Coursework 2: Non-Verbal Affective Computing for Emotion Recognition

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Mainstream emotion recognition AI relies primarily on facial expressions and has been controversially used in areas such as evaluating job applicants and identifying terrorists (Hagerty & Albert, 2021). In recent years, this technology has come under criticism for its weaknesses in detecting hidden emotions and accounting for racial differences in expression (Liu et al., 2021; Rhue, 2018).

The **first research frontier** aims to address these weaknesses, either by refining existing models or by using physiological signals instead of facial expressions. For example, academics are designing solutions that detect hidden emotions by analysing micro-expressions (X. Li et al., 2018), whilst software company Affectiva is attempting to reduce racial bias by building ethnically based benchmarks into their model (Schwartz, 2019). However, utilising these benchmarks introduces the new task of predicting ethnicity solely based on physical appearance, which is likely to be impossible in today's globalised world. The reason physiological signals have been receiving attention is that they bypass racial differences and are also very difficult to fake. Researchers have shown that a wide range of signals contain emotional information, for example EEG signals reflect emotions through the distribution of brain waves whilst galvanic skin response reflects emotions through changes in the electrical resistance of skin (Dzedzickis et al., 2020).

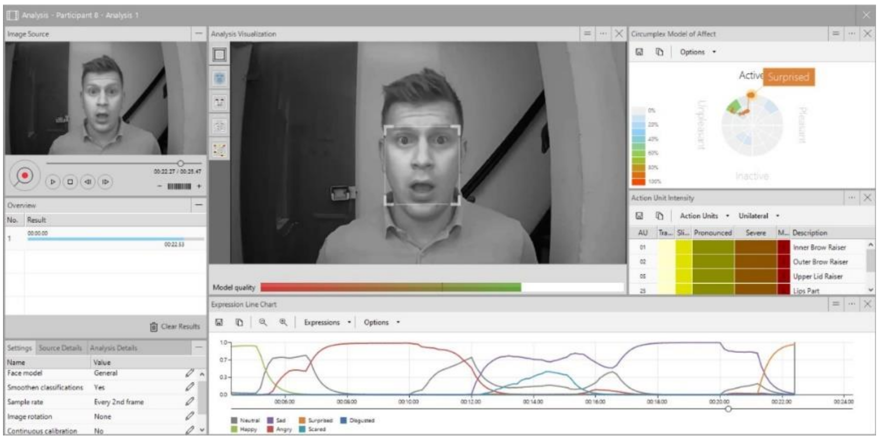

Figure 1. *Emotion recognition using facial expressions (taken from Noldus, n.d.)*

Out of all physiological signals, EEG has received the most recent interest with publications increasing exponentially to around 4600 in 2018 (Hu et al., 2019). However, Soleymani et al. (2016) found EEG signals to show inferior performance compared with facial expressions. Even worse, they found that contamination of facial muscle activity explained much of the valuable information from the EEG signals. Therefore, the **second research frontier** aims to improve the accuracy of EEG-based emotion detection. One proposal that has shown promise is to use deep learning techniques instead of traditional machine learning. For example, Algarni et al. (2022) used a stacked bi-directional LSTM model and obtained accuracies of 99.45% and 96.87% respectively in the valence and arousal dimensions. However, even the most popular emotional analysis datasets such as DEAP and DREAMER only have 20-60 subjects, which may be insufficient for reliable deep learning (Dadebayev et al., 2021). Alternatively, several studies recommend multimodal analysis by fusing EEG signals with data from other sensors (Dzedzickis et al., 2020). For example, D. Li et al. (2019) find that a combination of EEG signals and facial expressions outperform both individual markers. This suggests that data fusion may be the most promising way of eliminating the biases but retaining the accuracy of using facial expressions. However, each physiological signal involves a different sensor being attached to the body, so researchers must stay mindful of the trade-off between comfort and accuracy when designing fusion-based models.

