Feature extraction and selection of electrodermal reaction towards stress level recognition: two real-world driving experiences

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Résumé. Cette étude est basée sur l'analyse de l'activité electrodermale (AED) qui représente l'indicateur physiologique le plus pertinent dans la mesure de l'état d'excitation humaine. Les signaux résultants de deux différentes expériences de conduite réalisées en conditions réelles, permettent dans ce travail de classifier le niveau de stress du conducteur en supposant que la ville produit un niveau plus élevé de stress que l'autoroute. Pour chaque mesure d'AED, 6 descripteurs (moyenne, écart type et 4 descripteurs des startles) sont extraits à partir d'une minute de chaque signal. Dans ce travail, on a réussi à dégager l'ordre de pertinence de ces descripteurs en utilisant les forêts aléatoires et à confirmer cet ordre via une validation croisée d'un algorithme de reconnaissance. Les descripteurs de startles s'avèrent les plus pertinents pour une base de données tandis que la moyenne d'AED est la plus importante dans la deuxième base.

Mots-clés. Activité electrodermale et startles, réaction electrodermale, forêts aléatoires.

Abstract. This study is based on the electrodermal activity (EDA) which is a reliable physiological indicator of human arousal. Signals resulting from two different driving experiences, are used to classify the stress level assuming that city driving produces higher stress level compared to highway driving. For each EDA dataset, six features are extracted from each 1-min segment: the mean, the standard deviation and four electrodermal response characteristics defining the "startle" level. In our work, we were able to identify these features by order of relevance using random forest and to confirm this order using a cross validation on a recognition algorithm. Startle features were found to be the most relevant for the first database while the mean was selected as the best feature to recognize stress level for the second database.

Keywords. Startle and electrodermal activity, electrodermal reaction, random forest.

1 Introduction

The assessment of a vehicle driver alertness level can be achieved by examining his/her affective state (Ahuja et al. 2003)[1]. Helander (1978) predicted that changes occurring in the skin conductivity are the best measure to a rapid event because of its onsets which are fast, compared by heart rate response [2]. Even though the relevance of the electrodermal signal, which was discovered over a century ago, its use was limited to in-lab tests. With the rise of new wearable non-intrusive sensors, the human affective and cognitive state can be tracked in real time using portable EDA sensors [3]. Thereby, offering instant objective assessment of driver stress level, will help him to avoid accident and improve his emotional state. Despite the increasing number of studies using the EDA signal, its basic decomposition and analysis remains an area little explored compared to other physiological signals.

In this work, we considered two separate studies each of which measured the stress level of drivers as they traveled through different real-world routes, supposedly evoking different levels of stress. The first experience which generates “drivedb” database was carried out by MIT Media Lab team (affect.media.mit.edu/share-data.php) while the second providing “hciLabdb” database was conducted by hciLab team (hcilab.org/automotive/). In both studies, driver was equipped with an EDA sensor. In the MIT experiment, 6 EDA features were extracted for driver stress level assessment. While in the HciLab experiment, only the mean and standard deviation of the EDA were extracted. We have generated the same six features for all data sets (taken from both studies) and performed a random forest analysis [4] to order the different features according to their relevance then we computed the correct rate of a recognition algorithm to confirm the different results.

The remainder of the paper is organized as follows: Section 2 describes the context of the experiments and the EDA data acquisition along with a first examination of the proposed features. Section 3 presents two approaches to EDA feature selection, based on all data sets and identify the most relevant ones. The paper concludes with summary and perspectives towards a higher level analysis of EDA for a robust classification of stress state when driving in urban spaces.

2 Experiments and EDA Features Extraction

In this section, we present an overview of the different apparatus and protocols related to the two real world driving experiments previously indicated then describe features extracted from the EDA startle response.

