

# Inferring User Facial Affect in Work-like Settings

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**Abstract**—Unlike the six basic emotions of happiness, sadness, fear, anger, disgust and surprise, modelling and predicting dimensional affect in terms of valence (positivity - negativity) and arousal (intensity) has proven to be more flexible, applicable and useful for naturalistic and real-world settings. In this paper, we aim to infer user facial affect when the user is engaged in multiple work-like tasks under varying difficulty levels (baseline, easy, hard and stressful conditions), including (i) an office-like setting where they undertake a task that is less physically demanding but requires greater mental strain; (ii) an assembly-line-like setting that requires the usage of fine motor skills; and (iii) an office-like setting representing teleworking and teleconferencing. In line with this aim, we first design a study with different conditions and gather multimodal data from 12 subjects. We then perform several experiments with various machine learning models and find that: (i) the display and prediction of facial affect vary from non-working to working settings; (ii) prediction capability can be boosted by using datasets captured in work-like context; and (iii) segment-level (spectral representation) information is crucial in improving the facial affect prediction.

**Index Terms**—Affective states, Work-like tasks, Emotions in working environments

## I. INTRODUCTION

There are different ways of modelling and analysing human affect. The theory of six basic emotions (happiness, sadness, surprise, fear, anger and disgust) has been a good simplification but in the real-world, e.g., where people live and work, people do not display emotions in an exaggerated manner that can be categorized into these six categories. The dimensional perspective has been proposed as a viable alternative for non-acted emotions. It suggests that emotions are responses to environmental stimuli that vary along three key dimensions - valence/pleasure, arousal, and dominance/control. This approach has now been widely adopted by the affective computing community – see [1], [2] for extensive reviews.

Previous research studies explored facial affect recognition through hand-crafted features [3], [4] and deep neural networks [5]–[8]. However, all these studies are conducted on facial datasets recorded in the lab (controlled) conditions or in-the-wild (data scrapped from the internet) settings (please see [9] for details). Systems created for ambient assistive living environments [1], [10], [11] aim to be able to perform both automatic affect analysis and responding. Ambient assistive living relies on the usage of information and communication

technology (ICT) to aid in person’s every day living and working environment to keep them healthier and active longer, and enable them to live independently as they age. Thus, ambient assistive living aims to facilitate health workers, nurses, doctors, factory workers, drivers, pilots, teachers as well as various industries via sensing, assessment and intervention. The system is intended to determine the physical, emotional and mental strain and respond and adapt as and when needed, for instance, a car equipped with a drowsiness detection system can inform the driver to be attentive and can suggest them to take a little break to avoid accidents [12], [13].

Research shows that employees’ moods, emotions, and dispositional affect influence critical organizational outcomes such as job performance, decision making, creativity, turnover, prosocial behaviour, teamwork, negotiation, and leadership [14]. Therefore, analysing and understanding the affect of the employees in an organisational setting is crucial in shaping organizational behaviours and decisions. To understand and evaluate the emotional and affective states in working environment it is necessary to gather data from the actual working environment or work-like settings as emotional and affective states in these environments vary from other settings due to the specific physical and mental workload, and physiological activity of the worker [15]. More importantly, workers’ affect in working environments relate to their performance, well-being, risk perception and assessment, and can be even used for quality control [16], [17].

Therefore, in this paper, we aim to train and evaluate machine learning models to infer user facial affect when the user is engaged in multiple work-like tasks under varying difficulty levels. More specifically, we explore (i) an office-like setting where they undertake a task that is less physically demanding but requires greater mental strain; (ii) an assembly-line setting that requires the usage of fine motor skills; and (iii) an office-like setting representing teleworking and teleconferencing.

The rest of this paper is organised as follows: Section II describes the study protocol developed to acquire data, and tasks performed to simulate work-like settings. Section III presents the methodology and section IV analyses the results of the experiments conducted and concludes the paper.



Fig. 1. Illustration of the recording and data collection setting.

