Wearable Emotion Recognition System based on GSR and PPG Signals

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ABSTRACT

In recent years, many methods and systems for automated recognition of human emotional states were proposed. Most of them are trying to recognize emotions based on physiological signals such as galvanic skin response (GSR), electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), photoplethysmogram (PPG), respiration, skin temperature etc. Measuring all these signals is quite impractical for real-life use and in this research, we decided to acquire and analyse only GSR and PPG signals because of its suitability for implementation on a simple wearable device that can collect signals from a person without compromising comfort and privacy. For this purpose, we used the lightweight, small and compact Shimmer3 sensor. We developed complete application with database storage to elicit participant's emotions using pictures from the Geneva affective picture database (GAPED) database. In the post-processing process, we used typical statistical parameters and power spectral density (PSD) as features and support vector machine (SVM) and k-nearest neighbours (KNN) as classifiers. We built single-user and multi-user emotion classification models to compare the results. As expected, we got better average accuracies on a single-user model than on the multi-user model. Our results also show that a single-user based emotion detection model could potentially be used in real-life scenario considering environments conditions.

KEYWORDS

Emotion classification; GSR; PPG; physiological signals; signal processing; affective computing; wearable devices

MMHealth'17, October 23-27, 2017, Mountain View, CA, USA.

ACM ISBN 978-1-4503-5504-9/17/10...$15.00
https://doi.org/10.1145/3132635.3132641

1 INTRODUCTION

People can have difficulties when trying to express their own emotions; the degree of own emotional state can't be measured accurately. Today, one of the most interesting challenges is the recognition of human emotions using commercial sensors. This topic has been extensively researched in the past, but it is still not defined precisely enough to be used commercially. Human emotion recognition system, which has been used commercially in the face recognition system, can be tricked easily, so it can't be used as trustworthy source of information. Emotion recognition system based on sensors can provide a more objective way to measure emotions. It is easy to put a smile on the face and try to express joy. Physiological measures are much harder to conceal, they are more difficult to manipulate than facial gesture or strained voice. Those information sources (and some others), can be used to understand what person feels at the particular moment. This is the reason why in our research we decided to use sensors to detect emotions. Our aim is to develop a universal emotion recognition system, which will be compact, simple to use, and precise enough to produce valid results.

Big challenge in emotion recognition system is the fact that every human being is unique and that different brains will show emotions in different ways. So, the question is if emotion recognition system could be used universally - one system for all people. Maybe there could be a universal system, but it should be trained individually. In our research, we addressed this issue by building a single-user and multi-user emotion classification models to compare the results.

Sensors in emotion recognition systems are used to communicate with person on subconscious level. They receive the feedback from a person about something he feels, sees, hears without person being conscious of it. Earlier researchers showed that galvanic skin response (GSR) and photoplethysmogram (PPG) are the most indicative way to evaluate emotion. Beside GSR and PPG signals another bio-signals such as electrocardiogram (ECG), electroencephalogram (EEG), electromyogram (EMG), respiration, skin temperature etc., have been used into emotion recognition research.

However, we decided to acquire and analyse only GSR and PPG signals because there are suitable wearable devices that can collect signals from a person without compromising comfort and privacy. For acquisition of GSR and PPG signals, only electrodes on two fingers on the non-dominant hand are required. On the other hand, for obtaining EEG signals subject must wear headset or helmet, while for collecting ECG signal subject must put some electrodes on the chest. Our decision to use only GSR and PPG signals, is certainly going to affect precision of predicting emotions. Nevertheless, the results presented in this paper will show we can achieve good prediction accuracies even when using such a compact system.

2 RELATED WORK

Long time ago, psychologist Paul Ekman, a pioneer in the study of emotions, defined six basic emotions: anger, disgust, fear, joy, sadness and surprise [1]. In the meantime, several other researchers adopted lists of basic emotions more or less similar to Ekman's list. Emotion regulation is an important component of the affective computing. This topic was introduced by Rosalind Picard [2]. With J. Healey, she constructed the term "Affective Wearable" describing a wearable system equipped with sensors and tools, that enable recognition of wearer's affective patterns [3]. Affective patterns include expressions of emotion such as a glad smile, an irate gesture, a strained voice or a change in autonomic nervous system (ANS) activity such as heart rate or increasing skin conductivity.