Previous studies have predominantly used passive emotional elicitation methods to generate training data, usually involving subjects watching media on a screen in a controlled laboratory environment (Shu et al., 2018). The downside is that these conditions may not be engaging enough to trigger powerful emotional responses (Hu et al., 2019). The **third research frontier** explores the use of virtual reality as a way of retaining the control of passive methods whilst adding a layer of immersion and interactivity that generates a stronger training dataset. The ability of VR to evoke strong feelings is demonstrated by Marín-Morales et al. (2019) who find that self-assessed valence and arousal scores in a virtual museum are as high as in a real museum. However, these results may be biased upwards considering that all subjects were new to VR which may have exaggerated their emotions. Indeed, Marín-Morales et al. (2018) use a series of VR rooms to elicit emotional changes but only obtain accuracies of 71.21% and 75.00% respectively in the valence and arousal dimensions. This is lower than other studies using traditional passive elicitation and therefore consistent with the notion that current VR technology is still less powerful than real experiences. Despite this, we have seen rapid progress in the display resolution and graphical performance of HMDs, which suggests that VR will become an ever more valuable emotional stimulus in the coming years (Marín-Morales et al., 2020).

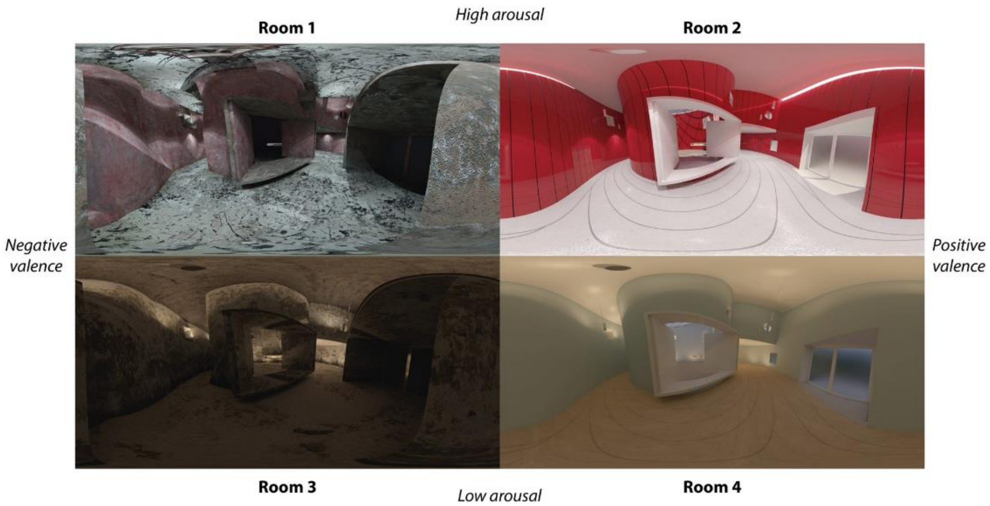

Figure 2. *Virtual environments designed to elicit different emotions (taken from Marín-Morales et al., 2019)*

The interactivity of VR also leads into the **fourth research frontier** which involves integrating more sophisticated psychological models into emotion recognition AI. Many existing systems are rooted in Russell's Circumplex, a model that attempts to classify emotions based on their levels of 'valence' and 'arousal' (Russell, 1980). Russell's full model contains a third dimension called 'dominance' that has been mostly ignored up until recently, however this can now be easily explored by varying levels of control in VR environments (Marín-Morales et al., 2020). Implementing the full model will provide more accurate depictions of emotion, for example anger and fear show similar valence and arousal levels, but anger is a much more dominant emotion. Another psychological theory commonly applied to affective computing systems is Ekman's Six Basic Emotions, which argues that all emotions fall into only a few classes that are universal across humanity and have distinctive physiology (Ekman, 1992). This theory has been criticised for being overly simplistic, for example only one of Ekman's basic emotions is positive, whereas Fredrickson (2013) offers a more nuanced view by recognising ten distinct positive emotions (Hu et al., 2019). However, incorporating a wider range of positive emotions would also make loosely happy states more difficult to classify, highlighting a trade-off between accuracy and emotional realism. Therefore, researchers might be reluctant to include new emotions in their models since these are primarily evaluated through accuracy scores. To encourage a more holistic view on model performance, it is recommended that future research is conducted by multidisciplinary teams rather than only by computer scientists (Barrett et al., 2019).