## II. THE STUDY

### A. Study Aims

To investigate the people's affective and emotional states in work-like settings, we designed a study and conducted different experiments that simulate the working environment conditions and challenges such as varying mental workload, varying physical load and varying stress levels. With this, we aim to investigate the following research questions:

- RQ1: Does facial affect (valence and arousal) predicted by the machine learning models vary significantly in work-like settings as compared to non-working conditions?
- RQ2: How does segment-level information as compared to frame-level information influence the accuracy of the facial affect predictions?
- RQ3: How well the predictions generated by the models in terms of valence and arousal match the self-reported affect reported using the Self-Assessment Manikin (SAM) - i.e., to what extent are the self-reported labels and system predicted labels agree? ?

### B. Recording Setup

The recording setup is illustrated in Fig. 1. A participant is asked to sit at a table, where a laptop displaying slides with instructions is provided to guide the participant through the required tasks. Meanwhile, two cameras (a Logit web camera and a Dahua IP camera) are placed in front of the participant and a GoPro camera is placed on the table. In addition, the participant is also asked to wear three sensors, i.e., a Jabra microphone around their neck that records the participant's voice, an Empatica wristband and a Muse sensor that record psychological signals. As a result, the dataset contains multi-modal recordings for each participant, including audio, video, and a set of psychological signals. In this paper, only the Dahua IPC-HFW1320S-W Camera recordings are considered for facial affect analysis .

### C. Participants

This study was approved by the University of Cambridge's Department of Computer Science and Technology Ethics

Committee. Following an explanation of the study and informed consent from each participant, the experiment was carried out in accordance with the principles outlined in ethical approval. Additional COVID related measures were also put in place prior to undertaking the study. Twelve participants were recruited from the University of Cambridge (5 male and 7 female from 9 countries) with an average age of 28.25 (max=41 and min=22). All participants were proficient in English.

### D. Data Collection Protocol

To simulate various working conditions, a standard protocol was designed to assess affect in work-like contexts. The experiments to stimulate working conditions included three tasks: the N-back task, the Operations Game task (they were looking down during this task), and the Webcall task. In N-back and Operations Game tasks, participants were asked to conduct different sub-tasks performed in varying challenging conditions namely baseline, easy (conducted twice), hard (conducted twice) and hard-under-stress conditions. For the Webcall task, there are three sub-tasks including baseline, conversation of a happy memory and conversation of a negative memory. The example facial displays triggered by different tasks are visualized in Fig. 2.

**The N-back task:** The activities in this task represent the office-like settings (less physical but with greater mental strain) and test the worker's memory load for a reasonable approximation of work load. In this task, a series of letters are presented on a computer screen and the participant is requested to press the button when the letter on the screen match the letter that appeared in previous  $n$  stages. The task's complexity can be modified by increasing the value of  $n$ , challenging participants to memorize more letters in order. In this study, the tasks are categorized into Baseline and three conditions, Easy, Hard and Hard-under-stress. Under all conditions, 21 Uppercase letters (33% target letters) were exhibited for 500 milliseconds with random inter-stimulus interval of 500 to 3000 milliseconds.

- Baseline (NBB): Participant observes the screen and the letters without pressing any button.
- Easy-0-back (NBE): The participant indicates when the current stimulus match the predefined letter.
- Hard-2-back (NBH): The participant indicates when the current stimulus matches the stimulus that appeared two stages before.
- Hard-under-Stress (NBS): The participant indicates when the current stimulus matches the stimulus that appeared two stages before (equivalent to NBH) but in the presence of additional noise (85dB) and white coat effect (presence of the experimenter in the room monitoring the participant performance).

**The Operations Game task:** The activities in this task represent an assembly-line setting and test the fine motor skills of the participant. In this task, the participant is presented with a board in the form of a patient, and is asked to use tweezers to extract several objects from several slots, without touching



Fig. 2. Example facial expressions displayed by two participants (005 and 006) and triggered by different tasks, where facial expressions during the webcam tasks are generally more expressive.

the edges. This study too involves activities with a baseline, two difficulty levels and one stress condition.

- Baseline (DBB): The participant observes the board-game (operations) without touching the board and the objects.
- Easy (DBE): The participant is asked to remove the five predefined objects (the easiest ones) within three minutes.
- Hard (DBH): The participant is asked to remove all twelve objects from the board within one minutes.
- Hard-under-Stress (DBS): The participant is asked to remove all twelve objects from the board within one minute (equivalent to DBH) but in the presence of additional noise (85dB) and white coat effect (presence of the experimenter in the room monitoring the participant performance).

