Quality of User Experience Evaluation with Emotion Recognition from Peripheral Physiological Signals

Mary Pidgeon[1], Nadia Kanwal[2], Niall Murray[1], Brian Lee[1]
Technology University of the Shannon: Midlands, Athlone, Ireland. [2]Keele University, Keele ST5 5BG, England

Introduction

Quality of Experience (QoE), which is a measure of a user's degree of delight or annoyance, is traditionally captured using human reports which are subjective by nature. Similarly, estimation of human emotions is grouped into subjective self reports as well as two other categories: behavioural (facial expression, eye tracking, body movement) and physiological (EEG, ECG, HR, GSR etc).

Wearables such as smart watches with sensors to accurately measure physiological data can be combined with Artificial intelligence (AI) machine learning and deep learning techniques to objectively extract information such as emotion categories from the sensor data.

Classification of emotions
What to measure as an emotion varies from measuring combinations of Arousal (A) and Valence (V), (HA, HV, LA,LV) or the four quadrants of emotion (LALV, LAHV,HALV and HAHV) to an attempt to identify discrete emotions such as happiness, fear, surprise, anger, sadness, disgust etc which can be mapped to an A-V quadrant as shown in Fig. 1.

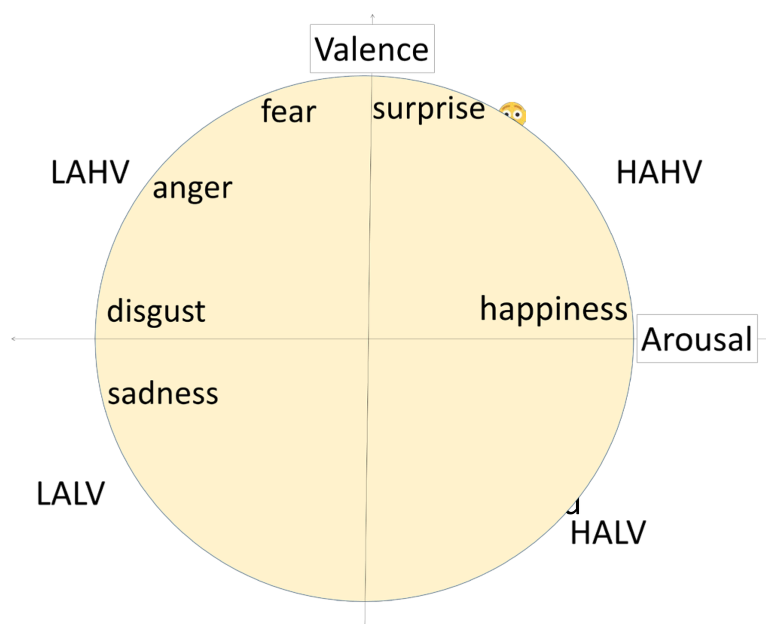

Fig. 1 Emotions in Arousal - Valence quadrants

Emotion recognition from physiological signals traditionally focussed on EEG signals with more recent research using peripheral signals whose sensors are less intrusive for the wearer.

Emotion elicitation in research involves the use of e.g. video or audio. Quality of User Experience (QUX) is a consolidation of Quality of Experience (QoE) and User Experience (UX) whereby the QoE is affected by the quality of emotion elicitation medium.

This study focuses on using one or more peripheral signals to predict an emotion quadrant based on emotion elicited from videos. The QoE will be intitially captured subjectively based on a likert-like scale of liking.

QoE evaluation and Emotion Recognition has applications in identifying stress levels of people in different scenarios especially in the workplace.

Literature Review

Using search Engines such as Google Scholar and IEEE, the approach to searching the literature uses the groups and keywords shown in table x.

