PAPER

Low Cost Wearable Sensor for Human Emotion Recognition Using Skin Conductance Response

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SUMMARY Malaysia is one of the countries with the highest car crash fatality rates in Asia. The high implementation cost of in-vehicle driver behavior warning system and autonomous driving remains a significant challenge. Motivated by the large number of simple yet effective inventions that benefitted many developing countries, this study presents the findings of emotion recognition based on skin conductance response using a low-cost wearable sensor. Emotions were evoked by presenting the proposed display stimulus and driving stimulator. Meaningful power spectral density was extracted from the filtered signal. Experimental protocols and frameworks were established to reduce the complexity of the emotion elicitation process. The proof of concept in this work demonstrated the high accuracy of two-class and multiclass emotion classification results. Significant differences of features were identified using statistical analysis. This work is one of the most easy-to-use protocols and frameworks, but has high potential to be used as biomarker in intelligent automobile, which helps prevent accidents and saves lives through its simplicity.

key words: *electrodermal activity, power spectral density, process stimuli, skin conductance response*

1. Introduction

Various studies that include costly programs to change driver attitudes and improve driver behavior were conducted to improve driving safety. Advance driver assistance systems [1], intelligent transport system [2], and in-vehicle driver behaviors warning systems [3] have slowly penetrated in the real-world implementation because of the high cost of installing such systems in public cars.

Vehicle tracking approach, drunk and drugged driving detection, distraction driving, fatigue detection, and emotion detection systems were investigated in previous studies [4] to improve the in-vehicle driver behavior warning system. Emotional detection was investigated in a real-world driving experiment or using an in-lab emotion elicitation process [5]. The changes in psychophysiological signals, such as brain signals and face muscle movements, as well as heart rate variability and cornea–retina size, are commonly reported in human emotion recognitions studies [6]. However, these biological signals frequently required stringent

preparations prior to signal data acquisitions and utilized expensive equipment and bulky instruments, such as voice recorder, cameras, and intrusive sensors.

This work investigated sympathetic responses toward human emotions defined only by using electrodermal activity (EDA). Electrodermal activity signal consists of tonic EDA or skin conductance level (SCL) and phasic EDA or skin conductance response (SCR). The SCR response system triggers contractions by activating the sympathetic system, which is related to emotions [7]. Thus, the SCR signal was chosen as physiological marker to recognizing the emotions. The investigation conducted in this work focused on negative emotions defined in Russell's circumplex model [8]. Negative emotions, such as anger and stress cause distractions that can seriously modulate attention and influence decision-making abilities [9]. Neutral and recovery states were used as an emotion baseline in each individual signal processing stage.

This SCR signal was measured using the Grove sensor constructed from the standalone LM324 quadruple operational amplifier based on the EDA sensor kit. The Grove sensor was selected in this study mainly because of its affordability to many institutions and industries in developing countries. The reliability and effectiveness of the Grove sensor were investigated.

The main difference between this framework and other reported works is that the proposed stimulus protocol efficiently uses digital images, videos, and audiovisual interactions in one session and learns specific features extracted from the EDA biological signal. Furthermore, driving tasks were conducted to investigate the effectiveness of the simulator in classifying two negative emotions. This investigation involved human subjects. The experiment protocol and study were approved by an institutional review board. All consents were obtained from the participants.

This paper is outlined as following, a brief description of the SCR biological signal based on the proposed framework deployed for data collection, signal processing, analysis and performance measurement methods is provided in Sect. 2. Section 3 presents and discuss the experimental, statistical and survey results of this work. Conclusions are drawn in Sect. 4.

2. Methodology

The emotion elicitation and pattern recognition of the

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Fig. 1 Reusable electrodes made of Ag/AgCl placed in cloth bands

Fig. 2 SCR electrode placement

recorded SCR signals are divided into six main stages: (1) subject recruitment; (2) SCR signal acquisition; (3) signal filtering; (4) feature extraction from the filtered signals; (5) emotion classifications; and (6) performance measurement.

2.1 System Design and Stimulus Protocol

This work utilized the Grove sensor to perform the SCR signal data acquisitions. The Grove set from Seeed Studio was constructed with a SCR sensor board and reusable dry electrodes made of silver chloride. Two Arduino Uno ATmega328P microcontroller boards were used to connect the sensor, the MATLAB program, and the external push button.

