Teaching Drones on the Fly: Can Emotional Feedback Serve as Learning Signal for Training Artificial Agents?

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Abstract

We investigate whether naturalistic emotional human feedback can be directly exploited as a reward signal for training artificial agents via interactive human-in-the-loop reinforcement learning. To answer this question, we devise an experimental setting inspired by animal training, in which human test subjects interactively teach an emulated drone agent their desired command-action-mapping by providing emotional feedback on the drone’s action selections. We present a first empirical proof-of-concept study and analysis confirming that human facial emotion expression can be directly exploited as reward signal in such interactive learning settings. Thereby, we contribute empirical findings towards more naturalistic and intuitive forms of reinforcement learning especially designed for non-expert users.

1 Introduction

We study the research question can emotional feedback serve as learning signal for intuitively training artificial agents on the use case of human-drone interaction. We present an experimental setting in which a user intuitively teaches a drone the meaning of commands such as gestures that can be detected by vision-based recognition [Minh Dang et al., 2020; Hummel, Pollak, and Krahofer, 2019]. Learning is based on emotional feedback, a naturalistic mode of interaction humans are familiar with from conventional human-to-human and human-to-animal interactions.

Learning Approach. We establish an analogy to animal training, where animals are instructed to learn the correct action for a given command. Here, learning is based on evaluative feedback from the animal’s instructor, traditionally in form of tangible rewards such as the animal’s preferred food [Vieira de Castro et al., 2021], but often also in form of the instructor’s emotional response, especially for social animals such as canines. Over time, the animal learns to correlate the received reward with the correct action. Similarly, an artificial agent – here, a drone – should interpret the emotional feedback of the user to learn.

The ability to process emotional cues can be considered as a key requirement for any socially intelligent agent. At the same time, the intuitiveness of emotional feedback allows to include users with little technical background in the training/rewarding task. Thus, we believe that providing a method to interpret affective evaluative human feedback represents a cornerstone in social human to machine interaction.

Contributions. (i) We present the design and implementation of a real-time interactive machine learning (IML) system based on reinforcement learning (RL), where rewarding is provided by human emotional feedback. We envision an artificial agent that makes use of a camera and facial emotion recognition and exemplify the agent by a small indoor drone that requires to learn a command-action mapping. Among the core features of the system, a rewarding algorithm is developed that converges fast and allows to cope with different expressiveness of individual facial emotions. (ii) To study whether emotional feedback can provide a useful learning signal for the drone, we conduct an experimental user study, where we mimic the drone’s actions upon receiving a command as sketched in Fig. 1. Our first results indicate that the approach is feasible.
2 Background and Related Work

We first motivate why emotions play an important role in human-robot interaction (HRI), summarize major results on the role of feedback in agent learning, and give an overview of emotion recognition as feedback signal and direct, naturalistic form of interaction.

The Role of Emotions in HRI. A large fraction of research studies on the role of emotions in HRI settings has focused on investigating the human’s preferences of interaction modalities to better understand the robot’s behavior, such as the studies described in (Reyes, Meza, and Pineda 2019; Thunberg and Ziemke 2021). Another field of study examines how typically humanoid robots’ emulated emotion expressions affect human performance. For example, studies on robot companions for children investigated the effect of the robot’s displayed emotional response as a feedback and motivation signal for children’s learning performance (Ahmad et al. 2019).

Yet, also the artificial agents’ ability to correctly interpret and react to human emotions has been acknowledged as a key requirement for socially intelligent agents and human-machine interaction in the fields of cognitive robotics, artificial intelligence (AI), and HRI, such as described in (Chakraborti et al. 2017; Biundo and Wendemuth 2016; Hörnle et al. 2017). The ability of a robot to infer the emotional state of a human reliably is a desired goal. Research has targeted the creation of emotional models and classification schemes of human emotions, and emotion recognition such as facial emotion recognition (FER) and analysis of body posture as well as brain activity as surveyed in (Spezialetti, Placidi, and Rossi 2020), yet only few works have focused on the feasibility of using emotion as reliable signal for feedback-based machine learning.

