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Continual Learning for Adaptive Affective Human-Robot Interaction

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***Abstract*—Unlike industrial robots, social robots such as Pepper, Nao, Furhat, and Moxi are being developed with the goal of assistance, collaboration, and even companionship to humans. However, such social robots at the moment are not suitable for continually changing real-world due to the inability to understand and adapt to the social ecosystem of human beings. Driven by advancements in affective computing and deep learning, social robots aim to recognise affective, social clues such as emotion for interaction. Existing deep learning based affective computing models for human-robot interaction are based on static data distribution; however, in the ever-changing real-world environment, the static nature of data distributions gets invalid. As a consequence, the performance of such social robots degrades substantially. This paper argues that continual learning based affective computing is a step forward for adaptive and personalisable human-robot interaction in a continually changing real world. We conducted an initial experiment on how a continual learning approach can be integrated into emotion recognition and observed that the continual learning approach could learn new emotions in a continuous setting. The intention is to use this insight to build more complex continual emotion recognition models that can adapt and personalise for support and collaboration in the social ecosystem.**

***Index Terms*—Continual Learning, Emotion Recognition, Human-Robot Interaction, Social Robotics**

I. Background

Continuously adapting with interaction is crucial in many fields, such as rehabilitation, education, workspace and private space. These fields also allow embedding robots in assistive and collaborative roles [1] [2]. However, such real-world spaces need reliable, adaptive and personalisable solutions for reaching possible human-robot interaction (HRI) over time. Moreover, with the future perspective of having robots and humans sharing a workspace or a private space beyond the industrial settings, the need for social robots to continuously understand the social ecosystem they will be part of, and its dynamics, is becoming more and more a pressing matter. Communication via verbal and non-verbal methods is vital in interaction with humans in a social ecosystem [3]. Among various modes of communication in the social ecosystem, the ability to understand affective clues such as emotions is crucial for HRI. Affective cues are very informative as these cues can provide a positive and negative signal [4] to social robots. Social robots can improve their interactivity to assist humans in long-term settings by understanding such cues. Social robots need to analyse their human counterparts from natural interaction modalities and generate the appropriate interactive response based on the information. Wherefore, the ability to analyse non-verbal social cues and appropriately respond will embellish social robots' decision-making, giving them the possibility to better aid humans in various tasks and situations. This ability can lead to better cooperation and acceptance of social robots by their intended users in the long term. As a consequence, emotion understanding represents a requisite for HRI [5]–[8]. However, it is a challenging task [9].

Existing deep learning methods (see [10] for an overview) can perform outstandingly on a train-validate-test setting for emotion recognition. However, this outstanding performance comes with caveats. Existing state-of-the-art deep learning methods require substantial data to be trained on to achieve such performance and perform poorly in real-world scenarios. Furthermore, most existing datasets on which trained deep learning methods are created from stationary and controlled environments. As a result, this leads to the underperformance of deep learning methods deployed in real-world situations, such as HRI in a dynamic, noisy environment. With similar deep learning approaches, a social robot interacting with a human still struggles because of constrained adaptation even with real-world datasets such as Aff-Wild2 [11]. This constrained adaptation is because, in the real world, all the data samples to be trained are not available at the initial training phase but are available continually as time progresses. Not to mention that most existing deep learning methods and datasets ignore the important variability factors such as socio-cultural dynamics [12], the spontaneity of facial behaviour [13], and interpersonal traits on expressiveness, gender, and age.

One of the problems with the existing conventional deep learning approach is the "stability-plasticity" dilemma, or catastrophic interference, where stability refers to sustaining previous knowledge while new information is encoded, and plasticity deals with fusing new knowledge. It reflects the context of affective HRI; social robots deployed "in the wild" are expected to interact with the users while recognising their emotions and learning new users' emotions without catastrophically forgetting. For instance, social robots may either observe a user expressing emotion in different environments; or observe a new user expressing unfamiliar emotions as new knowledge. In such settings, conventional deep learning methods, while trying to learn new knowledge (in the absence of previous raw knowledge), overwrite acquired knowledge, also known as catastrophic forgetting. Although some of the approaches try to address adaptation and personalisation in affective HRI by either selecting weights of human-specific attributes [14] and computing clustering [15] of individual specific information, as they use conventional deep learning methods, they face the problem of conventional deep learning methods.

In essence, the social robots need to generalise socio-emotional clues for generic social interaction with humans, personalise individual attributes and variability factors and adapt to changing environments. For the adaptive, personalisable and affective HRI [16], continual learning [17] can be a desiderata. Continual learning is also known as lifelong learning or incremental learning, which presents learning methods from the sequence of data from changing input data distribution and various tasks with the assistance of previously gained knowledge. From the developmental robotics [18] point of view, one of the crucial elements of learning methods is the ability to achieve skill accumulation and progressively perform diverse and complex tasks. Pointedly, continual learning is assumed to tackle this issue by learning incrementally.

