

Unsupervised Learning Approach for Emotion Recognition using Physiological Signals

Supervisors:

Latifa Oukhellou (latifa.oukhellou@univ-eiffel.fr) (GRETTIA/UGE)

Secil Ercan (secil.ercan@univ-eiffel.fr) (GRETTIA/UGE)

Targeted Programs & Level: AIC, DSIA & E5

Summary

Emotion recognition from physiological signals (e.g. ECG, EEG, etc.) is a rapidly growing field, with applications in human-computer interaction and health. Supervised approaches require costly and often subjective annotated datasets. This research aims to explore unsupervised learning methods to automatically identify emotional states from complex, multimodal signals.

There is an opportunity to continue with a PhD upon successful completion of the internship with collaboration with the GRETTIA Lab and DTU in Denmark.

Keywords : clustering, unsupervised learning, latent representation, physiological signals, mobility

1. Introduction

Emotion recognition from human facial expressions, speech, and physiological signals is a rapidly growing research field with applications in human-computer interaction, health monitoring, and behavioral analysis. Theoretical models and behavioral controlled experiments show a two-link between emotions and decision-making. In mobility, it is well established that emotions are associated with satisfaction (experienced utility), and the inverse link has also been proposed, namely that remembered emotions affect decision-making. However, measuring emotions is a complex and difficult task, driven mainly by the latent nature of the target measurement. Leveraging physiological signals has been shown to enhance the objectivity, reliability, and accuracy of emotion recognition, particularly when paired with advanced time-series analysis or machine learning techniques.

Traditional supervised methods [1-7] for emotion recognition require large, labeled datasets. However, acquiring large-scale, high-quality annotated data is expensive and time-consuming. Moreover, in this domain, labels mainly depend on statements of individuals which are subjective assessments. Hence, unsupervised clustering approaches propose a promising alternative. By leveraging latent representations, emotional aspects can be represented in a reduced space, allowing for more accurate clustering and detection of emotion states.

Unsupervised learning, however, has been less explored in this field [8-10]. Recent research also includes semi-supervised approaches [11-12], which combine small labeled datasets for learning with large unlabeled data for pattern recognition. Gaussian Mixture Models (GMM) have demonstrated effectiveness in various clustering tasks, including speech and image recognition, and are promising for emotion clustering due to their ability to handle variability and noise. Autoencoders have also been useful in reducing data dimensionality, capturing high-level emotional features.

This research aims to develop a robust emotion recognition framework by applying unsupervised learning techniques combined with latent space representations of the data. Clustering techniques, such

as GMM, will allow the identification of underlying emotional states from high-dimensional data, while dimensionality reduction methods, such as autoencoders (AE) or variational autoencoders (VAEs), can reveal latent representations of emotions. This combination can enhance the recognition accuracy and offer insights into how emotional states are distributed across individuals. The work can be extended to explore semi-supervised methods or approaches that handle label uncertainties, further improving the robustness and applicability of the framework.

2. Objectives of the research

The primary objective of this research is to design and implement an emotion recognition system using unsupervised clustering techniques combined with latent space representation. Specifically, we will focus on:

1. Developing a pipeline for emotion recognition using unsupervised learning methods.
2. Investigating various latent space representation techniques to reduce dimensionality while retaining relevant emotional features.
3. Evaluating the performance of the methodological framework on both open gold standard data sets (where the emotional stimulus is controlled/known) (such as **WESAD Wearable Stress and Affect Detection [13]**, **DEAP A Dataset for Emotion Analysis using EEG, Physiological and Video Signals [14]**, **SEED The SJTU Emotion EEG Dataset [15]**) and an outdoor mobility-related data set (where the emotional stimulus is uncontrolled) collected in Denmark.
4. Identifying challenges and potential improvements in the clustering-based approach for emotion recognition and Mobility analysis.

Bibliographie

- [1] L. Zhu, P. Spachos and S. Gregori, "Multimodal Physiological Signals and Machine Learning for Stress Detection by Wearable Devices," *2022 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, Messina, Italy, 2022, pp. 1-6, doi: 10.1109/MeMeA54994.2022.9856558.
- [2] K. Wang and P. Guo, "An Ensemble Classification Model With Unsupervised Representation Learning for Driving Stress Recognition Using Physiological Signals," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 6, pp. 3303-3315, June 2021, doi: 10.1109/TITS.2020.2980555.
- [3] K. Ross, P. Hungler and A. Etemad, "Unsupervised multi-modal representation learning for affective computing with multi-corpus wearable data", *J Ambient Intell Human Comput*, vol. **14**, pp. 3199–3224, 2023. <https://doi.org/10.1007/s12652-021-03462-9>.
- [4] S. Rovinska and N. Khan, "Affective State Recognition with Convolutional Autoencoders," *2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, Glasgow, Scotland, United Kingdom, 2022, pp. 4664-4667, doi: 10.1109/EMBC48229.2022.9871958.
- [5] Y. Dev, M. Namdev, R. Shrivastava and R. Srivastava, "LSTM Based Mental Stress Level Detection using Wearable Sensor Devices", *Current Trends in Technology & Science*, vol. 11, no. 1, pp. 1-4, Jan 2022.
- [6] N. Priyadarshini and J. Aravinth, "Emotion Recognition based on fusion of multimodal physiological signals using LSTM and GRU," *2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC)*, Jalandhar, India, 2023, pp. 1-6, doi: 10.1109/ICSCCC58608.2023.10176510.
- [7] W. Li, Z. Zhang and A. Song, "Physiological-signal-based emotion recognition: An odyssey from methodology to philosophy", *Measurement*, vol. 172, Feb. 2021.

- [8] P. Subathra and S. Malarvizhi, "Autoencoder-Based Human Stress Detection System Using Biological Signals," *2024 International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication, and Computational Intelligence (RAEEUCCI)*, Chennai, India, 2024, pp. 1-7, doi: 10.1109/RAEEUCCI61380.2024.10547833.
- [9] S. S. M, J. Medikonda and S. Rai, "Unsupervised Machine Learning Approach for Stress Level Classification Using Electrodermal Activity Signals," *2024 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT)*, Bangalore, India, 2024, pp. 1-6, doi: 10.1109/CONECCT62155.2024.10677181.
- [10] J. Zhu, F. Deng, J. Zhao, D. Liu and J. Chen, "UAED: Unsupervised Abnormal Emotion Detection Network Based on Wearable Mobile Device," in *IEEE Transactions on Network Science and Engineering*, vol. 10, no. 6, pp. 3682-3696, Nov.-Dec. 2023, doi: 10.1109/TNSE.2023.3271354.
- [11] L. Qiu, L. Zhong, J. Li, W. Feng, C. Zhou, J. Pan, "SFT-SGAT: A semi-supervised fine-tuning self-supervised graph attention network for emotion recognition and consciousness detection," *Neural Networks*, vol. 180, 106643, 2024. <https://doi.org/10.1016/j.neunet.2024.106643>.
- [12] Rui Zhang, Huifeng Guo, Zongxin Xu, Yuxia Hu, Mingming Chen, Lipeng Zhang, "MGFKD: A semi-supervised multi-source domain adaptation algorithm for cross-subject EEG emotion recognition," *Brain Research Bulletin*, vol. 208, 110901, 2024. <https://doi.org/10.1016/j.brainresbull.2024.110901>.
- [13] WESAD Dataset. https://ubi29.informatik.uni-siegen.de/usi/data_wesad.html
- [14] DEAP Dataset. <https://www.eecs.qmul.ac.uk/mmv/datasets/deap/>
- [15] SEED Dataset. <https://bcmi.sjtu.edu.cn/home/seed/>