Feedback in Agent Learning. In his characterization of the twelve potential roles that emotion could play in AI, (Scheutz 2004) pointed out the possibility of using emotion for learning, for example by using emotional evaluations as Q-values in reinforcement learning (RL), as we will attempt in this work. RL represents the machine learning paradigm employing learning from evaluative feedback. Classically, RL agents compute a reward score from their interactions with the environment, using a pre-defined reward function to provide the feedback signal for the agent. This way, the desired behavior is reinforced by rewarding. However, this reward function is specific for the given task, and consequently the agent’s learning capability often hinges on the designer’s capability of engineering an appropriate reward function for the problem at hand (Sequeira 2013; Russell 2019). To allow for more generic open-world learning, approaches such as presented in (Thomaz and Breazeal 2008; Knox and Stone 2009; MacGlashan et al. 2017) propose learning through human reinforcement, i.e., enable a human tutor to assess the agent’s behavior and to provide direct feedback. In past works, this feedback has to be provided in the form of predefined, numeric reward scores, which is not the natural interaction style we are aiming for.

Naturalistic Human Feedback. Human-robot interaction (HRI) can reach a next level if an artificial agent is capable of interpreting the human’s feedback in a more naturalistic manner. In terms of the RL paradigm, the agent should be capable of inferring its (numeric) reward scores from humans’ natural communication channels. For example, (Sumers et al. 2021) devised a learning approach using inverse RL to learn humans’ latent reward function from (unconstrained, thus naturalistic) textual feedback captured during a human–human collaborative game play setting. Other research work studied the utilization of emotional evaluations as rewards, as (Scheutz 2004) proposed. (Broekens 2007) indeed already experimented with incorporating humans’ emotional response as a reward signal in RL. However, in this approach emotional feedback is used only as an additional reward added on top of a base reward signal the agent obtained from its virtual environment (thus, essentially only makes the base reward signal more accurate). This is due to the chosen RL algorithm based on neural networks, which requires a large number of training iterations and hence is not amenable to continuous human feedback.

Our approach is similar in spirit to recent endeavors on learning rewards from unconstrained naturalistic human feedback such as (Sumers et al. 2021). Yet, we extend the aforementioned related work by utilizing the human’s emotional response as the sole source of feedback on the artificial agent’s performance. To overcome the problem of long training efforts, we propose to choose an RL approach well suitable for real-time learning, notably multi-armed bandits that require only a few training iterations until convergence.

3 Model and Study Design

We study the feasibility of using emotional feedback to train an artificial agent along the use case of human-drone interaction, where the drone is the artificial agent as depicted in Fig. 1. The user issues a search command by a gesture, which results in the drone navigating to the specific object the user searches for. The drone will learn the correct command-action mapping by reinforcement learning based on emotional user feedback. More formally, we can describe the system by an agent-based model.

Agent-based Model. We model the human-drone interaction as a multi-agent system consisting of

- a user agent \( u \in U \) that can issue a set of commands \( C \),
- a drone agent \( d \in D \) that can execute a set of actions \( A \),

where \(|C| = |A| = k\), and the sets \( U \) and \( D \) represent the sets of users and drones, respectively. During the training phase the drone agent \( d \) learns which action \( a \in A \) the user agent \( u \) desires when issuing a command \( c \in C \). The bijective mapping function \( f_u(c) = a \) expresses the personalized command-action mapping for a user \( u \).

Drone Learning by Emotional Rewards. Initially, the drone does not know the command-mapping \( f_u(c) = a \) for any command \( c \) and has to learn it by reinforcements from the respective user \( u \). The drone selects an action
a \in \mathcal{A}$ randomly (independently and identically distributed) and awaits feedback in form of emotional feedback from user $u$, which results in a reward $r$. Eventually, the drone will learn the desired command-action mapping function $f_u(c) = a$ for all commands $c$ after experiencing a sequence of interactions with user $u$ that can be described as $\{(c^0, a^0, r^0), (c^1, a^1, r^1), \ldots\}$. Yet, the learning outcome is also affected by learning confounders.

**Learning Confounders.** Naturalistic user interfaces rely on sensor-based signals and thus require the implementation of user recognition, command recognition, and feedback recognition and interpretation (feedback in form of text, visual, audio, etc.). Any such recognition involving the drone hardware is prone to classification errors, thus, impacting machine learning performance. In order to reduce this complexity when studying our research question, we design our experimental study to eliminate confounders, i.e., potential error sources that might interfere with the learning problem, here user and gesture recognition errors and interaction with a real hardware-embodied agent. Once we have evidence that emotional feedback is a valid source for teaching, we will extend our study to the hardware drone.