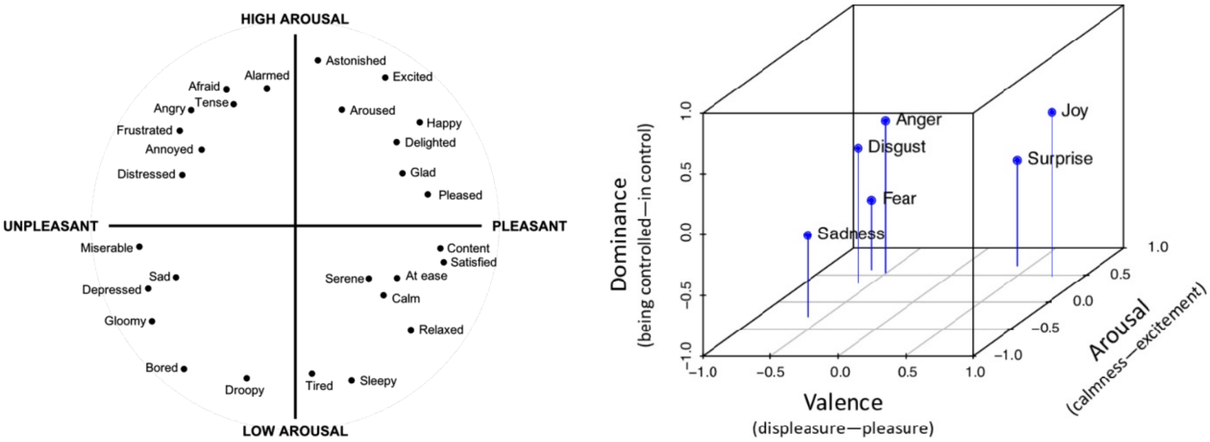

Figure 3. *2D and 3D versions of Russell's Model (taken from Feidakis et al., 2019; Winiger, 2020)*

Whilst the previous frontiers have been focused on model performance, the **fifth research frontier** recognises the importance of widening access to the technology. Recent smartwatches such as Fitbit's Sense are being equipped with stress detection capabilities, demonstrating the potential benefits of personal emotion detection (Kansal, 2022). We are also beginning to see the release of affordable EEG headsets, such as NeuroSky's MindWave which retails at $110 (NeuroSky, n.d.). Despite these positive developments, significant progress still needs to be made. Javaid et al. (2015) find that increasing the number of electrodes in an EEG headset from three to eight raises arousal detection accuracy from 59.10% to 87.62%. In contrast, the

MindWave has only a single electrode (Dadebayev et al., 2021). Additionally, consumer headsets use dry electrodes instead of gel-based electrodes to reduce set-up time, however these require uncomfortably high pressure to be applied to the scalp (Hu et al., 2019). Dadebayev et al. (2021) show that although some lower cost headsets can perform reliably, their performance is still inferior compared to research-grade headsets. This performance gap is likely to increase when sensors are taken out of a laboratory setting, for example the accuracy of smartwatch sensors is reduced when subject to high levels of movement noise (Sayed Ismail et al., 2022).

To conclude, it is recommended that researchers report results from both consumer-grade and research-grade sensors (Hu et al., 2019). This will help indicate when new affective technologies are ready for widespread adoption. At the same time, researchers and policymakers must consider the ethical issues of consent and privacy to ensure that people's emotional data is not used inappropriately (Murgia, 2021).

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