In recent years, research in the field of automated recognition of emotional states has intensified. Most of researchers are trying to recognize emotion using physiological signals. Some of them are using only GSR [4], while others are combining more signals: GSR, BVP, EMG, skin temperature and respiration in [5], BVP, EMG, GSR, skin temperature in [6], and ECG and GSR in [7].

Different researches use measured signals to get different information: emotions were detected in [4, 7, 8, 9], the state of health in [10], activity level in [11], and different information for the analysis of biking performance in [12].

In [8] researchers focused on emotions, and used signals to recognize emotions such as happiness, surprise, disgust, grief, anger and fear. They used video for eliciting emotional state: 6 video segments for 6 emotions. Each video segment lasted about 5 minutes, after which there was video (also about 5 minutes long) for calm recovery. To acquire signal for emotion detection they used only GSR.

In [6] researchers tried recognizing emotional states like sad, dislike, joy, stress, normal, no-idea. Based on this they classified emotional states as positive or negative. They used the international affective picture system (IAPS) images for eliciting emotions. Each image was displayed for 5 seconds. After participants have seen all images, they used a questionnaire to choose the exact emotional state. To detect the emotional state of the participant, researchers used eHealth platform connected to a Raspberry Pi computer.

Researchers in [5] have focused on recognizing 6 emotional states: amusement, contentment, fear, neutral, disgust and sadness. For each emotion, ten images were presented during 50 seconds. IAPS was used as an image source. We used similar method to elicit emotion in our work.

In [13] researchers used EMG and GSR signals as the source of information. Emotion detection was used to address affective gaming by adding real time emotion detection to a game scenario. They used arousal and valence scales. Arousal scale was divided into three groups: normal, high and very high. Valence scale was divided into two groups: positive and negative. In our research, we used similar division. Bayesian network was used for user's emotional state detection. Five emotional states could be detected: fear, frustrated, relaxed, joyful, and excited.

In [14] researchers used EEG, GSR, EMG, BVP, electrooculogram EOG and skin temperature as signals. In this very interesting paper, the most important thing was that researchers created affective databases for the emotion recognition. Their databases included speech, visual, or audio-visual data. Emotional labels included neutral, anxiety, amusement, sadness, joy, disgust, anger, surprise and fear. In our work, we also use database, that includes pictures used to elicit participant's emotion, which are randomly picked and presented. Furthermore, we use database to synchronize the data from participants and from sensor system, by giving timestamps of every phase of data acquisition.

Another research that is related to our work is [15]. It is based on measuring EEG, ECG, GSR and facial activity Since emotions were elicited using multiple means (audio, video) and expressed by humans in number of ways (facial expressions, speech and physiological responses), database was needed to acquire, organize and synchronize all data. Researchers used a multimodal database for implicit personality and affect recognition (ASCERTAIN database) for easier and better understanding of the relation between emotional attributes and personality traits. Multimodality is important part of this paper, thus for us it was a very important work.

3 METHODOLOGY

In our work, we used only GSR and PPG signals as a source of the information since we were looking for a compromise between accuracy and compactness. GSR, skin conductance (SC) or electro-dermal activity (EDA) is one of the most sensitive marker for emotional arousal. It is traditionally measured at the fingers or palms [16]. It modulates the sweat amount from skin pores. GSR is not under human conscious control. Sweating is controlled by sympathetic nervous system which controls, among others, human emotion experience. PPG is a low cost and non-invasive optical technique which is used to estimate the skin blood flow using infrared light [17]. This signal, obtained from a finger or ear-lobe, can be used to estimate heart rate (HR) which may be one of the features in emotion recognition process.

3.1 Signal Acquisition

We used Shimmer3 GSR+ module for collecting bio signals. It is a highly extensible wireless sensor platform for providing sampled GSR signal data in real-time. Shimmer3 has proven as reliable and accurate wearable sensor platform for recording bio-signals which can be used for biomedical research applications [18]. Likewise, the optical pulse sensor attached on GSR+ module can provide a PPG signal from a finger or earlobe. Shimmer3 GSR+ module weights around 20 g - it is small, light and compact. It operates with a 24MHz MSP430 microcontroller. It also contains inertial sensing system via integrated accelerometer, gyroscope, magnetometer and altimeter.