**Experimental Study Design.** To study the usefulness of naturalistic emotional feedback and the effectiveness of the rewarding algorithm without side-effects caused by confounders related to the hardware, we create a Web-based emulated drone agent. This way, we abstract user-drone interactions to deterministic, error-free user login (to emulate user recognition), button-clicks (to emulate gesture-based commands) and video replay of recorded real drone flights (to emulate actions performed by the drone). The user trains the drone by providing emotional feedback to the drone based on its action selection. Further, the user provides labels for every emotional feedback in terms “positive” and “negative” action assessment. Both the desired command-action mappings and the feedback labels serve as ground truth data.

4 **RL by Emotional Signals**

Learning by emotional signals is based on the following steps: (i) capturing emotional feedback as an assessment of the drone’s action choice by the drone’s onboard camera, (ii) recognizing emotions by analyzing the user’s facial expression on video frames resulting in an emotion distribution, and (iii) deriving a reward score based on the emotion distribution for drone actions to finally implement the command-action mapping $f_u(c) = a$, personalized for each user $u$.

**Capturing Emotional Feedback.** The user will try to convey to the drone visually how (dis)satisfied s/he was with the drone’s action choice for a predefined feedback time interval. The drone records a video stream of this evaluative feedback, i.e., a time series of video frames, intended as raw input for drone learning. Each detected face is analyzed based on facial emotion recognition. The number of frames to be considered is configurable (sampling fewer frames may lead to missed emotions, sampling more frames leads to higher processing effort).

**Facial Emotion Recognition.** We estimate the facial emotion expressions in each frame with the facial emotion classifier provided by the FER package [Arriga et. al., 2020], employing the MTCNN face detector [Zhang et. al., 2016] which has been trained on a large-scale facial expression dataset [Goodfellow et. al., 2013]. For each frame, FER predicts a discrete probability distribution characterized by the probability vector $P(E)$, which describes how likely the user’s facial expression corresponds to each of the seven universal facial emotions established by [Ekman et. al., 1987]. The emotions are defined in the set $E$, which we classify as: positive (‘happy’), neutral (‘neutral’, ‘surprise’), and negative (‘angry’, ‘disgust’, ‘fear’, ‘sad’) feedback.

**Inferring the Agent’s Reward.** Essentially, the desired reward signal $r$ corresponds to the user’s level of satisfaction, a latent variable that cannot be directly accessed but is inferred from the output of facial emotion recognition.

The RL problem requires a scalar reward value $r$. Thus, we define a mapping of the emotion probability vector $P(E)$ to $r$ that conveys the idea of satisfaction or dissatisfaction of the user. $r$ corresponds to the emotional valence score, representing the extent to which an emotion is positive or negative [Citron et. al., 2014; Kossaifi et. al., 2021]. In affective computing terms, this realizes a mapping from Ekman’s basic discrete model to the pleasure-displeasure scale of the continuous valence-arousal-dominance model (Mehrabian and Russell, 1974).

In detail, the scalar reward $r$ is calculated as the dot product between the emotion probability vector $P(E)$, and its corresponding scaling factors vector $s$:

$$r = P(E) \cdot s,$$

where $s$ is configured as $[+3 \text{ (happy)}, 0 \text{ (neutral)}, +1 \text{ (surprise)}, -3 \text{ (angry)}, -2 \text{ (disgust)}, -2 \text{ (fear)}, -3 \text{ (sad)}]^T$. Thus, positive emotions will increase, negative emotions will decrease the resulting score $r$. Note that alternative calculations are possible, e.g., just selecting the most probable emotion, yet this yielded worse results in our first experiments.

**Implementing Agent Learning.** We formulate our learning problem as a multi-armed bandit (MAB) problem [Sutton and Barto, 2018]: Each command $c \in C$ represents a context$^2$ thus instantiates an MAB with $k$ arms. Each arm represents one particular action $a \in \mathcal{A}$, whereby we will denote these actions by indexing their enumeration in vector $[a_1, \ldots, a_k]^T$. The user’s satisfaction with a chosen action $a$ is expressed by the reward $r$. The drone selects the action that is expected to maximize its collected reward $\sum_T r$ over time $T$, in other words, the action with the highest expected (reward) value.