**The Webcam task:** The activities in this task represent the teleworking setting via tele-conferencing and ask for positive and negative memory recalls of the participant. In this task, the experimenter hosts an MS Teams call with the participant to hear them talking about their positive and negative memories or experiences. This task involves baseline, a positive and a negative condition lasting for about two minutes each.

- Baseline (WEB): The participant observes the monitor without talking.
- Positive Condition (WEP): The participant recalls the happiest memory from their recent past.
- Negative Condition (WEN): The participant recalls a very negative / sad memory from their recent past.

These tasks were executed in random order, and balanced across all participants. We refer to the data collected through this study and these tasks as Working-Environment-Context-Aware Dataset (WECARE-DB).

#### E. Questionnaires and participant self-report

To compare the objective sensor data with subjective self-reported evaluations, a questionnaire called the **Self-Assessment Manikin (SAM)** was used. The Self-Assessment Manikin (SAM) is a picture-oriented questionnaire [18] developed to measure the valence/pleasure of the response (from positive to negative), perceived arousal (from high to low

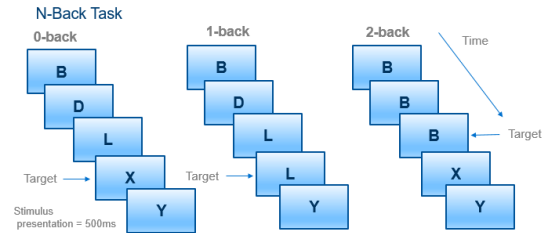


Fig. 3. Example of N-back task with 0-back, 1-back and 2-back conditions



Fig. 4. The Operations Game task which instructs the participant to pick as many things out of the "patient" as possible without hitting the metal boundary. The nose will glow red and the board will vibrate if the participant makes an error.

levels), and perceptions of dominance/control (from low to high levels) associated with a person's affective reaction to a wide variety of stimuli. The person is asked to provide only three simple judgments along each affective dimension (on a scale of 1 to 9) that best describes how they felt regarding the provided stimuli. In our study, SAM was filled in after each baseline task and after each condition within a task. The questionnaire was introduced at the beginning of the experiment with example exercises.

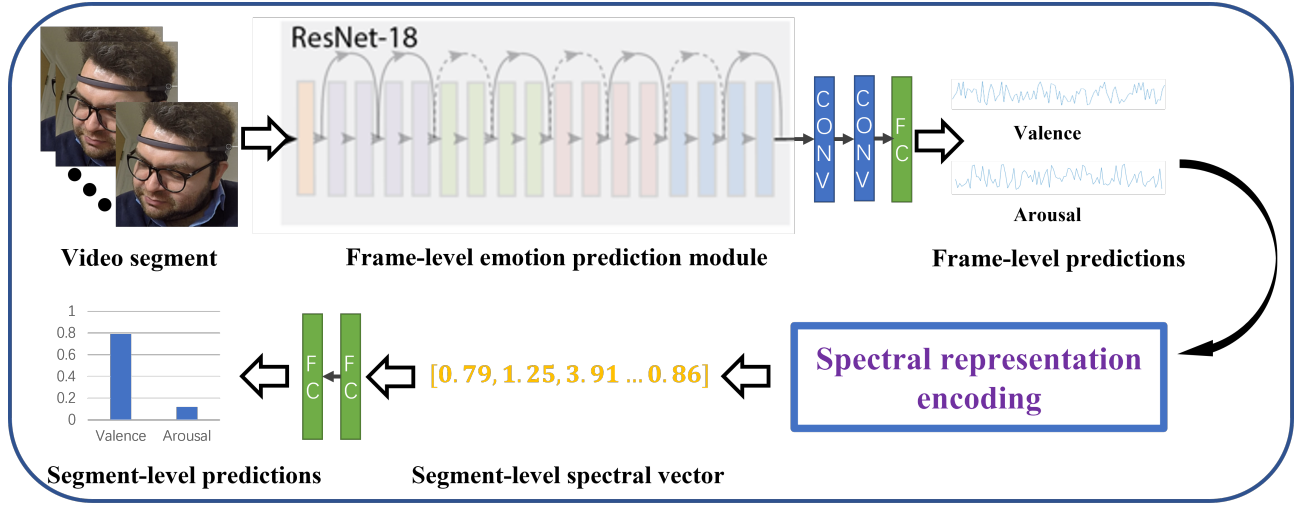


Fig. 5. Illustration of the proposed S-ResNet framework.

