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Comparative analysis of emotion estimation methods based on physiological measurements for real-time applications ☆

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ABSTRACT

In order to improve intelligent Human-Computer Interaction it is important to create a personalized adaptive emotion estimator that is able to learn over time emotional response idiosyncrasies of individual person and thus enhance estimation accuracy. This paper, with the aim of identifying preferable methods for such a concept, presents an experiment-based comparative study of seven feature reduction and seven machine learning methods commonly used for emotion estimation based on physiological signals. The analysis was performed on data obtained in an emotion elicitation experiment involving 14 participants. Specific discrete emotions were targeted with stimuli from the International Affective Picture System database. The experiment was necessary to achieve the uniformity in the various aspects of emotion elicitation, data processing, feature calculation, self-reporting procedures and estimation evaluation, in order to avoid inconsistency problems that arise when results from studies that use different emotion-related databases are mutually compared. The results of the performed experiment indicate that the combination of a multilayer perceptron (MLP) with sequential floating forward selection (SFFS) exhibited the highest accuracy in discrete emotion classification based on physiological features calculated from ECG, respiration, skin conductance and skin temperature. Using leave-one-session-out crossvalidation method, 60.3% accuracy in classification of 5 discrete emotions (sadness, disgust, fear, happiness and neutral) was obtained. In order to identify which methods may be the most suitable for real-time estimator adaptation, execution and learning times of emotion estimators were also comparatively analyzed. Based on this analysis, preferred feature reduction method for real-time estimator adaptation was minimum redundancy – maximum relevance (mRMR), which was the fastest approach in terms of combined execution and learning time, as well as the second best in accuracy, after SFFS. In combination with mRMR, highest accuracies were achieved by k-nearest neighbor (kNN) and MLP with negligible difference (50.33% versus 50.54%); however, mRMR+kNN is preferable option for real-time estimator adaptation due to considerably lower combined execution and learning time of kNN versus MLP.

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1. Introduction

In the last few years the research in automated emotion recognition methods is steadily growing momentum due to applicability in various domains which would benefit from an accurate understanding of human emotional states, like entertainment, safe driving, training and e-learning, telemedicine and home robotics (Nasoz and Lisetti, 2006; Picard, 1997; Rani et al., 2006). Furthermore, various mental health applications may benefit from automated estimation of patient's emotions, like treatment of stress-related disorders (Ćosić et al., 2010).

For a variety of these applications, individually adjusted emotion estimators rather than a generic emotion estimation may achieve higher accuracy (Kim and André, 2008; Picard, 2010), particularly if the estimator can learn emotional response idiosyncrasies of a particular individual over the course of multiple sessions. Such personalized adaptive emotion estimator system should perform real-time estimation of user's emotion and concurrently adapt itself over time based on the measured user's responses.

As a step forward toward this goal, this paper presents a comparative analysis of emotion estimation methods in order to find the most suitable methods for the development of a personalized adaptive emotion estimator. Therefore, the criteria for

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comparison are not only related to estimation accuracy, but also to execution and learning times of each emotion estimation method.

In the previous research related to emotion estimation the underlying emotional states have been determined based on cues such as facial expressions, speech, and physiology. This paper, however, focuses solely on physiological signals, which in comparison to facials expressions and vocal features are dominantly related to the autonomic nervous system activity. This makes voluntary and conscious manipulation of physiological signals more difficult than either vocal or facial emotional expressions (Kim and André, 2008), and allows continuous monitoring of emotional states, even in absence of user's motor activity. Physiological sensors are becoming less and less disruptive as their size is decreasing, and wearable, small and wireless physiological sensors may be an appropriate solution for unobtrusive real-time emotional state monitoring (Fletcher et al., 2010; Katsis et al., 2011; Liu, 2009).

Even though several feature reduction and machine learning methods have been so far successfully employed in the previous research to build emotional state estimators from physiological indices, a comparison of various methods used by different research groups, has been precluded due to the following reasons:

a) Emotion elicitation method diversity.
b) Emotional state representation method – discrete emotions or dimensional (valence-arousal) space.
c) Properties of used physiological signals and features.
d) Referent emotional state selection – subjective ratings or stimuli annotations.
e) Estimator evaluation method.

