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ABSTRACT

Affective computing gained much interest in recent years, as its promises, if fulfilled, would lead to creating emotion-aware technologies – a real breakthrough in human-computer interaction, and a powerful tool for understanding processes governing our everyday lives. In this dissertation, we involve ourselves with affective computing, focusing mainly on researching personalized methods for affect recognition in real-life contexts.

Firstly, we performed two literature studies: one critical review of the articles realizing emotion recognition in a manner befitting experiments in everyday life, and another one delving into the procedures for personalized affective computing. They allowed us to discover the necessity of focusing on real-life-ready solutions and personalized methods in our research. Also, as we summarized major differences between classical laboratory experiments and novel in-the-field studies, new challenges introduced by the latter became apparent. We comment on them and give recommendations regarding future endeavors in affective computing.

Other important contributions involve gathering and preparing the *LarField* dataset, a large information-rich dataset collected in everyday life, consisting of continuous recordings of multiple physiological and behavioral signals annotated with emotional states and broad contextual data. It is one of the most extensive datasets on emotion psychophysiology acquired in real life, containing data from 167 subjects, each recorded continuously during their day for one month. This dataset and the in-the-laboratory Emognition dataset that we also produced may be utilized to research affect recognition with off-the-shelf wearable devices.

We also developed and tested new personalized methods for affective computing studies. Among others, we researched the feasibility of using personalized models for affect recognition, utilizing per-group personalization to handle a cold-start problem, and developed a new two-fold personalization method and examined it on emotion recognition from ECG signals. Also, as experiments differed from each other, we had to carefully select modeling strategies, metrics, and validation procedures for each of them. Key findings from our experiments include the superiority of personalized models over general approaches, especially when trained in a subject-specific manner or equipped with features describing personality and demography as a context.

During our research, we experienced several challenges. A major one was handling the delays in data collection and processing from the large field study. Because of that, although two-fold personalization was designed mainly for real-life data, we could only test our methods on laboratory datasets from the literature. Also, in cold-start experiments, we were unable to train fully personalized models due to an insufficient number of per-person samples. These challenges inspired us to comment on the issues of organizing such studies, supervising them, and collecting emotional psychophysiology data. In our lessons learned, we especially focused on extensive outside-the-laboratory studies, as they are still a novelty, and many issues that we faced and shared may not be known to other researchers.

This dissertation emphasizes the importance of utilizing real-life data and respecting subjectivity while designing methods for affect recognition. Moreover, we highlight the need for continued investigations on the balance between the general and individualized modeling approaches. Our future work will focus on further researching patterns in self-reported affective states, their relationships with physiology and behavior, subject-wise and population-wise features that may be utilized for reasoning about people's daily lives, and novel methods and strategies for affect modeling, including foundational models. Most of them have recently been being explored by the Emognition team I am a member of.