. However, for users 11, 12, and 13, an EER < 0.05 is achieved even with split-2 and split-3. The EER on split-1 is less than 0.05 with the exception of users 4, 9, and 16. The median accuracy was about 99% across all data splits and even achieved an accuracy of 100% in many cases.

We further analyze the sensitivity and specificity analyses of the identification and authentication models for each user using split-1 and split-2 (Table 2). We did not include split-3 in the analyses because of the relatively very poor performance of split-3 compared to split-2 and split-1 especially for some of the users. The performance of the identification model in terms of specificity

Table 2: Performance metrics for identification and authentication models for 21 users and data split 1 and 2

	Identification				Authentication			
	Specificity		Sensitivity		EER (%)		Accuracy (%)	
Users	Split-1	Split-2	Split-1	Split-2	Split-1	Split-2	Split-1	Split-2
U1	1.00	0.99	1.00	0.97	1.64	10.21	99.84	98.98
U2	0.99	0.99	1.00	0.95	0.00	20.73	100	98.02
U3	0.99	0.99	0.98	0.99	4.68	5.03	99.55	99.46
U4	0.99	0.99	0.92	0.97	6.34	4.59	99.36	99.52
U5	0.99	0.99	0.97	0.97	2.40	4.92	99.77	99.53
U6	0.99	0.99	1.00	0.72	2.02	18.10	99.80	98.27
U7	0.99	0.99	0.98	0.98	3.16	5.89	99.70	99.42
U8	0.99	0.99	0.97	0.97	2.32	3.49	99.70	97.74
U9	0.99	0.99	0.91	0.88	7.98	23.55	99.21	97.74
U10	0.99	0.99	1.00	0.99	0.37	1.67	99.96	99.83
U11	0.99	0.99	1.00	0.99	0.52	1.32	99.91	99.86
U12	0.99	0.99	1.00	1.00	0.76	1.05	99.92	99.89
U13	1.00	0.99	0.97	0.95	2.27	6.88	99.78	99.28
U14	0.99	0.99	0.98	0.98	2.55	3.80	99.71	99.42
U15	0.99	0.99	0.97	0.95	1.82	2.84	99.73	99.66
U16	0.99	0.99	0.90	0.81	16.07	18.01	98.46	98.26
U17	0.99	0.99	0.99	0.97	0.75	2.46	99.92	99.74
U18	0.99	0.99	0.97	0.87	3.67	12.91	99.65	98.76
U19	0.99	0.99	0.98	0.95	1.51	5.89	99.85	99.43
U20	0.99	0.99	1.00	0.99	0.25	0.40	99.96	99.86
U21	0.99	0.99	1.00	0.99	2.15	1.85	99.78	99.79

is excellent regardless of the data split used. Even in the case of sensitivity, the performance is excellent for most of the users in split-1. The sensitivity score drops significantly for several users when trained with split-2 instead of split-1. The user authentication models perform well in terms of accuracy for both data splits. In terms of the equal error rate, most of the user authentication models performed exceptionally well on split-1 and several of these models also showed consistent performance in split-2 as well for example users 10, 11, 12, 15,17, 20, and 21.

4 DISCUSSION AND FUTURE WORK

In this work, we have proposed a novel approach for developing a continuous and real-time ECG-based biometric system using only 2 seconds ECG signal segments. Results are promising and they indicate the suitability of the proposed approach for developing reliable ECG-based biometric systems that are not sensitive to the changes in sympathetic activation because of stressful situations. The performance of both the identification and authentication model is competitive for split-1 but the performance degraded as less stressful periods were included in the training. This highlights the fact that the performance of such systems is poorer if the person is stressed, demonstrating the need for stressful data periods also when training such systems. Despite the performance degradation across the test splits, the results were still satisfactory and showcased the potential of the proposed approach, motivating further research.

Although the performance degradation across data splits could simply be the result of fewer training samples, some of the observations when carefully analyzed bring up interesting discussions. For one, the F1 score of some of the users in the person identification model (Figure 4), was very close with little difference between the data splits. Whereas, for other users, the difference was very prominent. One of the reasons behind this observation could be how different users react and adapt to the different stress scenarios which can significantly alter the ECG signal. Hence, further detailed research in this area needs to be done to understand the effect of stress response on the performance of ECG-based biometric systems on both healthy and diseased cohorts.

We observe from Table 2, that the specificity of the user identification model is very high across split-1 and split-2. This indicates the identification model is highly specific to the users and is highly unlikely to identify a stranger as an enrolled user thereby preventing an imposter from getting access. On the flip side, since the sensitivity is low for some of the users and especially in split-2, it also means that the system is more likely to reject an authorized person from getting access. Nevertheless, the sensitivity is very high and since the system relies on an ultra-short 2-sec snapshot of the ECG signal, subsequent authentication attempts can be used to grant access. The ECG signal can be collected continuously and without any active engagement from the user and hence, subsequent attempts for authentication will be carried out unobtrusively thereby more likely to increase user acceptance. Moreover, the results show great potential for suggesting the approach for one-channel ECG measurement devices and systems, for example, to wellness and consumer domain.

One of the limitations of this work is that we have used a relatively low number of users and the evaluation was performed only on a single session dataset. However, the objective of this work was to evaluate the effectiveness of the proposed novel method for an ECG-based biometric system in situations when ECG signals are vulnerable to acute changes such as stress. Hence, the dataset used was found to be suitable for this objective.

In the future, we will extend our work for a deeper analysis of the different stress responses and the respective performance of the biometric system. In this context, it is also important to include multi-session analyses in our future work to understand the daily variations that could add to the differences in ECG signal alongside stress. Furthermore, we will also validate our models for biometric identification and authentication for both normal and physiologically challenging situations in the future.

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