Physiology-based Affect Recognition During Driving in Virtual Environment for Autism Intervention

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Abstract: Independent driving is believed to be an important factor of quality of life for individual with autism spectrum disorder (ASD). In recent years, several computer technologies, particularly Virtual Reality (VR), have been explored to improve driving skills in this population. In this work a VR-based driving environment was developed for skill training for teenagers with ASD. Eight channels of physiological signals were recorded in real time for affect recognition during driving. A large set of physiological features were investigated to determine their correlation with four categories of affective states: engagement, enjoyment, frustration and boredom, of teenagers with ASD. In order to have reliable reference points to link the physiological data with the affective states, the subjective reports from a therapist were recorded and analyzed. Six well-known classifiers were used to develop physiology-based affect recognition models, which yielded reliable predictions. These models could potentially be used in future physiology-based adaptive driving skill training system such that the system could adapt based on individual affective states.

1 INTRODUCTION

Autism spectrum disorder (ASD) has a prevalence rate as high as 1 in 68 children in U.S. (CDC 2014). While at present there is no single accepted intervention, treatment, or known cure for ASD, there is growing consensus that intensive behavior and educational intervention programs can significantly improve long-term outcomes for individuals and their families (Rogers 1998; Cohen, Amerine-Dickens et al. 2006). However, many current intervention approaches show limited improvements in functional adaptive skills because traditional skill-based methodologies often failed to systematically match intervention strategies to specific underlying processing deficits associated with targeted skills. Additionally, such intervention approaches may have difficulties creating opportunities for addressing such skills and deficits within and across naturalistic settings in appropriately intensive dosages (Goodwin 2008). In this regard, technological intervention paradigms, including Virtual Reality (VR) platforms, have been suggested as potentially powerful tools for addressing these limits of current intervention paradigms. Moreover, given the limited availability of professionals trained in autism intervention, it is likely that emerging technology will play an important role in providing more accessible and individualized adaptive intervention in the future (Standen and Brown 2005; Tartaro and Cassell 2007; Lahiri, Bekele et al. 2013).

VR-based intervention could be utilized to help children with ASD generalize learned skill to the real world not only by providing more control over how the basic skills are taught, but also the ability to systematically employ and reinforce these skills within many different, controllable, realistic interaction environments. In addition, the virtual world can be designed to break down, repeat, add and subtract aspects of the environment in any manner necessary to achieve a task goal. While VR-based ASD intervention has become an active research field in recent years, more in-depth studies

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are required to explore how skills learned in virtual environment are translated into real-world situations.

Historically, VR environments applied to assistive intervention for children with ASD were designed to develop skills based on performance only (e.g., correct or incorrect and some other performance metrics). However, current research focuses the development of VR and other technologies that respond not only to explicit human-computer interactions (e.g., keyboard, mouse, joystick, etc.), but also to implicit interactions like eye gaze and physiological signals (Wilms, Schilbach et al. 2010; Bekele, Lahiri et al. 2013; Lahiri, Bekele et al. 2013). Such methods may offer potential to individualize applications. Ultimately, VR systems that not only assess performance in specific task but also measure eye gaze or physiological markers of engagement may lead to optimization of learning (Welch, Lahiri et al. 2009; Lahiri, Bekele et al. 2013).

The main objective of this paper is to explore the reliability of using physiological signals to detect affective states in a VR-based driving simulation environment. The results show that physiological signals can be used as a reliable way to detect participants' affective states in a driving task and these affective states together with performance could potentially be used to alter VR interactions.

While there exists a body of literature that discusses interventions for individuals with ASD to develop social skills, language development and emotion recognition (Sundberg and Partington 1998; Bauminger 2002; Golan, Ashwin et al. 2010), only a few studies have addressed how to improve driving skills of ASD population. Cox and his colleagues' study (Cox, Reeve et al. 2012) reported parents' experiences about driving of young adults with ASD and provided suggestions to teach driving skills for ASD teenagers. Huang et al. (Huang, Kao et al. 2012) also addressed the factors associated with driving in teenagers with ASD. Reimer and his colleagues (Reimer, Fried et al. 2013) explored the differences between an ASD group and a control group in terms of physiology. However, only standard statistical techniques were used in this study instead of detecting affective states by using physiological signals. Our previous study (Wade, Bian et al. 2014) explored the differences between these two groups in a more comprehensive way. These studies provide us with useful information to design the driving system and are the foundation of the proposed work. As far as we know, there is no work on physiology-based affect detection in driving skill training system for the ASD population.