Group	Keywords
Emotion Criteria	LALV, HALV, LAHV, HAHV, Discrete Emotion, Sad, Happy, Happiness, Arousal, Valence
Sensed Data	physiological, EEG, GSR, ECG, eye tracking, sensor, multimodal, DEAP,
Machine Learning	machine learning, deep learning,CNN
User Experience	user experience, UX, QoE, QUX

Table. 1 Literature Review Search terms

Keywords within each group are connected using the OR operator and the groups are connected with the AND operator.

Group combinations for search queries include:
- Emotion Criteria AND Sensed Data AND Machine Learning AND User Experience;
- Emotion Criteria AND data AND user experience;
- Emotion Criteria AND user experience;
- Emotion Criteria AND data AND machine learning.

Methodology

Developing the model follows the process shown in Fig. 2

The current problem is to predict arousal and valence from the DEAP dataset Data.

Understanding the data let to choosing four of the 40 channels and two (A and V) of five labels for processing.

Data preparation extracts the chosen data, scales and reshapes it for Conv1d.

Fig. 3 shows end-to-end process from data capture to classification of A and V including modelling and evaluation of the model.

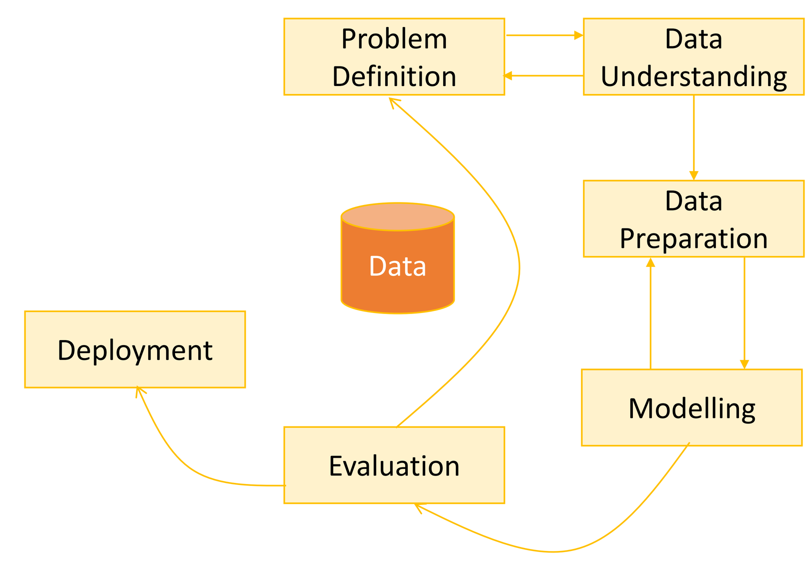

Fig. 2 Machine learning model development process

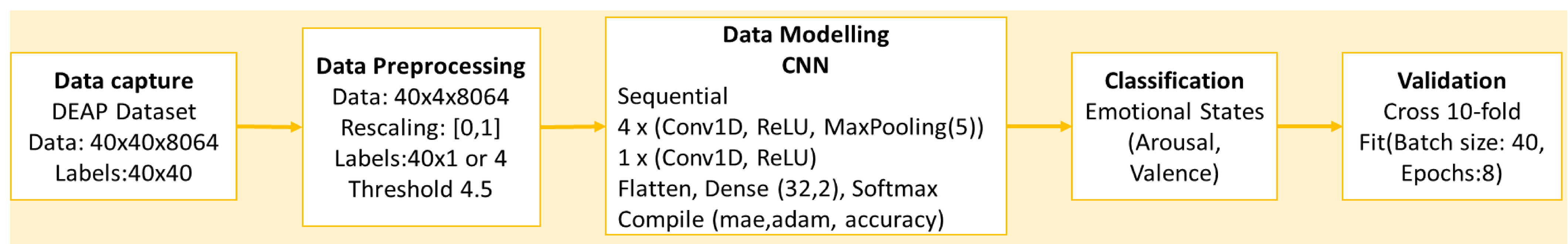

Fig. 3 Modelling and Evaluation Process

AIM

To capture QoE while predicting an emotion quadrant from peripheral physiological signals

Results & Discussion

The aim is to create a model that will predict arousal and valence using one or more physiological signals.