Shimmer3 GSR+ module performs the analog to digital conversion and provides real-time physiological data collection. Data is either streamed via Bluetooth to a host PC, or stored locally on a microSD card.

During measurements, we streamed the live data to workstation PC via Bluetooth and recorded at 400 Hz sampling frequency. Two dry electrodes, attached to velcro strips, were connected on the middle and index fingers. PPG measurements were obtained using optical pulse probe also connected to finger (Fig. 1.). For sensors, we used only non-dominant arm. Data was analysed using Matlab.

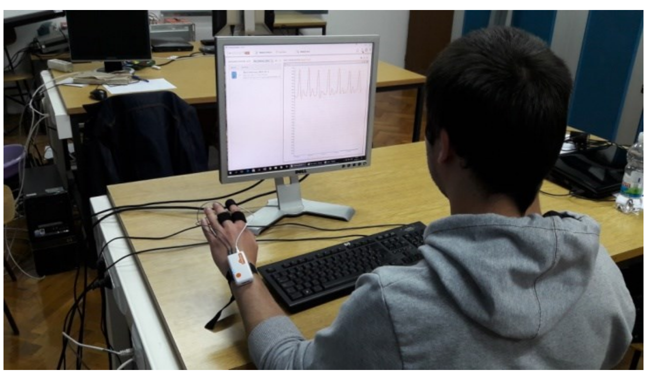

Figure 1: Participant with attached sensors during preparation for the experiment

3.2 Stimulus Material

There are various methods for emotion elicitation, such as self-eliciting, reminding, and using external stimulus such as picture, sound, videos and video games. There exist a lot of databases for emotion elicitation such as IAPS and International Digitized Sound System (IADS). In this research, we chose pictures from GAPED [19]. GAPED is a relatively new and large affective multimedia database with 730 pictures stored in six separate folders (named “A”, “H”, “N”, “P” “Sn” and “Sp”). Each of these folders presents one semantic category: “animal mistreatments”, “human concerns”, “neutral”, “positive”, “snakes” and “spiders”. Each contains over 100 pictures. All pictures from the database were resized and cropped to a 640 x 480-pixel size and each was given a unique name. Rating scales for both valence and arousal are each ranging from 0 to 100 points. Figure 2 shows the ratings in the valence and arousal space for each picture. The four folders (“A”, “H”, “Sp” and “Sn”) are emotionally negative and the others two folders (“N” and “P”) are emotionally positive.

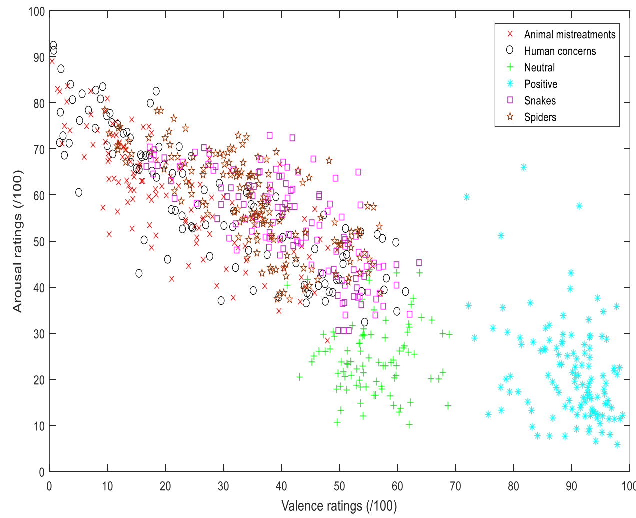

Figure 2: GAPED ratings in the valence/arousal space for each picture

3.3 Experimental setup

We recruited 13 participants for our testing procedure. All of them were students or employees from the Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture in Split, Croatia. Tests were performed with 11 males and 2 female participants (age: M=25.38, SD=5.41) and all of them were right-handed. Experiment procedures were performed in the quiet room without noise and harassment. One PC with one 17'' monitor was used for the experiment. The participants were briefed about the experiment by email and verbally immediately before testing. Furthermore, they performed several training sessions before the production experiment. Participants were also introduced to the meaning of arousal and valence (in the self-assessment procedure), and to the nature of the pictures content. Also, they were informed about approximate duration time of experiment (around 13 minutes) and number of pictures which will be displayed (30 pictures). If the participants agreed to participate in the experiment, they were asked to switch off the mobile phone and to provide the personal information about their age, gender and dominant hand. The sensors were placed on their non-dominant arm.