This paper is organized as follows. In Section II, we provide a brief background on VR-based driving task - the overall system description and how physiology is used to measure the affective states of the participants. This section is followed by a description of the driving task. In Section IV, we focus on the physiology-based affect detection system description and results of physiological data analysis. The implication of our results and future work are discussed in the last section.

2 SYSTEM DESCRIPTION

The Virtual Reality (VR) based driving system contained a VR module and three subsystems, which were a peripheral physiological data acquisition module, an EEG data acquisition module and an eye tracker module (Fig. 1).

The virtual environment was developed via the Unity game engine (www.unity3d.com). Within Unity, we developed a graphical user interface, created behavior for vehicles, pedestrians and traffic lights, designed the driving scenario and embedded traffic rules. Participants interacted with the driving environment by operating a Logitech G27 driving controller that was mounted on a playseat (Fig. 2). The VR system was modeled as a video game with three difficulty levels: easy, medium and hard. Each level contained three assignments. Each assignment had eight trials which were designed in order to improve specific driving skill such as turning, speed-maintenance, merging and following traffic laws. Physiological data, EEG data and eye gaze data were recorded continuously from the beginning of the experiment to the end. A therapist rated the participant's affective states via a custom-designed online rating program. More details of VR module could be found in our previous papers (Bian, Wade et al. 2013; Wade, Bian et al. 2014).

In this work, we only focused on the physiology-based affect recognition during driving in VR. Four categories of affective states, engagement, enjoyment, frustration, boredom, were chosen because of their importance in driving (Baker, D'Mello et al. 2010) as well as their detectability using peripheral physiological signals (Bradley and Lang 2000; Sarkar 2002; Rani, Sarkar et al. 2003; Liu, Rani et al. 2006; Welch, Lahiri et al. 2009). As can be seen from the framework of our study (Fig. 1), establishing an affect recognition model could lead to the development of an adaptive closed-loop driving skill training system.

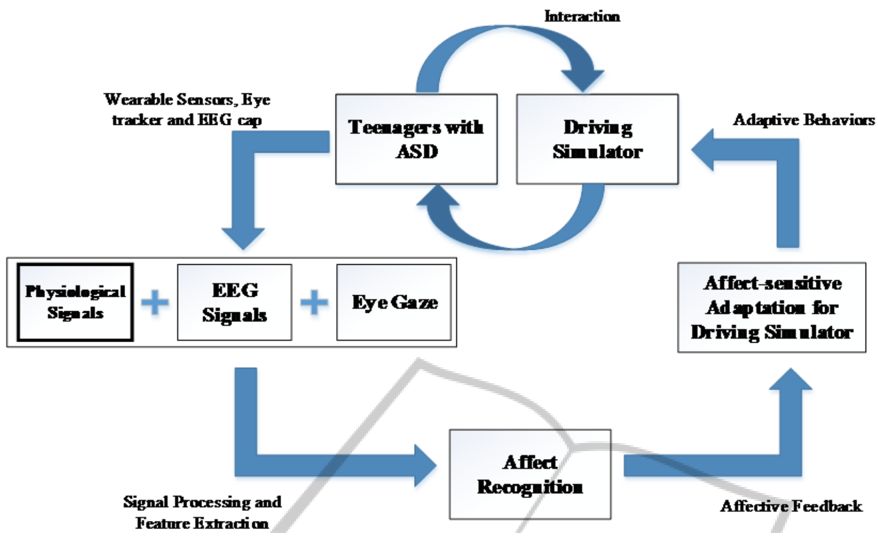

Figure 1: Framework overview.

3 METHODS AND MATERIALS

3.1 Experimental Setup

The physiological signals were collected using the Biopac MP150 physiological data acquisition system (www.biopac.com) with a sampling rate of 1000 Hz. Several physiological signals were investigated. The acquired physiological signals were broadly classified as cardiovascular activities including electrocardiogram (ECG), photoplethysmogram (PPG); electrodermal activities (EDA) including tonic and phasic responses from galvanic skin response (GSR); electromyogram (EMG) activities from Corrugator Supercilii, Zygomaticus Major, and Upper Trapezius muscles; respiration and skin temperature.