As such affective HRI can take reference from the continual learning formulation presented below for a new direction:

$$\forall D_i \,\epsilon\, D,\ F_i^{CL}\ :\ \langle\ h_{i-1},\ B_i,\ K_{i-1},\ t_i\rangle\ \rightarrow\ \langle h_i,\ K_i\rangle, \quad (1)$$

where h_{i-1} is hypothesis of previous learning model, K_{i-1} is knowledge of previous training data till time-step i. t_i is the task label with training dataset B_i with $j \,\epsilon\, [1...,m]$ samples $s_j^i = \langle x_j^i, y_j^i\rangle$ drawn from current distribution. F_i^{CL} adapts with learning model hypothesis obtained from new information and updated its previous memory.

II. Research Objectives

The main aim of this research is:

Improving human-robot interaction through personalisation and adaptation by leveraging user-specific emotions with continual learning methods.

This project raises a series of research questions (RQ) that will shape our objective, design and experimental approaches.

- **RQ1**: How can continual learning and affective computing leverage personalisation and adaptation on HRI?
- **RQ2**: Are unimodal data such as images enough to improve adaptation and personalisation in HRI, or can we integrate other modalities such as audio to improve the learning methods?
- **RQ3**: What kind of behaviour generation methods can help in improving continual learning-based emotion recognition for HRI?

III. Methodology

Several continual learning methods (See [19], [20] for the overviews) have been proposed based on the Eq. 1: **regularisation-based**, **memory replay**, and **dynamic architecture**. In regularisation-based methods, the learning model's weights are constrained while updating. The neuroscience model for consolidating knowledge typically inspires these methods. While in the memory replay-based method, the learning model stores samples of previous tasks or uses generative models to replay regularly. Furthermore, neural resources are extended for learning new tasks in dynamic architecture. In addition, [21] classified continual learning into three scenarios: **task-incremental**, **domain-incremental** and **class-incremental** continual learning. In task-incremental continual learning, information regarding the task ID is always available for learning models for operation. In this continual learning scenario, learning models typically consist of an output layer with a multi-head for each task. While in the domain-incremental continual learning, the model needs to classify among instances of tasks without a task ID. Furthermore, in class-incremental continual learning, the learning model needs to classify among instances of the tasks and infer from which task ID. Similarly, [22] classified continual learning into three scenario types: **New Instance**, **New Concept**, and **New Instances and Concepts**. A new data distribution sample of the same tasks becomes available sequentially in New Instance. While in New Concept, the learning model receives new data distribution of different tasks in sequence. Furthermore, the learning model continually receives data samples from known and new tasks with New instances and Concepts.

For developing adaptive and personalisable affective HRI, considerations are taken from recommendations of [23] such as acquiring user-specific data, obtaining normative baselines, and balancing between plasticity and stability. Furthermore, based on methods and scenarios from [21], [22], we present a continual learning approach for affective HRI called continual emotion recognition. Here we combine the notion of regularisation, task-incremental continual learning and New instances and concepts. Based on these notions, continual emotional recognition needs to adapt to the new user's emotion and personalise to the user's emotion.

Based on Eq. 1, [23] formulated continual learning for affective human-robot interaction.

$$\forall U_i \,\epsilon\, U,\ F_i^{ER}\ :\ \langle\ h_{i-1},\ B_i,\ a_i,\ K_{i-1},\ e\rangle\ \rightarrow\ \langle h_i,\ K_i\rangle, \quad (2)$$

where h_{i-1} is hypothesis of previous emotion recognition model, K_{i-1} is knowledge of training data till users i. e is the fixed collection of emotions (for example: Happiness, Neutral, Sadness, Anger, Surprise, Fear, Disgust, Contempt) for all users with training dataset B_i with $j \,\epsilon\, [1...,m]$ samples $s_j^i = \langle x_j^i, y_j^i\rangle$ drawn from current user data distribution with user specific attributes a_i. F_i^{ER} adapts with model hypothesis obtained from new user information and updated its previous user memory.

