Abstract—Real-world application require affect perception models to be sensitive to individual differences in expression. As each user is different and expresses differently, these models need to personalise towards each individual to adequately capture their expressions and thus model their affective state. Despite high performance on benchmarks, current approaches fall short in such adaptation. In this dissertation, we propose the use of continual learning for developing personalised affect perception.

I. INTRODUCTION

Current approaches in affect perception predominantly focus on instantaneous analysis of human behaviour. They rely on glimpses of heightened audio-visual stimuli to infer the affective state of the user [1], [2]. Even though this works well in providing a short-term evaluation of human expression, where only a snapshot of user behaviour is required, analysing long-term interactions, under varying affective contexts, is still an open problem [3]. As a result, despite current (deep) learning approaches achieving high performance on expression recognition benchmarks (see [1], [4], [5] for an overview), they are not able to sufficiently model human affective behaviour in long-term interactions.

The development cycle for most (deep) learning approaches follows a fixed transition from first, being trained in isolation on a ‘large enough’ dataset with high variability, and then being applied to real-world applications [6]. With a lot of the existing datasets capturing posed expressions recorded in fixed laboratory conditions, generalisation to real-world scenarios becomes problematic [5]. As a result, the research has turned towards training and testing models on data that capture affect in-the-wild [7], containing samples collected from real-world scenarios. Yet, these models still follow the same development cycle, with little to no adaptability in their application, facing difficulties in capturing individual differences in expression.

There is a need for models to adapt to individual differences in expression, enabling them to personalise towards individuals, in real time. Personalisation, in this context, can mean the ability to account for individual differences in expression, as well as individual behaviour patterns while sensing and analysing their affective state during an interaction. Despite some efforts focussing on individual expression to realise generic-to-specific perceptual adaptations [8], [9], more work is needed on personalised affect perception.

Continual Learning (CL) research [10], [11] aims to address this very problem of long-term adaptability in agents, enabling them to learn incrementally as they interact with their environment. CL models are commonly applied learning different objects and tasks for an agent in an incremental manner [11]. The basic principles of CL, however, can also help in developing models for affect perception [12], [13] that learn individual differences in expressions to personalise towards different users. This can be particularly beneficial in real-world interactions where social agents, embedded with such affect perception mechanisms, learn and adapt with each user they interact with. Starting from a limited understanding, they can learn to personalise towards each user, while at the same time, learning global and generic features.

In this dissertation work, we propose Continual Learning as a learning paradigm for Affective Computing. In this paper, in particular, we discuss learning mechanisms that model generic-to-specific adaptations in Facial Expression Recognition (FER) models to enhance their personalisation capabilities. Our focus on CL approaches for lifelong learning of affect presents a two-fold problem. On the one side, the model should personalise towards a particular user, learning how they express their affective state, yet, at the same time, it also needs to adapt to different users. Thus, learning happens at two-levels, individual, that is, learning different expressions of a particular user, and between-individuals, that is extending the learning to be sensitive to different subjects. In our current work [14], we examine the former, learning different facial expression categories for the same individual. Current and later work focuses on extending this to between-individual adaptation, where the same model is applied to learning with different subjects.

II. WORK SUMMARY

A. Proposed Framework

Our recent work [14] presented a novel framework that integrates a Complementary Learning System (CLS)-based [15], neuro-inspired approach for learning facial expressions. The proposed framework for Continual Learning with Imagination for Facial Expression Recognition (CLIFER) (see Fig. [1]) consists of two components: (i) a generative auto-encoder model for imagination, that is, generating additional facial images for individual subjects for unseen classes to augment learning; and (ii) a dual-memory-based learning model for FER that adapts to novel
data and balances long-term retention of knowledge. The imagination model learns to generate facial images for 6 expression classes, namely, anger, happy, fear, sad, surprise and neutral. These generated images augment learning in the dual-memory model that learns to classify these images. The two components of the framework are briefly described here:

1) Auto-Encoder-based Imagination Model: The recent success of generative models [16], has enabled the generation of images containing human faces with different emotion expressions [17]. Thus, having seen only a few images of a subject, the model can generate additional data (akin to imagination in humans) for the individual to preempt future interactions. For an agent, such a model can be applied to realise imagined contact [18] with a participant simulating imagination as a substitute for sensory experience. To achieve this, we use a Conditional Adversarial Auto-Encoder (CAAE)-based [17] imagination model (see Fig. 1) that takes an original (input) image ($x_r$) and generates translated images ($x_{gen}$) for each of the 6 expressions.