These signals were measured by using light-weight, non-invasive wireless sensors (Fig. 2). ECG signal was collected from the chest using two disposable electrodes to record electrical activity generated by the heart muscle. PPG and GSR were measured from toes instead of fingers in order to reduce the motion artifact from driving. EMG was measured by placing surface electrodes on Corrugator Supercilii and Zygomaticus Major and Upper Trapezius muscles. Respiration was used to measure changes in thoracic circumference that occur as a participant breathes. Skin temperature was collected from the upper arm by using a temperature sensor. In addition, an EEG cap and an eye tracker were also used to detect EEG signal and eye gaze in this setup.

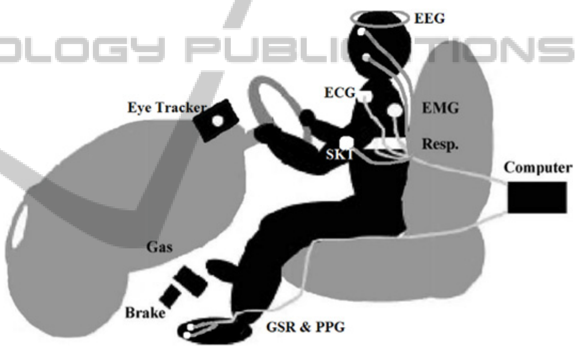

Figure 2: Physiological sensors setup.

A socket-based communication module was developed to transmit task-related (e.g., trial start/stop) event triggers from the virtual driving environment to the Biopac. Physiological signals along with task-related event triggers were sent over an Ethernet link to a physiological data logger computer to enable acquiring and logging of the signals in a time-synchronized manner with the VR-based driving task (Fig. 3).

3.2 Procedure

Each participant completed six sessions in different days. The first and last session were pre and post sessions, which contained the exact same assignments. Participants usually completed a single session within approximately 60 minutes. At the start of each session, physiological sensors and EEG cap were placed on a participant's body and the eye tracker was calibrated. Participants watched a short

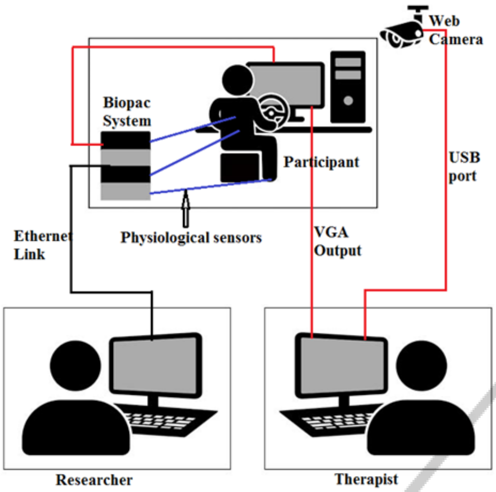

Figure 3: Experimental setup diagram.

instruction video which explained basic instructions and game controls. After the tutorial, participants were asked to remain calm and relax for three minutes during which physiological, EEG, and eye gaze baseline data were collected. The baseline data were later used to offset environmental variability. Participants also had three minutes free practice in which there were no pedestrians and no other vehicles in the VR environment. This practice mode allowed participants to familiarize themselves with the game controls and virtual environment.

After the three-minute practice, participants began the first of three assignments. Through the assignment, participants followed the navigation system and tried to obey traffic rules. Disobeying any traffic rules (i.e., running red light) caused a performance failure. In addition, in gaze contingent group, failing to look at a specific region of interest in specific trials (i.e., did not look at speedometer in school zone) also caused a gaze failure. Four failures would cause the assignment end and the game would go back to assignment selection menu. Time duration for each assignment varied from 2 minutes to 5 minutes depending on the participants' performance.

Because of suspected unreliability of self-report of teenagers with ASD, an experienced therapist was involved in the experiment. The therapist was seated next to the experiment room, watching the experiment from the view of two cameras (Fig. 3). The therapist rated the participants' affective states in four categories: engagement, enjoyment, frustration and boredom by using a continuous rating scale from 0 to 9 via an online rating program. For each assignment, an overall rating was given after the assignment. Also, the therapist provided ratings when she felt the participants had obvious affective state changes.