Two wired dry electrodes were placed on the distal phalanx of the middle and index finger [10] and connected to the first Arduino Uno microcontroller. The finger sites were wiped with alcohol swab before recording to remove any remaining impedance on the skin surface. Figure 1 and Fig. 2 show the selected dry electrode and the placement of the electrodes.

The transmission wires connected to the computer running the MATLAB program were used as a recording tool. The Arduino Uno microcontroller performed the data packaging and serial data transmission from the electrodes to the MATLAB recording program. The program converted the recorded signals from analog to digital form. The digital integer data formed a line of packages in every second with a sampling rate set at 240 Hz. The frequency sampling 240 Hz was chosen as it more than twice as fast as the highest frequency component that we want to maintain after sampling. Notably, the frequency range of the SCR signal is 0.5 to 2 Hz [1], [11].

The second Arduino Uno microcontroller transmitted the trigger condition, which was executed using the push button. This trigger condition was also used as an event marker for signal segmentation in the signal processing

Fig. 3 Grove system architecture

stage. A window popped up when the push button was used to initiate and to terminate the signal recording process. Figure 3 summarizes the Grove system design employed in this work.

The simulation and experiment involved two stages; Phase 1 was developed using the in-lab emotions elicitation process; Phase 2 was conducted to examine the SCR signal using a driving simulator unit. The sessions of these phases were scheduled at different time slots. The main goal of these experiments was to determine the robustness of the SCR signal recorded by using the Grove unit in both phases. The efficiency of the selected stimulus methods for emotion recognition was also examined.

2.1.1 Phase 1

A stimulus set was carefully designed in Phase 1. The proposed display stimulus were designed to sufficiently adapt to the SCR changes when the emotions were evoked or neutralized. The proposed stimulus, which consisted of a digital image display, a video clip, and an audiovisual clip edited using the FlashIntegro video editor, was used to evoke emotions. Previous work reported that anger and happy emotions were video dominant compared with audio tracks [12].

In this work, video and audiovisual stimuli were included to investigate its efficacy in eliciting human emotions. The used of dynamic stimulus such as video clips had demonstrated specific emotions and effective features captured [13] and induced stronger positive and negative effects than the music clips [14]. Video and audiovisual contents of this work were kept as is to avoid a disappointing end of the events viewed by the participants. The different time range of stimulus was also implemented in electromyogram (EMG) study [15], electrocardiogram (ECG) and SCR research works [16].

Images were also used in the stimulus database because this method is globally accepted in the research on eliciting emotions [17]. Previous study and from our preliminary tests showed that 25 seconds of cooling period in between the stimuli episodes was sufficiently neutralized the evoked emotions and recovered the participant's physiological signal to allow for the subsequent stimuli tests [18].

The happy stimulus was arranged at the beginning of

Time in seconds	180	40	70	314	40	95	129	180
Emotion Stimulus	NEUTRAL Digital images Soothing music	HAPPY 8 Digital images	HAPPY 1 Video clip	HAPPY 1 Video audio	ANGER 8 Digital images	ANGER 1 Video clip	ANGER 1 Video audio	RECOVERY Eyes closed
Cooling period (25 seconds)								Break (5 minutes)

Fig. 4 Proposed display stimuli

Fig. 5 In-lab experiment setup

the elicitation process and followed by the negative emotion [19]. Neutral and recovery sessions were utilized as control. In the proposed stimulus, the images for the neutral segment were carefully chosen to ensure that only nice scenery was selected [20]. In the recovery segment, the participants were instructed to relax with their eyes closed. Five minutes break before recovery session was found sufficient for participant's body to adequately recover from the given scenario. Figure 4 shows the stimulus of Phase 1.

A self-assessment online survey was conducted after the session. This survey was used to verify the efficacy of the developed stimulus in eliciting the emotional state that the participant experienced during the experiment. The session took 45 min, including briefing, filling up of the forms, experiment setup, and signal data acquisitions.

A total of 25 participants volunteered for this experiment. Figure 5 shows the in-lab experiment setup. At least 10 min was allocated for the subjects to completely rest and sit in position before the Grove sensor and electrodes were placed on their fingers. Prior to the stimulus, breathing tests were randomly conducted during the signal calibration period and instant change was observed in the recorded signal.

