state s_t. Joy is calculated before updating $V(s_t)$.

Hope and fear should emerge after joy and distress, should be dependent on the expected joy/distress and likelihood of a future event [12], and should allow fear extinction (e.g, through a mechanism similar to *new learning* [10]). We model the intensity of hope/fear HF as follows:

$$HF(s_t) = V(s_t) \tag{2}$$

3. VALIDATION

We now briefly report on whether the model adheres to several important requirements. For details see [8]. We observed in our agent-based simulation experiments that joy/distress is the first emotion to be observed followed by hope/fear. As mentioned earlier, human emotions have an order in their developent in individuals from simple to complex [19]. We observed joy habituation when the agent was repeatedly presented with the same reinforcement, and fear extinction over time due to a mechanism a mechanism similar to *new learning* [10]. We were unable to confirm if lowered expectation decreases hope and results in a higher intensity for joy/distress [21, 12]. Finally, we were able to confirm that increasing the unexpectedness of results of actions (by modulating task randomness) also increases the intensity of the joy/distress emotion [12, 15].

4. DISCUSSION

We conclude that our model is a plausible RL-based instrumentation for joy/distress and hope/fear. Our results support the idea that the function of emotion is to provide a complex feedback signal for an organism to adapt its behavior. We show this feedback signal can be operationalized for RL agents. This is important for several reasons. First, RL-based models can help understand the relation between emotion and adaptation in animals. The function of emotions is to provide complex feedback signals aimed at informing the agent about the current state of affairs during learning and adaptation [6, 13, 1]. What do such signals look like in an adaptive agent? If we can operationalize such signals for RL agents, a popular computational model for reward-based learning in animals [4, 11], we can computationally tie emotion to adaptation. Second, the emotional state might be used to increase adaptive potential of artificial agents [16, 17]. Third, from a human-robot interaction point of view the emotional signal can be expressed to a human observer. If this signal is grounded in the learning mechanism of the agent [2] it could help interpret the learning process of the agent or robot. However, we are aware of the difficulties of labeling RL-based signals as particular emotions, and we feel that in general a more structured approach is needed to develop scenarios (tasks/learning approach/RL parameters) to test for the plausibility of affective labeling of RL-based signals.

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