3.3 Participants

We have recruited 12 male teenagers with ASD for this phase of the study. While it was not our intention to recruit all male participants, they were recruited randomly through the existing university clinical research registry and happened to be all males. This may partially be due to the fact that ASD prevalence in male population is four times as high as it is for female population (CDC 2014). All participants had a clinical diagnosis of ASD from a licensed clinical psychologist as well as cores at or above clinical cutoff on the Autism Diagnostic Observation Schedule (Lord, Risi et al. 2000). The Institutional Review Board (IRB) approval was sought and received for conducting the experiment. Ten participants' physiological data were used for this paper because two of them were not able to follow the instructions to get valid physiological data.

Table 1: Participant data.

Participant NO.	Age	IQ	ADOS total raw core	ADOS CSS
ASD01	13.6	--	--	--
ASD02	15.1	80	16	9
ASD03	14.3	86	14	8
ASD04	14.6	99	--	--
ASD05	17.1	118	8	5
ASD06	13.2	108	14	8
ASD08	17.5	125	13	8
ASD09	15.5	117	11	7
ASD10	16.6	88	22	10
ASD12	14.1	--	11	7

Note: ADOS_CSS = Autism Diagnostic Observation Schedule Calibrated Severity Score; IQ = composite score: Differential Ability Scales (General Conceptual Ability) or Wechsler Intelligence Scale for Children (Full Scale IQ).

4 PHYSIOLOGICAL DATA ANALYSIS

In this study, a group model was developed to classify affective states in four categories: engagement, enjoyment, frustration and boredom. A 90-s window was chosen for sampling the continuously-recorded physiological data. The 90-s window was chosen for several reasons: it approximates the time needed for autonomic signal such as skin conductance to recover and it also provides a level of smoothing when the features were extracted. The samples were labeled by the therapist's overall rating for each assignment. The therapist's ratings were mapped into high and low intensity for each category for binary classification.

The recorded physiological signals were preprocessed for feature extraction. First, each signal was filtered using different filters such as high/low pass filter, notch filter etc. to reject outliers and artifacts. The signals were then standardized to be zero mean and unity standard deviation. In addition, baseline wander was removed from the PPG signal before peak detection as this signal is known to be affected by baseline wander.

Several features were extracted for each channel of physiological signal. A brief explanation for all the features are listed in Table 2.

The Waikato Environment for Knowledge Analysis (WEKA) (Hall, Frank et al. 2009), which is recognized as a landmark system in machine learning nowadays, was used to do feature selection and classification in this study. For each category, CorrelationAttributeEval (Hall 1999) algorithm was used to select features. This algorithm evaluated the value of a feature by measuring the correlation between it and the class. It ranked feature subsets according to a correlation based heuristic evaluation function. The bias of the evaluation function was toward subsets that contain features that were highly correlated with the class and uncorrelated with each other. Irrelevant features were ignored because they would have low correlation with the class. Redundant features were screened out as they would be highly correlated with one or more of the remaining features. Top ten features (Table 3) that had the highest correlations with the classes were chosen for further classification.

Six different well-known classifiers were used for classification for each category. These classifiers were:

BayesNet: SimpleEstimatior estimator and K2 search algorithm were chosen.

NaiveBayes: Numeric estimator precision values were chosen based on analysis of the training data.

SVM: Radial basis function was chosen with a degree of 3.

MultiLayerPerceptron: HiddenLayers were chosen by using (attribs + classes) / 2, learningRate was 0.3.

RandomForest: The number of trees to be generated was 10, maxDepth was unlimited.

J48 DecisionTree: The minimum number of instances per leaf was 2, 1 of 3 folds data was used for reduced-error pruning.

10-fold cross validation was used. The classification accuracies for each category from different classifiers are shown in Figure 4.

The highest accuracy for engagement, enjoyment, frustration and boredom were 77.78%, 79.63%, 79.63% and 81.48%, respectively. These results are comparable to the accuracy of most up-to-date affective computing systems (Tao and Tan 2005; Jerritta, Murugappan et al. 2011).

As we can see from the selected 10 features of each category, PPG, RSP, SCR, EMG_C and EMG_Z are most common for the chosen affective states. This indicates the possibility of using a smaller set of features with a relatively low computational cost for a potential closed-loop system.