2.1.2 Phase 2

In Phase 2, a Logitech G25 steering wheel kit was used. The driving simulation was developed using the Speed Dreams software. The simulator consisted of casual driving with side track (80 km/hour) [21], a snowy and narrow tracks with poor vision to stimulate stress driving, and included time constraint, tailgating, reckless driving and overtaking to elicit the anger emotions [21]. Figure 6 shows the block diagram of the Phase 2 driving simulator unit.

The driving simulation session was developed to evoke the anger and stress emotions. Neutral (control) and recovery sessions were used to define the emotion baseline of all subjects. The proposed driving stimuli is shown in Fig. 7. Prior to the simulation, each subject was given 3 minutes

Fig. 6 Driving simulator unit

Time in seconds	60 - 150	120	300	120
Driving simulator	Signal calibrations	Control session	Driving simulation session	Recovery session
	Push-button 1st marker	Push-button 2nd marker	Push-button 3rd marker	Push-button 4th marker
				Push-button 5th marker

Fig. 7 Proposed driving stimuli

to familiarize themselves with the driving unit. The participants were instructed to close their eyes and rest their palms during the recovery session. The experiment took 50 min, including briefing, filling up of the forms, experiment setup and signal data acquisitions.

2.2 Subjects

A total of 25 subjects aged between 21 and 39 (mean = 23.92, SD = 4.51) were participated in Phase 1, whereas 20 subjects aged between 19 and 30 (mean = 22.83, SD = 2.54) participated in Phase 2. All participants were of Malaysian origin with a Malaysian driving license and have a real-world driving experience. The background of the experiment, experimental guidelines, potential harm, and contact information of supervisory committees were explained to the participants. The subjects were free to terminate the session if they experienced any uneasy feeling during the experiment. Emolument was granted to the subjects for their participation in both experiments.

2.3 Signal Processing

MATLAB version 2013b was used as the processing tool. Notably, the frequency range of the SCR signal is 0.5 to 2 Hz and the SCR signal components were confirmed with power spectrum analysis using fast Fourier transform (FFT). The raw SCR signal was filtered using a bandpass filter, which consists of low-pass filter cutoff frequency = 2 Hz and high-pass filter cutoff frequency = 0.5 Hz.

Typically, meaningful SCR features were extracted from its characteristics including latency value as well as rise and fall times [22]. However, power spectral density (PSD) has been successfully adopted in electroencephalography (EEG) research work to extract the informative features of the raw signal [23]. In this work the changes in SCR signal using PSD were investigated.

High performance two-class and multiclass support

vector machine (SVM) classifiers were reported can efficiently eliminate data overtraining in emotion recognition [24]. Various studies employing psychophysiological signals which investigated emotion, affective states and cognitive workload had reported that SVM was insensitive to dimensionality issues and often produced high classification accuracy [25]. In this study, the SVM classifier with cross-validation technique adopted to evaluate emotion recognition performance.

2.4 Statistical Analysis

The statistical study was performed to determine (1) the most effective stimulus in each phase and (2) the most significant difference in the PSD mean value of the investigated emotions. Whether the recorded data met the assumption of independence was examined using analysis of variance or ANOVA (data collection was performed through random sampling). The dependent variables were identified in continuous scale, and they satisfied the scale of measurement assumption. The log (10) transformed approach [26] was employed to achieve less skew data set and distributed normally.

In this work, a stringent test, that is, repeated-measures ANOVA was used to compare the mean value of the affective stimuli between all emotional states (i.e., happy, anger, stress, neutral, and recovery) in both phases. Two post hoc tests using the Bonferroni correction and least significant difference at 0.05 level of significance were conducted to obtain specific information on which the means significantly differed from each other.

A post-experiment survey was also conducted after the session to assess the actual affective state of the subject during the process stimuli.

3. Results and Discussion

3.1 Experimental Results

The generalized Equiripple finite impulse response method was used in the signal filtering stage as the SCR frequency components are relatively small compared with the acquisition frequency (240 Hz). The filter was modeled using a minimum filter order with density factor of 20 and a linear phase and consisting of $A_{stop1} = 75$ dB, $A_{pass} = 0.1$ dB, and $A_{stop2} = 75$ dB. This filter can sufficiently eliminate the noise component of the SCL at a very low frequency of 0.01 Hz, power line interference at 50 Hz, movement noises at 100 Hz, and undesired frequencies other than the SCR frequency components.