We developed application and database for logging all participant's actions: preparation time, elicit time, rating time and displayed pictures. All personal information participants entered using the user form and they decided when experiment will be started by pressing "Start test" button. Before the experiment was performed, the experimenter paired Shimmer3 module with PC via Bluetooth and started online streaming and logging of signals on local PC, using Consensys software provided by Shimmer company.

In our experiment, each participant session lasted about 13 minutes, and contained 30 trials. Each trial included a fixation period (white cross on black background) lasting 5 seconds, the picture presentation lasting 6 seconds and rating period lasting 15 seconds (Figure 3.).

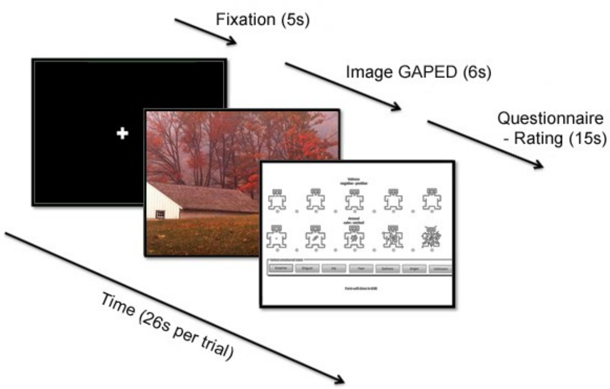

Figure 3: Timeline for each trial. One session contains 30 trials.

In the rating interval, participants were asked to self-assess their emotions using the self-assessment manikins (SAM) to evaluate the valence, the level of perceived arousal [20] and emotional labels (surprise, disgust, joy, fear, sadness, anger and unknown). Arousal scale ranged from calm (1) to excited (9) and valence scale from unpleasant (1) to pleasant (9). The measurement data was stored on PC. Sampled GSR and PPG signals in picture presentation period are presented on Fig. 4 and 5.

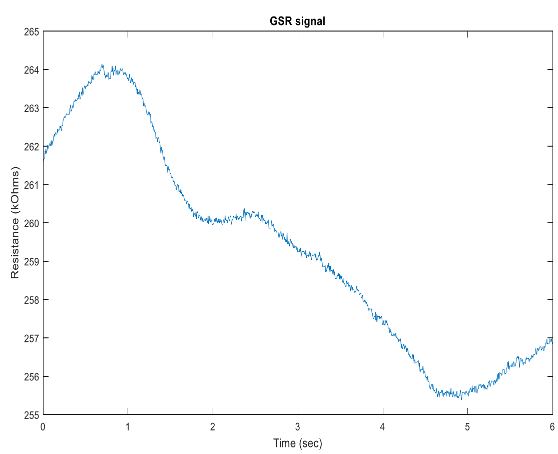

Figure 4: Example of GSR signal for picture presentation period (6 sec.)

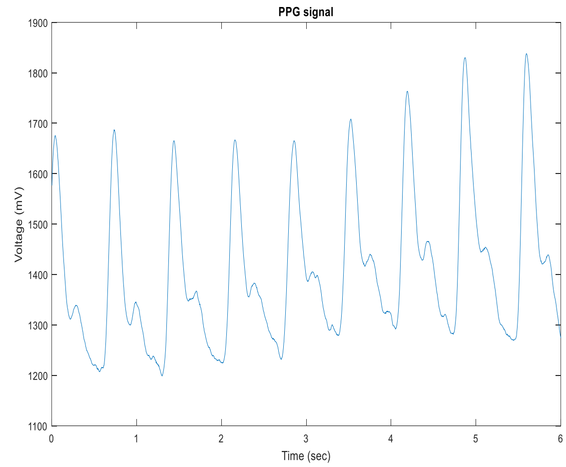

Figure 5: Example of PPG signals for picture presentation period (6 sec.)

For each session, application prepared 5 random pictures, from 6 GAPED folders and then displayed them randomly. After completing the session all subject answers and pictures ID's were stored in database with session identifier and timestamps. Thus, sensors data had to be synchronized with database session logs and post-processed.