In this study, we focused on developing a group affective state prediction model instead of model for each individual. In the future, we want to use this group model to provide affective state feedback in a closed-loop system and potentially develop a more efficient driving system to teach teenagers with ASD basic driving skills.

5 DISCUSSION

There is a growing consensus that development of computer assistive therapeutic tools can make application of intensive intervention for teenagers with ASD more readily accessible. In recent years, several applications of advanced intervention that address deficit in driving for teenagers with ASD were investigated. However, these application lacked the ability of detect the affective cues of the teenagers, which could be crucial given the affective factors of teenagers with ASD have significant impacts on the intervention practice.

In this work, we presented a physiology-based affect recognition framework for teenagers with ASD. 68 features were extracted from the recorded physiological data. Subsequently 10 features were selected by using CorrelationAttributeEval algorithm to overcome the overfitting problem. Six most commonly used machine leaning algorithms were used to classify four category of affective states. The developed model could reliably recognize affective states of the teenagers with ASD and provide the basis for physiology-based affect-sensitive driving skill training system.

In the future, a real-time affect recognition system which dynamically shape the driving task will be developed. We will also incorporate EEG

Table 2: Physiological features.

Physiological signal	Feature extracted	Label used	Unit of measurement
	Sympathetic power	power_sym	Unit/s^2
	Parasympathetic power	power_para	Unit/s^2
	Very low-frequency power	power_vlf	Unit/s^2
Electrocardiogram (ECG/EKG)	Ratio of powers	para_vlf	No unit
		para_sym	
		vlf_sym	
	Mean Interbeat Interval (IBI)	mean_ibi_ekg	ms
	Std. of IBI	std_ibi_ekg	Standard deviation(no unit)
Photoplethysmogram (PPG)	Mean and std. of amplitude of the peak values	ppg_peak_mean	µV
		ppg_peak_std	No unit
	Mean and std. of heart rate variability	hrv_mean	ms
		hrv_std	No unit
	Mean and std. of tonic activity level	SCL_mean	µS
		SCL_sd	µS/s
	Slope of tonic activity	SCL_slope	µS
	Mean and std. of amplitude of skin conductance response (phasic activity)	SCR_mean	
Electrodermal activity (EDA)		SCR_sd	µS
	Rate of phasic activity		
	Mean and std. of rise time	SCR_rate	Response peaks/s
		tRise_mean	
	Mean and std. of recovery time	tRise_std	
		tHRecovery_mean	
		tHRevovery_sd	
	Mean of Corrugator, Zygomaticus and Trapezius activities	Cemg_mean	µV
		Zemg_mean	
		Temg_mean	
	Std. of Corrugator, Zygomaticus and Trapezius activities	Cemg_std	No unit
		Zemg_std	
		Temg_std	
	Slope of Corrugator, Zygomaticus and Trapezius activities	Cemg_slope	µV/s
		Zemg_slope	
		Temg_slope	
	Number of burst activities per minute of Corrugator, Zygomaticus and Trapezius	Cburst_count	/min
		Zburst_count	
	Mean of Corrugator, Zygomaticus and Trapezius burst activities	Tburst_count	
Electromyographic Activity (EMG)		Cburst_mean	mS
		Zburst_mean	
	Std. of Corrugator, Zygomaticus and Trapezius burst activities	Tburst_mean	
		Cburst_std	No unit
		Zburst_std	
	Mean and Median frequency of Corrugator, Zygomaticus and Trapezius	Tburst_std	
		Cfreq_mean	Hertz
		Cfreq_med	
		Zfreq_mean	
		Zfreq_med	
		Tfreq_mean	
	Mean of the amplitude of Corrugator, Zygomaticus and Trapezius burst activities	Tfreq_med	
		Cburst_amp_mean	µV
		Zburst_amp_mean	
		Tburst_amp_mean	

Table 2: Physiological features (cont.).