Figure 8 shows the noisy raw and filtered SCR signal collected from a user responded to the 1018 seconds of process stimuli as depicted in Fig. 4. Signal spikes can be observed visually in the filtered signal. The amplitude fluctuations of the SCR signal interpret the detected presence of emotions caused by the stimulus events. Conversely, the filtered signal of the recovery session is persistently stable,

Fig. 8 Plot of SCR signal reactions to the emotional stimuli

Fig. 9 Plot of SCR signal during recovery session

as shown in Fig. 9, which reveals that the lack of emotion in reacting to an event caused only minimum physiological response on the skin surface.

The filtered SCR signal was segmented according to the stimulus events as depicted in Fig. 4 and transformed using the short-time-Fourier-transform (STFT) technique. In the STFT, the processed data were segmented into window or frames. Each frame has been Fourier transformed and the backend results hold the information of each point's magnitude and phase in time-frequency manner.

In this work, a non-overlapping windowing approach was utilized to analyze each dataset [27]. The window size was set at 960 with no window overlap, and the FFT length (nfft) set at 1,024 with sampling rate of 240 Hz to perform STFT. The algorithm specifies the number of these frequency points that used to calculate the discrete Fourier transforms. The program returned the information of spectrum, frequency, time, and PSD values. The statistical data that include the mean, standard deviation, variance, and median of each image, video and audio-visual stimuli segment were calculated from the PSD output data for the emotion classification and statistical analysis.

The spectrogram was used to visualize a precise time of the continuous stimulus at which the SCR signal frequency components changed between 0.5 Hz to 2 Hz. A 0.25 Hz frequency step was used for better viewing purposes. Figures 10 to 13 show the plots of the SCR power spectrum occurred during image display stimulus, which was obtained from one of the subjects. The PSD mean value (Watt/Hz) versus time-frequency was used to show the SCR changes

Fig. 10 Power spectrum of anger evoked by image stimulus

Fig. 11 Power spectrum of happy evoked by image stimulus

Fig. 12 Power spectrum of neutral stimulus

Fig. 13 Power spectrum of recovery session

measured at the event of happy, anger, neutral and resting (recovery).

The power spectral density (PSD) of elicited emotions (anger and happy) were shown higher density with reference to the spectrogram colour intensity bar compared with neutral and recovery states. Low PSD density was changed from recovery (blue dominates) to higher PSD density detected during anger emotional state (yellow dominates). We can deduce that the level of PSD density affected by an excessive sweat glance activities detected by the measurement sensor placed on the skin surface when the emotions evoked by the respective stimulus.

Two class SVM and multiclass SVM were employed to confirm whether the protocol, methods, and SCR signal can successfully recognize the investigated emotions. SVM

Table 1 Two-class SVM classification accuracy

	Stimuli	Emotions	Accuracy (%)
Phase 1	Image-Video-Video audio	Happy-Anger	56.67
		Happy-Neutral	66.67
		Happy-Recovery	70.00
		Anger-Neutral	80.00
		Anger-Recovery	66.67
		Anger-Recovery	83.33
	Video	Happy-Anger	70.83
		Happy-Neutral	79.17
		Happy-Recovery	66.67
		Anger-Neutral	75.00
		Anger-Recovery	60.00
		Anger-Recovery	60.00
Phase 2	Driving simulator	Happy-Anger	75.00
		Happy-Neutral	79.17
		Happy-Recovery	79.17
		Anger-Neutral	80.00
		Anger-Recovery	83.33
		Anger-Stress	65.00
		Anger-Neutral	100
		Stress-Neutral	100

Table 2 Multiclass SVM classification accuracy

	Stimuli	Emotions	Accuracy (%)
Phase 1	Image	Happy-Anger-Neutral	40.00
		Happy-Anger-Recovery	46.67
	Video	Happy-Anger-Neutral	30.56
		Happy-Anger-Recovery	44.44
	Video audio	Happy-Anger-Neutral	40.00
		Happy-Anger-Recovery	53.33
Phase 2	Driving simulator	Anger-Stress-Neutral	76.67

was utilized as it allows the researcher to generate non-linear classifiers through the non-linear mapping of input patterns (features) into a high dimension feature space [28]. Hence, the SVM hyperplanes can optimize the separation margin of both separable and non-separable class efficiently using its modelling options such as radial basis function (RBF) of kernel function (k).