As noted in the previous research (Rani et al., 2006), given these issues, finding a common ground for comparing methods and analyzing their features is very challenging. Therefore, this paper uses appropriate experimentally collected dataset to compare accuracy, execution and learning times of seven feature reduction and seven machine learning methods commonly employed in emotion estimation based on physiological features. Tested methods of feature reduction and machine learning are listed in Table 1. During comparative analysis, each feature selection method, alone or in combination with FP, is paired with every listed machine learning method. Therefore, a total of 84 combinations of feature reduction and machine learning methods were considered.

The comparative analysis of methods for physiology-based emotion estimation was based on an experiment involving 14 participants, conducted in cooperation with the Department of Psychology at University of Zagreb, Faculty of Humanities and Social Sciences. The experiment compared performance of all aforementioned combinations of feature reduction and machine learning methods using the same acquired dataset.

The experimental paradigm was designed to correspond with the idea of incremental adjustment of emotion estimator over the course of multiple sessions in the context of its personalization for a particular participant. The corresponding conceptual timeline is shown in Fig. 1, where real-time emotion estimation takes place during the sessions while the participant's physiological signals are acquired, and estimator adaptation/learning with search for the most appropriate features can be continuously performed during the sessions, as well as between consecutive sessions. Duration of a single session is typically in minutes or up to a couple of hours, while the period between two consecutive sessions can last days, weeks or months. Before the first session, participant's data are collected, such as demographics and lifestyle, and the participant fills out relevant questionnaires, such as emotional expressiveness and anxiety sensitivity questionnaires, a life events list, etc. In the period between consecutive sessions, offline learning is performed which includes longitudinal personalization of the estimator to a particular participant with enough time at disposal to perform the most complex machine learning and feature reduction algorithms. During the session, the acquisition of physiology and emotional state estimation are continuously

Table 1
Tested feature reduction and machine learning methods. Methods for feature reduction are divided into feature selection and feature transformation methods. During comparative analysis, each feature selection method, alone or in combination with FP, is paired with every listed machine learning method.

Feature reduction methods		**Machine learning methods**
Feature selection	Feature transformation	
Sequential floating forward selection (SFFS)	Fisher projection (FP)	K-nearest neighbor (kNN)
Minimum redundancy – maximum relevance (mRMR)	(none)	Support vector machine (SVM)
ReliefF		Random forest (RF)
Information gain (IG)		Multilayer perceptron (MLP)
OneR classifier (OneR)		RIPPER algorithm for production rule generation
Chi-squared (Chi^2)		C4.5 decision tree
		Naive Bayes classifier (NB)

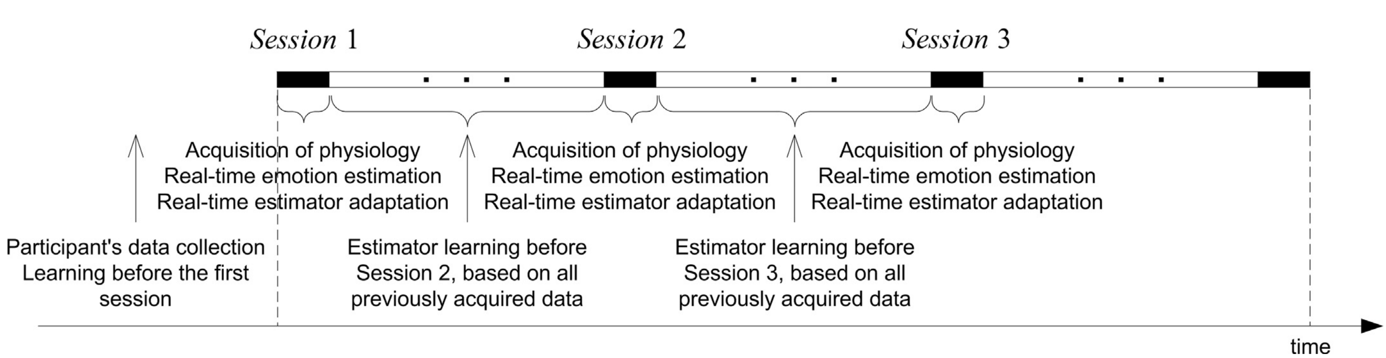

Fig. 1. The timeline of emotion estimation.

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