2) CLS-based Dual-Memory Model: The Growing Dual Memory (GDM) architecture [15] is used as the basis for incrementally acquiring and integrating knowledge in CLIFER. It consists of two hierarchically arranged recurrent Growing When Required (GWR) neural networks representing the episodic (GDM-E) and semantic (GDM-S) memories, respectively.

   - Episodic Memory: Each input image is encoded and sequentially passed to the GDM-E which rapidly learns (using a high learning-rate) non-overlapping representations. This is achieved using a distance-based similarity measure, implementing unsupervised Hebbian-based learning. As it receives data, one class at a time, it creates feature prototypes for each input sample, adapting to novel data.
   - Semantic Memory: GDM-S learns compact overlapping representations that can generalise across a particular class. After each episode (mini-batch) of sequential input, GDM-S receives the winner neurons from GDM-E, along with label annotations. A frequency-based associative labelling scheme [15] is used to associate feature prototypes with their respective labels (depicted by the mode of the histogram). New neurons are added to GDM-S only if the existing neurons are not able to correctly classify the input.
   - Imagination: After receiving data samples from a particular class, winner neurons from the GDM-E are passed to the imagination model which generates facial images for each expression class, preserving the identity of the subject. These imagined images are replayed to both GDM-E and GDM-S, augmenting learning in CLIFER.

B. Experimentation and Results

To evaluate the CLIFER framework, we conduct two experiments to evaluate the model’s ability to (a) remember previously seen expression classes on an individual and (b) to extend its learning to yet unseen facial expressions. CLIFER is trained and tested separately for each subject from the RAVDESS [19], MMI [20] and BAUM-1 [21] datasets. While RAVDESS and MMI datasets provide an evaluation on posed samples, BAUM-1 evaluates the model on spontaneous FER.

In our experiments we compare four different models, namely; (i) the GDM model without replay, (ii) GDM model with a pseudo-replay mechanism (see [15] for details), (iii) the proposed CLIFER framework, and (iv) a Multilayer Perceptron (MLP)-based classifier that acts as a baseline.

1) Results: The GDM architecture aims to learn distinguishable feature representations for each class, making learning class-order agnostic. In practice, however, for FER we found the model’s performance to be sensitive to the order of learning different classes for each subject. To quantify this, we selected 6 different class orders, starting with each of the 6 classes used in this work. The rest of the order was selected randomly.

Kruskal-Wallis H-test results show a significant difference ($p < 0.05$) in model performance for Experiment (b) between the 6 class orders. Starting with neutral results in the best performance, on average. A similar effect is seen for Experiment (a). As the model learns how a specific individual expresses different emotions, the learnt feature representations overlap significantly resulting in the order impacting model performance. Other approaches in curriculum-based learning [22], that focus on learning facial expressions one class at a time, have also witnessed a specific order of learning (starting with high-intensity samples) enhancing model performance although they do not evaluate the models for continual learning. Starting with neutral could be beneficial for FER models implementing continual learning for two reasons. Firstly, neutral represents a baseline for
an individual’s expressions and learning this norm enables the model to form distinct prototypes for subsequent images that differ from this baseline. Second, as imagination impacts model performance, the generated images can carry forward some of the features from the original image to the generated samples. Starting with neutral thus results in the least influence of the original image.

As a result, for experimentation, we set the order of learning classes to start with neutral, followed by (randomly selected) happy, surprise, anger, fear and sadness. The results for the RAVDESS, MMI and BAUM-1 datasets for the two experiments can be seen in Fig. 2a and Fig. 2b, respectively. The GDM model outperforms the MLP baseline on all the 3 datasets for both the experiments. The GDM + Replay and the proposed CLIFER framework (that is, GDM-E + Replay) perform better than the standard GDM model, with CLIFER, on average, performing the best across all settings resulting in high F1-scores; RAVDESS (episodic: F1>= 0.97, semantic: F1>= 0.75), MMI (episodic: F1>= 0.75, semantic: F1>= 0.46) and BAUM-1 (episodic: F1>= 0.87, semantic: F1>= 0.51).