More precisely, the MAB estimates the actions’ values as $Q_t(a)$ by consistently updating the mean rewards received for each of its actions up to its current trial step $t$. Fig. 2 depicts an example from our user study for inspecting the drone’s learning. It is shown how the drone’s action value estimates $Q_t(a)$ evolve with repeated human reinforcement through emotional rewards $r$. At each trial step (x-axis), the

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$^2$Note that the corresponding context is directly observable and hence does not have to be inferred, thus our problem corresponds to a classical MAB setting involving multiple bandits rather than a contextual/associative bandit.
The study considers three command gestures and three actions (i.e., k = 3): finding a hammer, a book, or a bottle. The drone is required to learn each command-action mapping, then the following teaching loop is performed: (1) the user selects a gesture command; (2) the (emulated) drone chooses the action with the maximum action value (or, if multiple actions with maximum action value exist, chooses one of those actions randomly) and a video is played emulating the drone’s flight towards the anticipated object to be found; (3) the user provides real facial emotional feedback recorded by a Web cam over a time period of 5 seconds and labels his/her emotional response as positive or negative (ground truth feedback).

With this setting, we abstract from the embodied hardware agent to limit the learning confounders and focus on the evaluation of the usefulness of the facial emotional feedback per se. Yet, we performed initial experiments with our hardware drone (Parrot Anafi) to make sure that video processing (frame selection and FER-based emotion classification) and taking a video with the on-board camera of the drone is of comparable video quality. This is important as we plan to extend the investigation by a lab-experiment with a real drone, where we will study the influence of practical factors such as light conditions and camera angle.

**Video Frame Rate and Reward Calculation.** The frame rate of the video stream is 25 frames per second (FPS), which is down-sampled for emotion classification by only retaining every j-th frame. We set j = 12, which makes real-time emotion classification feasible that takes about 32-42 seconds per face. We then compute the average emotion probability vector $P(E)$ by computing the mean of the derived sequence of $P(E)$s obtained on the frames of the down-sampled set. The overall emotional reward $r$ is calculated by applying Eq. 1 to $P(E)$.

**Study Participants and Sessions.** 16 volunteers are included in the discussion, all with an academic background, among them 56% female and 44% male, who performed in total 21 drone teaching sessions with a total of 157 feedback rounds.

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5 Experiments

We conduct an experimental user study in the form of a custom Web app emulating the drone in the interactive learning loop, see Fig. 1.

**Experiment Setup.** The study considers three command finger gestures and three actions (i.e., k = 3): finding a hammer, a book, or a bottle. The drone is required to learn each of the command-action mappings in one teaching session. The study participants first specify their desired command-action mapping (ground truth mapping), then the following teaching loop is performed: (1) the user selects a gesture

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We initially implemented classical $\epsilon$-greedy action selection: In $1 - \epsilon$ % of the trials the action with the max. $Q(a)$ is chosen (exploitation), in $\epsilon$ % a random action is selected (exploration) to refine $Q(a)$ estimates. After initial tests, we chose to disable exploration and realize deterministic action selection by setting $\epsilon = 0$, since in our setting learning will be actively “steered” by the user.

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We did not include sessions not completed by the respective user in order not to bias the data. Thus, only sessions are included where each of the three commands has been selected at least once.
the scores derived by our FER-based RL algorithm correlate with the users’ intention (ground truth feedback). We dissect this result further by analysing the capabilities of FER per se. Finally, we quantify the quality of learning, i.e., assess the magnitude of how well desired and undesired actions can be distinguished in the drone’s learned action values.

(1) Did users succeed in teaching the drone their desired command-action mapping? – The majority of users successfully taught the drone agent based on a few trials only (see Fig. 3a): 57% of the training sessions succeeded to correctly teach all three command-action mappings and 19% succeeded in correctly teaching two out of three; only less than 10% of the sessions yielded in no success at all. These first results indicate the overall feasibility of our approach using emotional response as a reward signal.

(2) Are the reward scores correlated with the ground truth feedback? – We can analyze whether the reward scores based on Eq. 1 correlate with the ground truth feedback labels provided by the users (positive or negative rating of the drone’s chosen action). Fig. 3b shows the reward scores wrt. their corresponding ground truth label across all trials and participants. The distributions of positively and negatively intended reward scores indeed differ, as visually observable, which is confirmed by a two-sample Kolmogorov-Smirnov test that rejects the null hypothesis $H_0$ with $p < 0.001$ ($H_0$: The positively and negatively intended reward scores come from the same distribution). Yet, we also see that the reward scores of a considerable amount of negatively labeled scores have positive values.