3.4 Features Extraction

We extracted statistical features from both time and frequency domains. For the time domain, we used the method of feature extraction from Augsburg University in Germany [21]. This feature set represents a group of the statistical features of GSR signal. Median, mean, standard deviation, minimum, maximum, ratio of minimum and maximum were extracted. After that the signal was processed by the first order difference and same statistical features were extracted again. Finally, signal was processed one more time for second order difference and same statistical features were extracted once more. Overall, we extracted 21 features from the time domain.

We used Welch's power spectral density (PSD) for feature extraction in the frequency domain for GSR signals. Because GSR signal has maximum frequency distribution up to 5 Hz we extracted features in the range 0 - 15 Hz (Fig 6.). Median, mean, standard deviation, maximum, minimum and range were extracted in the frequency domain for GSR signals.

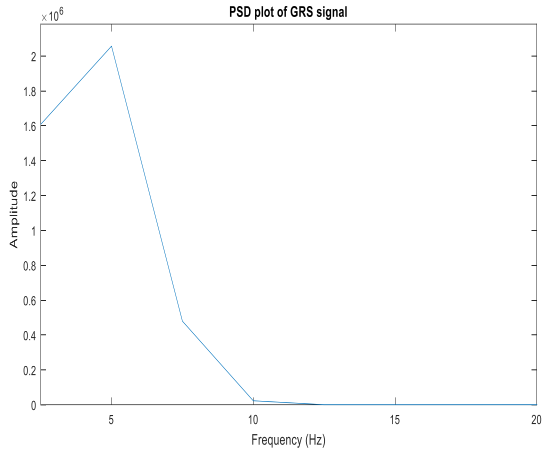

Figure 6: PSD of GSR signal

For PPG signals, we used statistical features from the time domain. Overall, we extracted 21 features from the time domain as well as for a GSR signal. Median, mean, standard deviation, maximum, minimum and range were extracted in the frequency domain for PPG signals. To estimate the heart rate, we transformed the signal to frequency domain using FFT transformation and wrote a Matlab function to calculate the heart rate.

The features were normalized for each trial because of individual differences in GSR and PPG signals of each participant. We normalized features using:

$$X_i' = \frac{X_i - X_{imin}}{X_{imax} - X_{imin}} \quad (1)$$

where X_i is the i-th GSR initial pattern data, X_{imin} is the minimum value of this observed pattern data, X_{imax} is the max value of this observed segment data and X_i' is the sample value after normalized. The normalizations were done for the overall datasets (training and validation dataset) and datasets were balanced.

3.5 Classification

We classified the arousal and the valence which range from 1 to 9 in two classes: low and high (Table 1). Classification was performed using SVM and KNN classifiers, according to participants self-assess rating.

Table 1: The Arousal and Valence classes

Arousal classes	Valence classes	Range
Low arousal	Low valence	1 - 5
High arousal	High valence	>5 - 9

Efficiency of the proposed classifiers has been already proved by other researchers [22,7]. For imbalanced dataset, researchers proposed imbalanced fuzzy SVM (IBFSVM) as classifier [23].

SVM is a supervised machine learning algorithm which creates a set of hyper-planes in an infinite-dimensional space, that can be used for classification. It is a non-probabilistic binary linear classifier. Each data is plotted as a point in n-dimensional space, in which n is number of features with the value of watch feature being the value of a particular coordinate. Classification is performed by finding the hyper-plane which adequately differentiate two classes. SVM can be used for both classification and regression, but is mostly used in classification problems.

KNN is a supervised machine learning algorithm, just like SVM. It is a non-parametric lazy learning algorithm, very simple and easily to learn. Besides, KVM is an example of instance-based learning, where new data are classified based on stored labelled instances. Number k is number of neighbours which influence the classification. KNN is powerful, yet simple algorithm which is successfully used in various areas: commercial advertise system, computer vision, fingerprint detection. As SVN it can be used for both classification and regression.

4 RESULTS AND DISCUSSION

Study [24] showed that the duration of emotions varies from 0.5 to 4 seconds, so we decided to analyse only the first 2 seconds of presentation period for each trial. Therefore, we truncated original signal from the beginning of the elicit time, lasting for 2 seconds, and extracted features from the resulted segment.