These results highlight the framework’s ability to adapt to an individual subject, extending its knowledge to novel classes while retaining previously learnt information. The model performance is comparable (if not better) to the state-of-the-art for RAVDESS (0.79 [23]), MMI (0.78 [24]) and BAUM-1 (0.47 [21]) datasets. Yet, it will not be correct to compare these scores directly as they do not use incremental learning for training the models and have all the data available to them apriori. Furthermore, one thing to note here is that, we select a sub-set of subjects from these datasets that provide data samples for each of the 6 expression classes [14].

III. FUTURE PLANS

A. Expanding CLIFER

Experimentation with CLIFER [14], as discussed above, highlighted the applicability of CL approaches for affect perception. Yet, one thing to be noted here is that such an application of CL is not as straightforward as other learning tasks, for example, as learning to classify objects. Important aspects such as the order of learning and context have a huge impact on learning to classify facial expressions. Furthermore, human expressions should not be viewed as isolated instances of occurrence, particularly in real-world interactions, but need to be understood as context-driven responses that evolve over a period of time in response to affective stimuli. Thus, accounting for such a temporal evolution of expression becomes crucial in recognising the affective state expressed by a user.

Furthermore, adopting a lifelong and adaptive view on affect modelling, it is important not only recognise expressions but also model the person’s long-term behaviour. Analysing how their affective behaviour evolves over time, the model can learn not just their expressions but also estimate the mood of an individual during an interaction as well as their long-term personality. We are currently exploring recurrent and self-organising neural models for spatio-temporal feature learning that can enable modelling the affective state of an individual at varying temporal resolutions. Based on neuro-inspired mechanisms for affective learning, that is, the interplay between the short-term and long-term memory models in our brain that contribute towards affective association [25], [26], these models will fit well with the CLIFER framework, extending it towards a multi-memory set-up.

B. CLIFER for Human-Robot Interaction

Real-world human-robot interactions provide the best application conditions for CLIFER as they require robots to adapt to the dynamics of each interaction, offering personalised interactions to the users. In particular, longitudinal interactions, where a user and the robot interact with each other repeatedly, over several interactions, require the agent to incrementally improve its understanding of user behaviour. In such interactions, CLIFER, after each interaction, should be able to imagine the user under different interaction conditions and update its learning to improve its performance for each subsequent interaction round.

To evaluate such personalised affect perception, we will conduct a user-study with the Pepper Robot. The user-study will involve participants repeatedly interacting with Pepper over multiple interaction sessions. Each session will be designed in a manner that it elicits a specific affective

\[1\text{https://www.softbankrobotics.com/us/pepper}\]
response (for example, anger or happiness) from the user. The task for the robot will be to learn to recognise the user’s expression, personalising towards their expressions. Two conditions will be compared. In the first condition, Pepper will use a state-of-the-art FER model while the second condition will implement the CLIFER framework for affect perception. It is expected that the CLIFER framework should perform better in recognising the facial expressions of the users, even after only a few interactions, and incrementally improve its performance.

C. Challenges

One of the key challenges faced for person-specific adaptation is the lack of long-term interaction data for training the models. Most of the existing datasets, even if recording spontaneous expressions, consist of data recorded for different individuals only over a handful of interaction sessions. Also, as these interaction sessions are usually recorded all together, the data does not enable modelling affective behaviour dynamics of the individual, over time.

In the CLIFER framework, we tackle the issue with lack of data by using the imagination model. It enables us to generate additional data for an individual for the different expression classes. Yet, this may restrict the model’s capability to handling only a few expression classes. Thus, our future work plans to extend the framework to recognising different Action Units (AUs), which will enable adaptation to a wide variety of facial expressions. Additionally, we aim to consider dimensional (valence-arousal) information, moving away from categorical labels to enhance the applicability of the framework to the real-world.

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