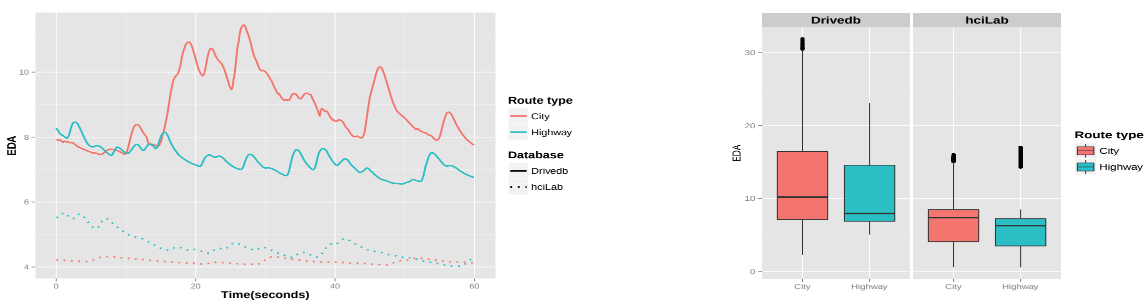
2.1 Protocol Description of “drivedb” and “hciLabdb” Experiments

The experimental protocol proposed by Healey (2000) was based on situations that approximate the real driving conditions [5]. The different periods of rest, highway and city around Boston area experienced in this experiment (Figure 1.a) are assumed to produce respectively low, medium and high stress levels. These assumptions were verified using driver questionnaire and actions coded from videotape presented by Healey and Picard (2005) [6].

(a) (b)

Figure 1: Routes participant drove during two experiences (a) Boston area (b) Stuttgart area.

The second study conducted by hciLab in "real-world" driving conditions (Figure1.b) and described by S. Schneegass et al (2013), consists on driving and recording various physical and physiological signals [7].



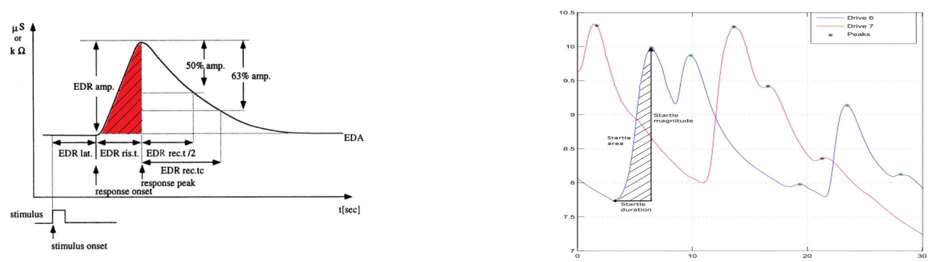
(a) (b)

Figure 2: Preliminary Presentation of EDA signal: (a) Simple EDA presentation of the third drive from each database, (b) Boxplot of EDA distribution per route type.

For the hciLab database, we do not notice a difference in the trend of the EDA signal or an important number of startles in city vs. highway unlike drivedb which we can observe a difference in the EDA response in highway vs.city (Figure2). This may be due to the different "city ambiance" conditions in the two countries or to the different temperament.

2.2 EDA Signal Extraction for Experiments Comparison

The first database "drivedb" proposed by Healey and Picard (2005) was recovered from PhysioNet (physionet.org/physiobank/database/drivedb/)[6]. Only 10 datasets can be used from the database. While, for the second database "hciLab" downloaded from hciLab website (hcilab.org/automotive/), all the 10 datasets were used in the analysis. In order to offer a fair comparison between the two databases, we choose to extract the EDA signals from the beginning of the two city period assumed to produce a high level of stress and two highway period supposed to generate a medium stress level. As the hciLabdb highway period does not exceed 1 min, we were limited by using frames of 1 min duration from the two databases.



(a) (b)

Figure 3: EDA feature extraction: (a) An ideal 1-DC EDA reaction and stratles parameters[8], (b) An illustration of EDA signals and features extracted respectively the mean, standard deviation, sum of startle Magnitudes, sum of startle durations, total startles number and sum of total startle area.

We denote $X_{ki}^{j} = (X_{ki1}^{j}, X_{ki2}^{j}, ..., X_{kin}^{j})$ a vector of n observations of EDA segment corresponding to the j-th drive, where k refers to the database (1:drivedb and 2: for hciLabdb), i corresponds to the route type (1:city, 2:highway). Since the sampling frequencies of the two EDA signals are different ($F_s(drivedb) = 15.5$ and $F_s(hciLabdb) = 128$), the resulting vectors do not correspond to the same length n. We transformed then these vectors by applying startle detection algorithm developed by Healey (2000), thus each X_{ki}^{j}becomes $v_{ki}^{j} = (v_{ki1}^{j}, v_{ki2}^{j}, ..., v_{ki6}^{j})$ respectively the mean, standard deviation, total number of startles, startle magnitude, startle duration and the total area contained under startles approximated by a triangular model Area=$\frac{1}{2} * Mag * Dur$ (Figure 3.b).