IV. Work done so far

We trained the learning model as presented in Fig.1 with a **regularisation-based** approach called Elastic Weight Consolidation (EWC) [24]. The learning model continually learns a

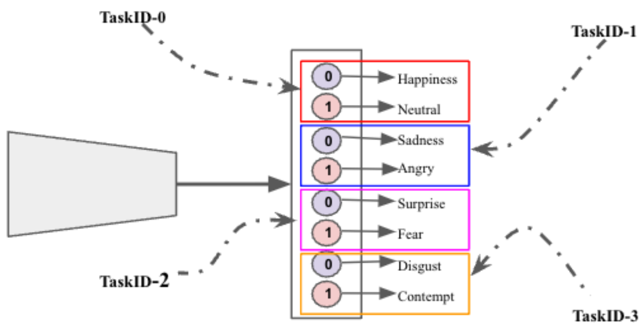

Fig. 1. Learning model for continual emotion recognition.

new set of emotions while handling the problem of stability-plasticity dilemma by regularising the trained model weights. For training the learning model, we used AffectNet dataset [25]. Based on continual learning formulation, the learning model learns a new set of emotions **(New Concept)** from the current emotion data distribution sample while preserving the previously learned set of emotions. While training the current set of emotions, the learning model does not have access to previous data samples but needs to rely on weight constraints. For the feature extractor for the learning model, we used convolutional layers of AlexNet [26] followed by two layers of fully connected layers of 500 nodes followed by eight output layers for recognition of a set of emotions in a continual learning setting. The learning model follows **task-incremental continual learning** scenarios; we separated the eight output layers into four parts, each employed to recognise a set of emotions as shown in Fig. 1.

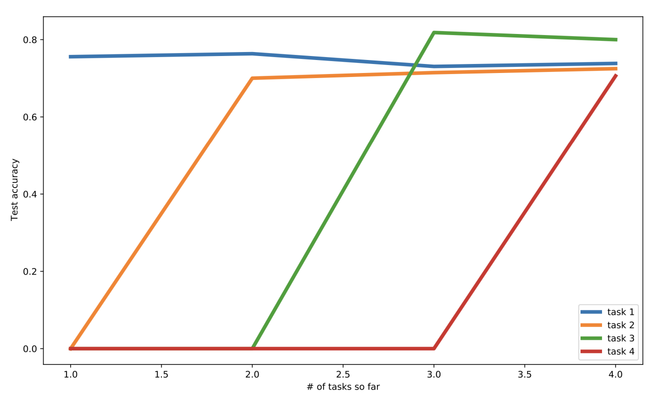

Fig. 2. Results of learning model.

As explained in section I, existing deep learning approaches require all the training data samples to be available in advance for training the learning model. However, indifferent to existing deep learning approaches, our learning model continually receives new data samples from a new set of emotions. Additionally, while training the learning model in the data samples of a new set of emotions, previous data samples of a set of emotions are not available. Hence, the learning model

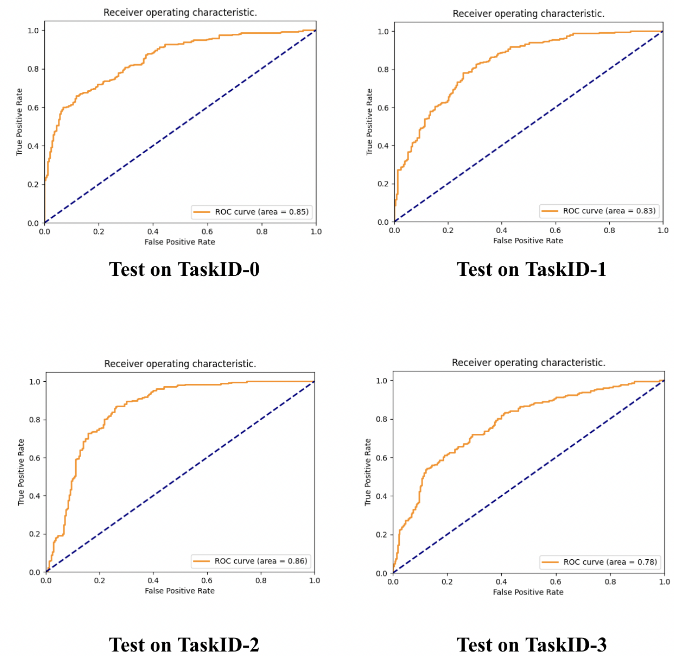

Fig. 3. ROC curve on test data of learning model.

needs to rely on previously learned weights to update weights so that the learning model can perform better on a new set of emotions and previous ones. We computed the accuracy and AUC and observed the results to be promising on all tasks, with above-68% accuracy on all the tasks and more than 0.85 in AUC as shown in Fig. 2 and Fig. 3. This result is promising because the learning model continually learns and recognises a new set of emotions, which differs from learning all eight emotions at once in conventional deep learning.

V. NEXT STEPS

As affective HRI for continual setting requires personalisation and adaption of the emotion of previous users and new users, we extended the learning model of learning a new set of emotions as shown in Fig. 1 to learning all the emotions of new users as shown in Fig. 4. As such, the learning model will be able to learn and recognise the emotion of new users. Hence, we are extending the learning model beyond just a new concept and integrating new instances and concepts. Here, new instances and concepts mean the learning model will be able to learn and recognise all eight emotions of new users and improve the performance on emotions of previously learned users. As such, the learning model will be able to adapt to new users and personalise to previous individuals in new environments.

