Machine Learning and Sensor Data Fusion for Emotion Recognition

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INTRODUCTION

Emotions have massive influences on our lives. Negative emotions have become determinants of human health. Long-term unpleasant reactions are associated with health issues, including migraines, asthma, ulcers, and heart disease (Kim, J., & André, E., 2008). Growing usage of sensors and wireless networks have led to development of low-cost, efficient wearable devices collecting and transferring data in real-time for long periods (Kanjo, E., Younis, E. M., & Ang, C. S., 2019). These data sources provide a chance to create innovative algorithms for identifying human emotions. This can aid in treatment of chronic diseases, including diabetes, asthma, and heart disease (Pollreisz, D., & TaheriNejad, N., 2017, July).

Researchers made several attempts to integrate ML techniques with sensor datasets for automatic emotion identification (Busso, C., & Deng et al., 2004; Jerritta et al., 2011; Kanjo, E., Kuss, D. J., & Ang, C. S., 2017; Katsis et al., 2008). Many studies on automatic emotion identification have focused on visual, auditory, and movement data (e.g., facial expressions, body postures, speeches) (Busso, C., & Deng et al., 2004; Jerritta et al., 2011; Katsis et al., 2008; Basiri, M., Schill, F., U. Lima, P., & Floreano, D., 2018; Kanjo, E., Al-Husain, L., & Chamberlain, A., 2015). With growing availability of low-cost wearable sensors (e.g., Fitbit, Microsoft wristbands), research interest in using human physiological data for emotion identification has grown. Due to possibility and diversity of human emotional manifestations, automated human emotion categorization remains difficult despite the capacity to sense a wide range of information (from human physiology to surroundings) (Plasqui, G., & Westerterp, K. R., 2007). In addition, they extracted specific emotions based on controlled samples in lab settings using audio-visual stimuli (e.g., showing participants photos or videos or asking participants to complete designed tasks to induce emotional states (Agrafioti, F., Hatzinakos, D., & Anderson, A. K., 2011). That sort of controlled study is limited to strictly controlled environments despite effectiveness.

Authors used several standard ML techniques to capture variability of multi- modal data at sensor and feature levels for mood categorization “in the wild” using smartphones and wristbands, based on integrating many sensors of various modalities (physiological [EDA, HR, Body-Temperature, Motion] and environmental [Air-Pressure, Env-Noise, UV]).

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The purpose of this chapter is to compare several supervised ML techniques (SVM, KNN, RF, DT) to classify five distinct emotional states. Authors collected data from participants wandering about Minia - university campus using physiological and mobile sensors in real-world settings to develop prediction models. Using sensor data, authors applied ML approach for emotion classification in this work, which incorporates a set of ML algorithms to achieve the following goals: - 1) Using on-body and environmental factors to predict emotional reactions. 2) Constructing a user-dependent model based on various modalities associated with several sensors using various ML techniques.

Authors organize the rest of this chapter as follows. Section 2 presents some background knowledge about affective computing, data fusion and machine learning. Section 3 surveys related research. Section 4 presents system description including data collection and tools used in the experiments. Section 5 presents implementation framework and design of the proposed procedure, data preprocessing, and statistics. Results are presented and discussed in Section 6. Finally, authors present conclusions and future work in Section 7

BACKGROUND

Affective Computing

Affective computing is a cross-disciplinary research area to enable intelligent computers to recognize, predict, and interpret human emotions. It includes computer science, artificial intelligence, cognitive science, neuroscience, neuropsychology, and social science.

Affective computing is a collection of approaches for identifying affect from data in various modalities and granularities. Sentiment analysis and emotion recognition are two of the most common subjects in affective computing research.

Multi-Sensor Data Fusion

Sensor data fusion is the process of fusing sensory input with data from other sources to provide knowledge with less uncertainty than using sources separately. Collecting data from many sources, like video cameras and Wi-Fi localization signals.

The data sources for a fusion process aren't required to come from the same sensor. There are three types of fusion: direct fusion, indirect fusion, and fusion of the outputs of the former two.

Direct fusion is used to combine sensor data from a set of heterogeneous or homogeneous sensors, soft sensors, and sensor data history values. Indirect fusion uses information sources like priori knowledge about the environment and human input. Sensor fusion is a subset of information fusion and also known as (multi-sensor) data fusion.

Authors can apply sensor fusion in various ways, including combining raw data from many sources, extrapolated characteristics, and even single-node decisions.

Sensor fusion is divided into various levels, including (data-level), (feature-level), and (decision-level). These levels are discussed in more detail in the section 3.

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