Initial classification results, shown in the confusion matrices in Fig.4 , indicate that the model is underperforming in that it is classifying at a rate close to 50:50 chance.

This could be due to overfitting/underfitting of the model and/or due to several other factors.

Four Channels
GSR, Respiration, Plethysmography, Temperature

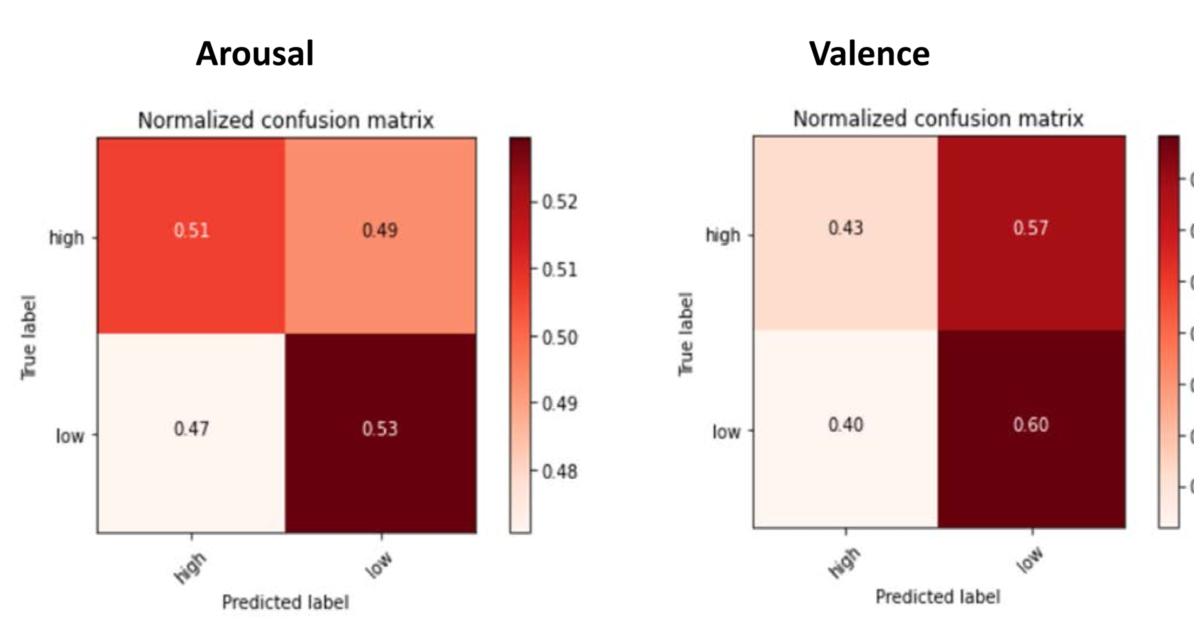

Fig 4 Literature Review Search terms

The next steps to improve the prediction results will involve:

- Rerunning the model with each of the physiological signal data for Galvanic Skin Response (GSR), Respiration, Plethysmography(for heart rate) and Temperature
- Fine tuning the hyperparameters of the CNN Conv1d model
- Consider other validation methods
- Rerun the model with different combinations of the physiological signals
- Trying machine learning techniques other than CNN Conv1d.

Planned Work

Improve results of the current arousal and valence prediction model.

Create a model that predicts the four quadrants (LALV, LAHV,HALV and HAHV).
Apply the model to other emotion recognition using peripheral physiological datasets (DREAMER, AMIGOS, ASCERTAIN, WESAD)

In parallel, continue literature research on both emotion recognition and QuX to fine tune research question and find studies for comparison.

Test the model on live participants who will be wearing sensors to capture the chosen physiological signals. An ethics review for the study will be performed.

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