### III. METHODOLOGY

Firstly, to be able to use the self-reported SAM labels as *ground truth*, we first map the collected values to valence and arousal dimensions. Specifically, we map the unhappy-happy dimension to valence and the calm-excited dimension to arousal. For both dimensions, we use 5 as the threshold to map the corresponding values to negative ( $< 5$ ), neutral ( $= 5$ ) and positive ( $> 5$ ).

Secondly, to process the camera input, for each grabbed frame we apply face detection followed by facial landmark detection [19]. The facial landmarks are utilized for face alignment [20]. The aligned facial image is then fed to a *ResNet-18* network [21] with two additional convolution layers to provide deeper feature representation for valence/arousal prediction. This network is trained with a Mean Squared Error (MSE) loss to predict the valence and arousal values for each incoming facial image. The employed network is pre-trained using the AffectNet dataset [9]. This dataset contains large number of images from the Internet that were obtained by querying different search engines using emotion-related tags. 450,000 images in this dataset are manually annotated with valthe valence and arousal dimensions).

Thirdly, we fine-tune this network using our collected WECARE dataset and we refer to this model as *F-Res*. Finally, as the goal is to predict the affect of a user for a certain period in time, the spectral representation [22], [23] is utilised to summarize the frame-level predictions for a certain period, which is then fed to another two-layer fully connected layer to generate the segment-level valence/arousal predictions. We refer to this model as *S-Res*. This pipeline is also illustrated in Fig. 5.

The performance of all three models is evaluated using three metrics: Concordance Coefficient Correlation (CCC), Pearson Coefficient Correlation (PCC) and Root Mean Square Error (RMSE) as these are well known metrics utilised for automatic prediction of affect [24], [25].

	Valence			Arousal		
	ResNet-18	F-Res	S-Res	ResNet-18	F-Res	S-Res
<b>RMSE</b>	0.38	<b>0.35</b>	<b>0.35</b>	0.38	0.37	<b>0.33</b>
<b>CCC</b>	<b>0.56</b>	<b>0.56</b>	0.55	0.52	0.55	<b>0.59</b>
<b>PCC</b>	0.41	0.39	<b>0.44</b>	0.38	0.43	<b>0.47</b>

TABLE I  
VALENCE AND AROUSAL PREDICTION RESULTS OF THE EMPLOYED MODELS IN TERMS OF RMSE, CCC AND PCC.

### IV. RESULTS AND DISCUSSION

Table I presents the valence and arousal predictions provided by three models: 1) ResNet-18 pre-trained by AffectNet [9] (*ResNet-18model*); 2) ResNet-18 fine-tuned by our WECARE-DB (*F-Resmodel*); and 3) F-Res model with spectral representation-based segment-level prediction (*S-Resmodel*). Looking at the table we observe that the model fine-tuned on WECARE-DB outperformed the ResNet-18 model pre-trained on AffectNet, indicating that the facial behaviours displayed in work-like environments are different compared to the in-the-wild Internet settings utilised in the AffectNet DB. Thus, it is necessary to acquire datasets and train models for recognising facial affect in work-like settings. Importantly, we found when using spectral representation [22], [23] to summarise segment-level information provides a large improvement suggesting that representing facial displays along time is crucial for predicting facial affect in work-like settings.

Table II presents the average and standard deviation of the sign agreement between the model predictions and self-reported SAM questionnaire. The values show that higher the agreement, the better the model performance. We observe that S-Res model that incorporates information from multiple frames performs best as compared to the other two models, thus supporting **RQ2**, that temporal information improves model performance.