Now that we have generate 6 features for EDA signal for 2 different yet similar driving experiments, it is important to find the most relevant ones, this will be next presented.

3 Feature Selection and Stress Level Recognition

In order to perform a preliminary classification of the stress level, we applied the recognition algorithm proposed by Healey (2000) to both databases to obtain a correct rate that evaluate the relevance of each feature combination. Then, we propose a random forest algorithm as a way to automate the feature selection.

3.1 Stress Level Classification via LDF Fusion Algorithm

To classify the stress level, Healey (2000) performs a recognition analysis based on a Linear Discriminant Function (LDF). The "Leaving One Out Method" is performed as a cross validation approach. The database is used to train and test the recognition algorithm.

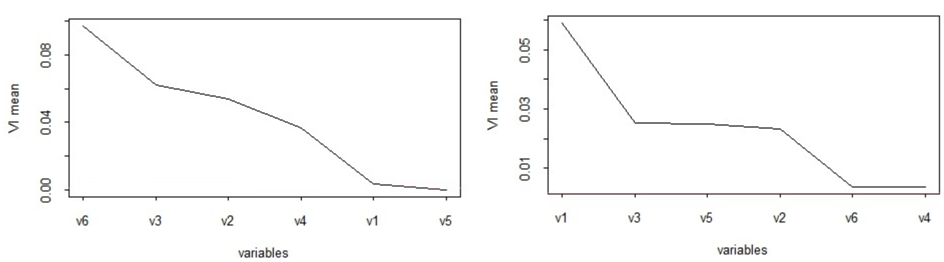
The different training vectors are used to compute a Fisher projection matrix and a linear discriminant function. Linear classifier for which the function $g_c(\hat{y})$ is maximized. This function is determined by the a priori probability $\Pr[w_c]$ for each class c, the pooled covariance K and m_c(the sample mean)

$$g_c(\hat{y}) = 2m_c^T K^{-1}\hat{y} - m_c^T K^{-1} m_c + 2ln(Pr[w_c]),$$

where $Pr[w_c] = \frac{1}{n_k}$and n_k is the total number in a class c.

3.2 Feature Selection using Random Forest Approach and Results

The Random Forest (RF) approach is based on combining many binary decision trees built using several bootstrap samples extracted from the learning sample and randomly selecting a subset of explanatory variables at each node[4]. VSURF R [9] package consists of a preliminary elimination and ranking followed by variable selection. The first step of the procedure computes the Random Forest (RF) scores of importance and eliminates the variables of small importance. Then, it descendingly orders the remaining variables again by an order of importance. The second step of variable selection differs according to the purpose[4]. Applying the RF approach produced the following results: For drivedb, the startle area (v6) was the most relevant (Figure 4.a). For hciLabdb, the EDA Mean was the most relevant (Figure 4.b). In deed, a 80% correct rate is obtained when using the startle area while 52.5% correct recognition rate for the hciLabdb when using only the mean. One of the advantages of using RF approach is the option to decide if further features can be added to increase recognition correct rate up to certain limits.



(a) (b)

Figure 4: RF Variable selection for classification: (a) “drivedb” and (b) “hciLabdb” .

Finally, it is important to note that no-unique EDA feature is able to perform correct stress recognition, the context of the experience is the key in these kind of studies.

4 Conclusion

In this work, we present a stress level recognition algorithm applied by Healey (2000) to a multivariate physiological real world driving database. With a focus only on EDA information we were able to study the most relevant features in stress level classification. Since this classical approach evaluates only the feature selected by the user, we extend this simple and preliminary application of a random forest in order to automate the feature selection. Startle area was selected in the case of Boston area, USA when the mean was mainly selected in Stuttgart area, Germany. These results encourage to perform new protocols that unify experiment conditions to perform a fair comparison. In future works, the multivariate aspect of the physiological signals (in addition to EDA) can be studied and may extend the database to more consistent when using random forests.

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