The PSD statistical value of each participant obtained in each of the emotion stimulus and driving tasks was utilized. These feature attributes were compiled according to the sample size (N) and investigated emotions.

In this work, the SVM classifier model involved a routine to choose the best hyperplane based on the tested radial basis function (rbf_sigma) and constraint (boxconstraint). Both values ranged from -5 to 5 in the classification algorithm, and the optimum values of rbf_sigma and box constraint that obtained the best hyperplane were utilized in the classification. The training (learning) and testing samples of this work were split 50/50. The 2-fold, 5-fold, and 10-fold cross-validation techniques were employed to obtain the optimal kernel constraint and to separate the training samples into k -folds for cross-validation purposes. The SVM classifier with 10 k -fold cross-validation of this work contributed the highest classification accuracy compared with the other number of folds. Finally, the average of these SVM cross-validation accuracies was then computed.

Tables 1 and 2 summarized the accuracy of the emotion classification results in the two-class and multiclass SVM.

In Phase 1, the SVM classifier had successfully classified the studied emotions which elicited using image, video clip and audio-visual stimuli method. Table 1 shows the audio-visual process stimulus obtained 75% to 83.33% clas-

sification accuracy in the two-class SVM emotion classification results which higher than the image and video stimulus. The audio-visual stimulus of this work has proved both efficacious and induced stronger positive and negative effects in emotion elicitation [13], [14].

Only 56.67% accuracy was obtained in the happy-anger classification using these four features assembled from digital image, video and audio visual display stimuli. This result indicates that more features fed into the classifier were unnecessarily increase the classification accuracy. Thus, feature selection and reduction were crucial at this stage. Table 2 shows the lower accuracy of the three-class SVM than that of the two-class SVM. This finding can be explained by the single continuous kernel function that generated for the three-class SVM classifier. This kernel function bypassed all of the three examined classes that reduced accuracy.

In Phase 2, the SVM classifier with 10-fold cross validation had acquired the highest classification accuracy because the optimal kernel constraint was obtained and utilized for emotion classification. The classifier successfully differentiated the neutral-stress and neutral-anger emotion groups with 100% accuracy. However, only 65% accuracy was obtained for the differentiation of the stress-anger emotion group during the simulated driving task because similar physiological responses occurred during these emotions [29].

Similarly, the stress-anger emotional state classification accuracy in Phase 2 was not as high (i.e., 65%) as the happy-anger emotional state classification accuracy in Phase 1 (i.e., 66.67% to 75%). Furthermore, 76.67% accuracy was attained in Phase 2 when multiclass SVM was employed at 10-fold cross-validation. Thus, emotion classification exhibits one of the most promising performances in the areas of study that consider EDA.

3.2 Statistical Analysis Results

The PSD mean values of the segmented SCR signals in the display and driving stimuli were compiled. The affective and emotion stimuli, as well as driving stimuli of anger, happy, stress, and neutral states were investigated using repeated-measures ANOVA. The descriptive statistics for the assumption of normality using the computed PSD mean value of the participants showed that all of the skewness and kurtosis values were in the range of -1 and 1 . The Greenhouse-Geisser correction was obtained (i.e., $\epsilon > 0.75$). The tests of normality using Lilliefors significance correction showed that the Kolmogorov-Smirnov and Shapiro-Wilk test values were > 0.05 . The data set value were normally distributed using log-10 data transformation approach. The data of six subjects from Phase 1 and one subject from Phase 2 have been eliminated from the analysis to fit the assumptions of an ANOVA.

In Phase 1, the within-subject effects tests showed an overall significant difference between the means of the different investigated emotion stimuli. In the audio visual

test, the repeated-measures ANOVA with the Greenhouse-Geisser correction revealed that the PSD mean value indicated statistically significant differences among the happy, anger, neutral, and recovery states ($F(2.506, 45.109) = 3.524$, $p < 0.0005$).