Respiration (RSP)	Mean amplitude	RSP_mean	No unit
	Std. of amplitude	RSP_std	
	Subband spectral entropy	RSP_subbandSpectralEntropy({1,2,3})	
	Minimum and maximum difference	RSP_minmax_diff	
	Change rate	RSP_rate	
	Power spectrum density	RSP_low_power	
		RSP_high_power	
		RSP_firstOrder_std	
	Std. of Poincare plot geometry	RSP_poincare_SD1	
		RSP_poincare_SD2	
	Mean and std. of peak valley magnitude	PVM_mean	
	Mean and std. of breath per minute	PVM_std	
		RRI_mean	
		RRI_std	
Peripheral temperature (SKT)	Mean temperature	temp_mean	F
	Slope of temperature	temp_slope	F/s
	Std. of temperature	temp_std	No unit

Table 3: Selected features for each category of affective states.

Category	Features selected
Engagement	RSP_subbandSpectralEntropy(1), hrv_mean, SCR_rate, Zemg_mean, RSP_mean, PVM_std, SCL_sd, SCL_slope, Cburst_amp_mean, ppg_peak_mean
Enjoyment	hrv_mean, RSP_mean, ppg_peak_mean, Cburst_count, Cemg_slope, Zburst_count, Temg_slope, PVM_std,Zburst_mean,Cburst_amp_mean
Frustration	Cemg_std, RSP_subbandSpectralEntropy(2), RSP_subbandSpectralEntropy(3), PVM_mean, RSP_firstOrder_std, temp_slope, RSP_std, RRI_std, Zfreq_med, RSP_low_power
Boredom	tRise_sd, hrv_mean, temp_mean, tRise_mean, SCR_sd, SCR_rate, RSP_subbandSpectralEntropy(3), RSP_subbandSpectralEntropy(2), Zfreq_mean, Cburst_count

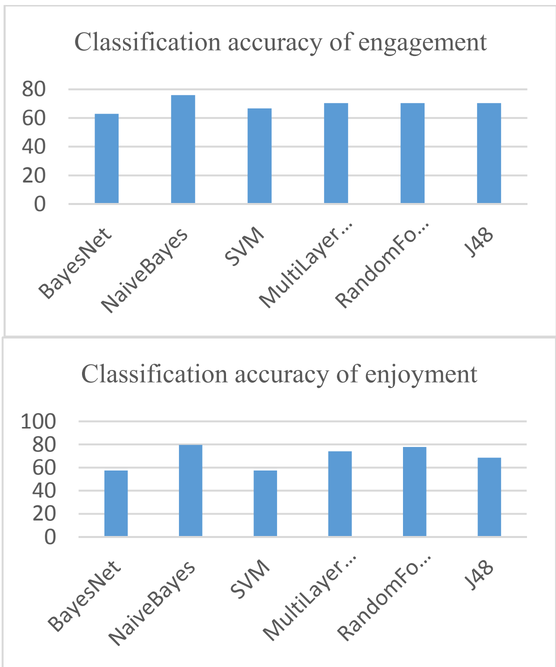

Figure 4: Classification accuracies for each category of affective states.

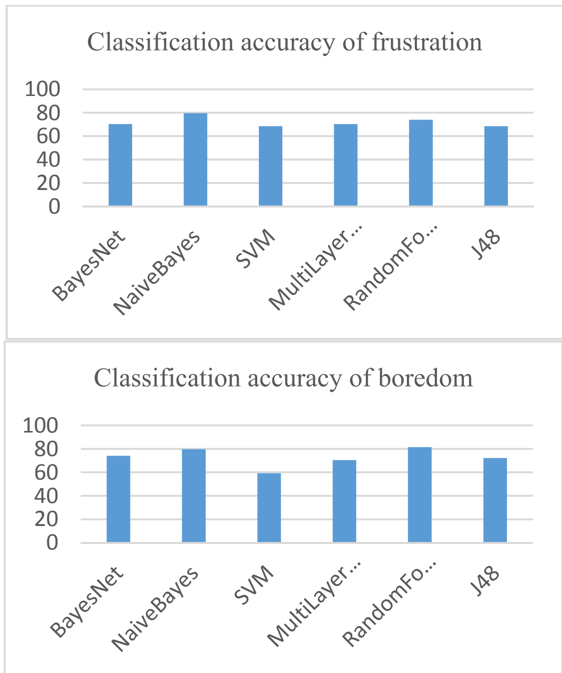

Figure 4: Classification accuracies for each category of affective states (cont.).

signal and eye gaze in order to give more individualized feedback.

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