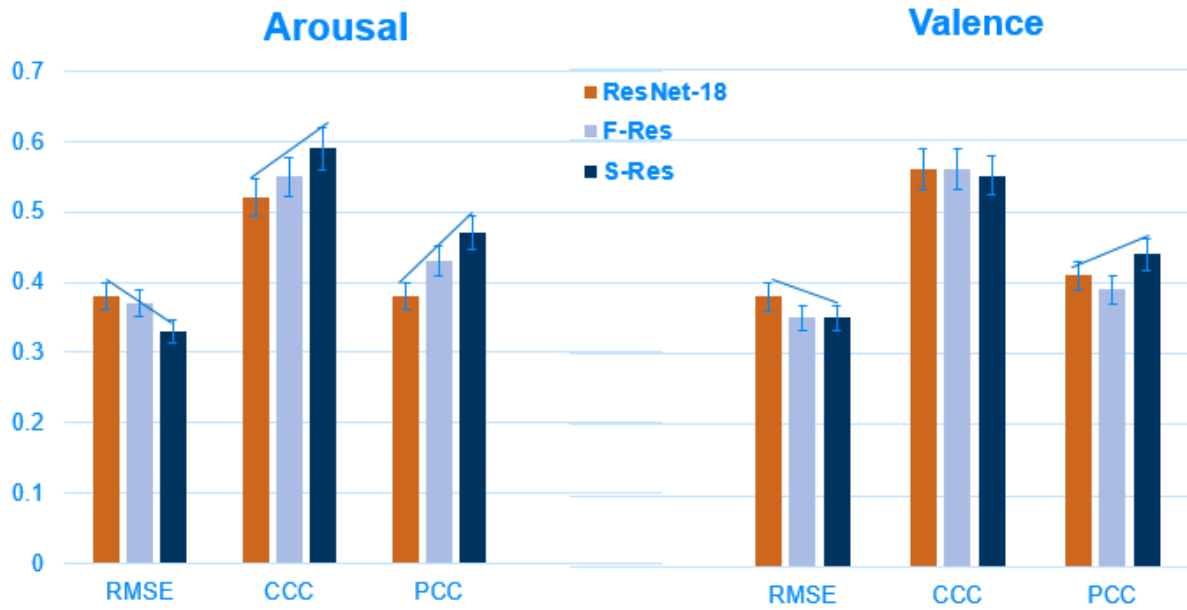


Fig. 6. Illustration of Valence and Arousal prediction results of the employed models in terms of RMSE, CCC and PCC.

Tasks / Model		N-Back				Webcall*			Doctor Game			
		NBB	NBE	NBH	NBS	WEB	WEP	WEN	DB	DBE	DBH	DBS
<b>ResNet-18</b>	Mean	0.33	0.33	0.25	0.16	0.25	0.41	0.08	0.08	0.16	0.33	0.25
	Std	0.49	0.49	0.45	0.38	0.45	0.51	0.28	0.28	0.38	0.49	0.45
<b>F-Res</b>	Mean	0.41	0.49	0.33	0.25	<b>0.31</b>	0.51	0.16	0.33	0.25	0.33	0.33
	Std	0.52	0.55	0.49	0.45	0.51	0.52	0.38	0.49	0.45	0.49	0.49
<b>S-Res</b>	Mean	<b>0.51</b>	<b>0.51</b>	<b>0.58</b>	<b>0.67</b>	0.16	<b>0.58</b>	<b>0.25</b>	<b>0.56</b>	<b>0.75</b>	<b>0.68</b>	<b>0.56</b>
	Std	0.52	0.52	0.51	0.49	0.38	0.51	0.42	0.51	0.44	0.47	0.51

TABLE II

THE AVERAGE AND STANDARD DEVIATION OF THE SIGN AGREEMENT RESULTS BETWEEN MODEL VALENCE AND AROUSAL PREDICTIONS AND THE SELF-REPORTED SAM VALUES. TASKS ARE DIVIDED WITH RESPECT TO THE DEGREE OF TASK DIFFICULTY.

As future work, we will extend this study to a larger multi-site dataset that has been acquired at different European sites where the acquisition and study protocol used in this paper has been utilised to record participants performing work-like tasks. We will also investigate the information contained in other modalities such as psychological signals for predicting user affect when performing work-like tasks. The ultimate goal is to implement and use the trained models in real time and in real work settings to provide input to decision support systems to promote health and well-being of people during their working age in the context of the EU WorkingAge Project [26].

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