To dissect this phenomenon, we analyze the score distributions of each individual participant, as shown in Fig. 4. We generally observe a visible difference between the distributions of the positive and negative scores, indicating that our generic reward score computation (Eq. 1) produces a suited learning signal. Yet, we find that both positive and negative score medians differ widely between the different participants. For example, whereas the positive and negative feedback distributions of the participant with user ID 1 appear rather weakly separated, users with IDs 2–3 and 13–15 show extremely well separated positive and negative feedback distributions.

(3) Are the facial emotion classifications correlated with the ground truth? – We now evaluate the initial emotional responses before applying the reward function. Fig. 5 and Fig. 6 visualize the 2-dimensional projections of the 7-dimensional average emotional probability vectors $P(E)$, labeled according to the ground truth feedback labels (positive/negative). The projection is achieved with multi-dimensional scaling (MDS) [Kruskal and Wish, 2009], a method that aims to preserve the distances between the data points in the lower-dimensional projection. It can be observed that positive and negative emotional responses tend to cluster across different subjects. However, we also note an overlapping area where a clear separation is not possible, mainly caused by the individual effects of a specific user (User ID 4).

To provide a quantitative assessment of the general cor-
relation between the emotion vectors and the ground truth labels, we fit a logistic regression model onto the original 7-dim. average emotion vectors $P(E)$ to predict the ground truth feedback labels (positive/negative), which results in a prediction error of 20%, which can be interpreted as a quantification of the overlap between the positive and negative feedback across different users, likely corresponding to the interspersed area of positively and negatively labeled emotional responses in Fig. 5. Fig. 6 dissects this 2-dimensional projection for four selected individual participants, revealing typically well-separated “clusters” of positive and negative emotional responses, but also outlining a user with emotional characteristics that are difficult to distinguish (User ID 1). These results indicate the need for learning a user-specific feedback inference model, and thus, confirm the fit of our RL-based approach to the emotional feedback case. Further, our MAB-approach for rewarding allows to consider relative distances of each individual user’s feedback scores, thus mitigating the problem of different individual inter-cluster distances of emotional vectors.

(4) How well have users been able to teach the drone? – The MAB-based approach allows the drone to learn a command-action mapping even when the difference between the average rewards for desired and non-desired actions is small. In our last analysis, we thus inspect the drone agent’s final learning outcome at the last time step $T$ of each teaching session, by quantifying the difference between the participant’s desired and undesired actions, with actions referred to by their position index in vector $(a_1, \ldots, a_k)^T$. The final action values $Q_T(a)$ represent the drone’s “view”, where the desired action $a_d$ should ideally yield the maximum action value estimate $Q_T(a_d)$. Fig. 7 visualizes the difference $d(a_i) = Q_T(a_d) - Q_T(a_i)$ $\forall 1 \leq i \leq k$ across all final command-action mappings in all sessions.

It can be observed that some sessions show a strong pattern, i.e., $d(a_i)$ is large for all undesired actions $a_{i \neq d}$, meaning that teaching was efficient (which corresponds to well-separated feedback scores as given in Fig. 4). Conversely, negative values of $d(a_i)$ indicate that a non-desired action has received a higher action value than the desired action, indicating a wrongly learned mapping. Based on this coloring, we can easily identify unsuccessful teaching, and participants (e.g., user ID 2 and 15) who have been most effective in successfully instructing the drone as well as participants who have given rather weak feedback signals (e.g., user ID 1). This again reveals considerable individual differences among participants.

7 Conclusion

We contributed insights on developing artificial agents that learn based on human emotional feedback, studied along the use case human-drone interaction. We conducted a user study with 16 participants. Our initial empirical findings confirm that humans’ facial emotion expressions indeed can be exploited as reward signals in interactive human-in-the-loop reinforcement learning. For the majority of the study participants, teaching the drone worked successfully, supporting in particular by our reward function derived from emotional feedback. The learning process accounts for individual differences in expressing emotions, without necessitating any further personalization to individual users.

This is a first study on the feasibility of emotion-based reinforcement learning for flying robots. Many practical aspects are subject to future studies, including the limitations of emotional feedback wrt. complex tasks, the inaccuracies introduced by noise and low-quality video feed, and that observing human emotion may be a threat to privacy.
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