The overall ANOVA results of the image and video stimuli were insignificant. Thus, the pairwise comparison tables were not further examined for Phase 1. Post hoc tests using the Bonferroni correction showed an increase in the PSD value in the happy emotional state (i.e., -2.251 ± 0.92384 W/Hz) compared with that in the recovery state (i.e., -2.802 ± 0.62080 W/Hz), which was statistically significant ($p = 0.19$). An increment in the SCR PSD value was also observed in the anger emotional state (i.e., -2.248 ± 0.92384 W/Hz) compared with that in the recovery state (i.e., -2.802 ± 0.62080 W/Hz), which was also statistically significantly different from the recovery state ($p = 0.16$).

The recovery session showed the lowest mean, indicating that recovery has the least instantaneous increase in signal amplitude detected because of minimal skin conductivity and quantity of sweat expelled. This finding illustrates that recovery befits control more compared with neutral stimulus.

In Phase 2, the mean values of stress, anger, and neutral driving tasks were not equal ($F(1.14, 39.9) = 181.54$, $p < 0.05$). Post hoc tests using the Bonferroni correction showed an increase in the PSD value in the stress driving task from the neutral driving task (i.e., -1.3673 ± 2.45176 W/Hz increased to 6.3387 ± 1.15299 W/Hz), which was statistically significant ($p = 4.0257E-10$). An increment in the SCR PSD value was also obtained in the anger driving task from the neutral driving task (i.e., -1.3673 ± 2.45176 W/Hz increased to 6.7510 ± 0.73585 W/Hz), which was also statistically significantly different from the neutral state ($p = 6.0636E-11$).

Thus, stress and anger emotion elicitation using the driving simulator in Phase 2 obtained a statistically significant increment in the SCR signal PSD level, but was relatively uncertain using the image, video, or audio visual stimulus.

Moreover, the audio visual stimulus was statistically more efficient in happy, anger, neutral, and recovery emotion elicitation compared with the digital image and video stimuli in Phase 1.

However, the mean value of the stress-anger emotion group was insignificant ($p > 0.05$) in the Phase 1 and Phase 2 experiments.

3.3 Survey Analysis Results

An online survey was conducted after the experiment in Phase 1. All twenty-five subjects voluntarily participated in the survey. The respondents were giving feedback of their feelings that occurred when the subjects watched the display stimuli. The questions evaluated the efficacy of the display stimuli used to evoke the emotions. Each question has a scale weight of 0 for least felt to 10 for most felt for each

stimulus they saw. The perfect score from all respondents was 250. Each unmatched answers that not tally with the examined stimulus were excluded and not account in the total score.

Audiovisual stimulus was reported the most efficient display stimuli to evoke both anger emotion with the score of 241. In all segments, the stimulus used to elicit the anger emotional state obtained higher score (image = 217, video = 213, audiovisual = 241) compared with the stimulus used to evoke happy emotions (image = 209, video = 186, audiovisual = 213).

This finding showed that the proposed stimulus materials used in this work was sufficient to evoke the investigated emotions and had obtained high efficacy score. The neutral stimulus material utilized this work was rated as happy by a small group of participants (62%). The result obtained from this survey was tallied along with the findings presented in Sects. 3.1 and 3.2, where recovery was found to be more efficient used as the emotion baseline compared with the neutral states.

4. Conclusion

This work aimed to recognize SCR patterns of the investigated emotions measured using the proposed Grove sensor. This purpose was achieved using the proposed emotion elicitation process that consists of the digital image, video, and audio visual clip stimuli in Phase 1 and the driving simulator in Phase 2.

The main findings of this work indicate that the Grove sensor with dry electrodes sufficiently recorded the SCR signal. In addition, the PSD features successfully recognized the SCR signal patterns of the happy, anger, stress, neutral, and recovery emotional states. Moreover, the two-class SVM classifications modelled in this work and the statistical analysis of the audio visual stimulus utilized in Phase 1 effectively evoked the investigated emotions compared with the digital image and video clip stimuli. Furthermore, the driving simulator successfully elicited the stress and anger emotional states and obtained high classification accuracies.

The results of the statistical analysis and SVM classification indicate that the reliability of this framework has a high potential for emotion monitoring of real-world automotive vehicles to prevent road crashes. More importantly, this work used an affordable sensor and an effective experimental protocol that exhibited promising results, which will benefit other studies in the future.

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