However, most publicly available emotion datasets are unsuitable for adaptation and personalisation but are focused on generalisation. Most of the existing emotion dataset does not consist of facial emotion dataset with relevant psychological traits, i.e. extraversion, agreeableness, openness, conscientiousness, and neuroticism. We believe these traits are crucial. This is because social robots will personalise themselves to humans by integrating psychological traits in the learning models. Secondly, existing datasets consisting of all individuals' emotions are created in non-social settings. Here non-social settings refer to the closed environment where participants are asked to mimic certain emotions or act/sing in a certain way to reflect non-spontaneous emotion. Hence, we are in the initial data collection phase for adaptation and personalisation in affective HRI. As our motive is to improve affective computing on HRI, we will use a real-world social robot called Furhat [27] for data collection and later for experiments and performance evaluations. We are integrating the psychological traits into the new dataset with the help of the questionnaires developed by [28]–[30]. We are setting up a "real-world" environment where Furhat and participants can interact with each other. Furhat will ask contextual questions based on [31] and will record facial images and audio. For data collection, we are developing the methodology to collect data in the ethical manner approved by the ethical committee of the University of Manchester. As we are dealing with personal pieces of information, we are designing strict ethical and consent forms that will be submitted to the ethical evaluation committee at the University of Manchester for approval.

After the approval from the committee and data collection, we will evaluate the effectiveness of the learning model in the real-world environment. After the publication related to the collected new dataset, we will provide access to the dataset to academic researchers based on the End-user license agreement (EULA) document. In the case of the regularisation-based continual learning model, as shown in Fig. 4 not performing well due to the possibility of constraining weights for the tradeoff between the performance of new and old tasks, we are further exploring and developing replay based methods such as deep generative replay mechanism and dynamic architecture for adaptation and personalisation.

The formal dissertation prospectus, built on the extended learning models and real-world experimental evaluations, is currently planned for late September 2024, allowing for expansion or changes or refinements to be made following participation in the consortium.

VI. Contributions

Outputs from this dissertation will have several contributions. This research will contribute to the domain of continual learning. Research on continual learning is achieving high performances on different benchmarks. There is limited research on continual learning for emotion recognition for social robots **"in the wild"**. This research will present a novel way of continually personalising and adapting human affective states. The developed experiment design and questionnaires for the interactive data collection will present a new way of collecting data for the affective computing research community. Furthermore, as personalisation and adaptation can be valuable in the real world, through extensive experimental evaluations in this research, we will be identifying potential social robotics application fields that can make an impact.

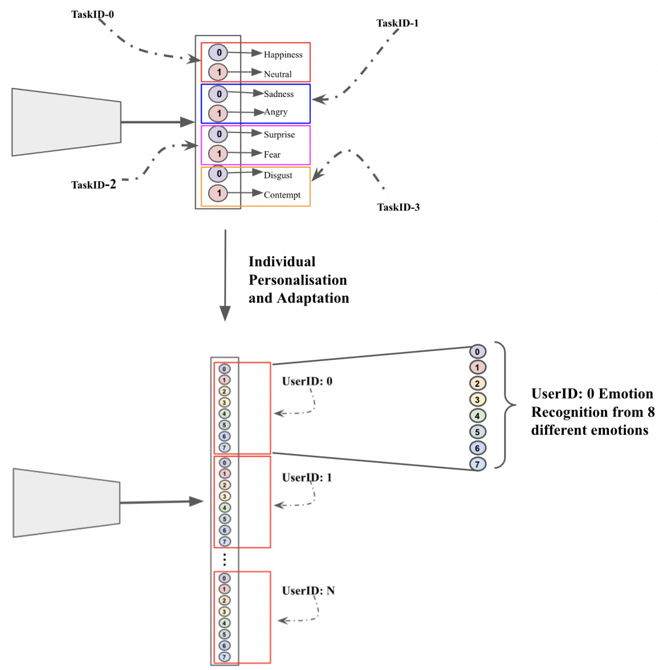

Fig. 4. In proposed continual emotion recognition, initially, we assume the model can recognise one user. As it interacts with new users based on the experiment setting explained in section V with every new user's emotion and attributes, it updates itself to recognise the emotion of both new and previous users. While training new users, the continual emotion recognition model will not have access to previous users' emotion data and attributes in raw form. It will have access as a memory/weight representation as written in eq. 1.

As we aim to evaluate our continual learning model in real-world applications, our research will indirectly contribute to understanding how humans perceive the social robots in their private space in continual settings. Additionally, personalising and adapting in a continual setting will help uncover new methods to recognise other social cues, such as gestures and vocalisation. Finally, this research's contribution will support the human-centric robotic approach to various robotic applications, where industrial stakeholders will be able to take inspiration for developing social robots with adaptive and personalisable features.

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