We used leave-one-session-out cross-validation and leave-one-subject-out cross-validation for assessing single-user model (only single user data was used for training and testing) and multi-user model, respectively. Both cross-validation methods required training and validating the model N times, where N is the number of sessions or subjects in the initial set.

We divided 13 participants into 2 groups by selecting 10 participants for the multi-user model and 3 participants for the single-user model. Each of 10 subjects from the multi-user group recorded 1 session with 30 trials, while each of 3 subjects from the single-user group recorded 4 sessions per subject. Therefore, we post-processed 300 trials in the multi-user group, and 360 trials in the single-user group. SVM and KNN implementation was done using Matlab.

In the leave-one-session-out cross-validation method applied in the single-user models, one session was set to be the test dataset and the rest of the sessions were used for training and validation. Then the classification model was built for the training dataset and the test dataset was classified using this model to assess accuracy. This process was repeated 3 times using different sessions as test datasets, until all 4 sessions had been used as test datasets. Total accuracy for single-user model is average accuracy of all 3 subjects. Valence and arousal results for the single-user model are tabulated in Table 2.

Table 2: Accuracy (%) for single-user model

	Valence		Arousal	
	SVM	KNN	SVM	KNN
Time-signal features	86,7	86,5	80,6	80,6
PSD features	86,7	86,7	80,6	80,5

For multi-user model, we build new classifiers. Similar, in the leave-one-subject-out cross-validation method applied in the multi-user model, one subject was set to be the test dataset and rest were used for training and validation. Then the classification model was built for the training dataset and the test dataset was classified using this model to assess accuracy. This process was repeated 9 times using different subjects as test datasets, until all 10 sessions had been used as test datasets. Total accuracy for the multi-user model was average accuracy of all 10 subjects. Valence and arousal results for the multi-user model are tabulated in Table 3.

Table 3: Accuracy (%) for multi-user model

	Valence		Arousal	
	SVM	KNN	SVM	KNN
Time-signal features	67	65,7	67,7	68,3
PSD features	66,7	66,7	68,3	70,3

Our results show that multi-user trained models have lower accuracies for both valence and arousal and are not quite suitable for precise detection of human emotional states. On the other hand, single-user trained models achieve much better accuracies and could potentially be used in a real-life scenario where pre-training for a single user is not an issue.

5 CONCLUSIONS

This research was based on gathering of sensor data from human skin, analysing it and concluding which emotion human feels at the particular moment (based on valance-arousal model). The most important point of this research was to find a way to measure and conclude which emotion person feels, but in the way in which subject's privacy and comfort would not be compromised. This is very important for the future use of emotion recognition systems. If this requirement can be fulfilled, such system could be commercially used in various devices. Since the compactness was for us a very important feature we compromised not to use all measurable signals, which reduced the accuracy. During testing, we used only GSR and PPG signals from Shimmer3 device which is a small, light, compact and easily wearable device.

Furthermore, important part of our research was the development of our own application with database, that was used to synchronize data. Application provided random pictures from database for each participant, saved his answers and timestamps so the synchronization between sensors and participants' answers went smoothly. We have designed the application in a flexible and modular manner. Temporal parameters of presentation can be changed using global application parameters, and the application can use any kind of multimedia content to elicit participant's emotions.

In the post-processing process, typical statistic parameters from time-domain signals and PSD were used. KNN and SVM classifiers were built from training data. Emotions were divided into two classes based on valence and arousal values.

Focus of this research was on the comparison of two models: the single-user and the multi-user model. In the multi-user model, goal was to check if it was possible to construct the model which could be used universally. As we expected, the multi-user model was not suitable for precise detection of human emotional states. The single-user model provided better accuracy in detecting human emotional states and could potentially be used in a real-life scenario where pre-training for a single user is not an issue.

In the future work, we will focus our research on developing new features that could lead to better performance in detecting emotions only from GSR and PPG signals in order not to compromise user's comfort. We also plan to do more extensive testing with higher number of subjects and to develop an application for detecting person's emotional state in real time.

ACKNOWLEDGMENTS

This work has been fully supported by the Croatian Science Foundation under the project number UIP-2014-09-3875. The authors would like to thank all participants for the valuable time to be a part of this research, and they would also like to thank GAPED for the affective pictures.

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