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Deducing human emotions by robots: Computing basic non-verbal expressions of performed actions during a work task

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Abstract— **We have established an emotional model to enhance a virtual worker simulation, which could be also used to support robots in a joined human-robot work-task inside an industrial setting. The robot is able to understand people‘s individual and specific knowledge as well as capabilities, which are ultimately linked to an emotional consequence. As a result, the emotional model outputs the emotional valence calculated as positive or negative values, respective to reward and punishment. This output is applied as value function for a reinforcement learning agent. There we use an actor critic algorithm extended by eligibility traces and task specific conditions to learn the optimal action sequences. We show the influence of emotional reward leads to differences in the learned action sequences in comparison to a simple task performance evaluation reward. Therefore the robot is able to calculate emotional feelings of a human during a given working task, is able to decide if there is a better, more emotional stable path to doing this working task and moreover the robot is able to decide when the human is needed help or even not.**

I. Introduction

The “Smart Virtual Worker” (SVW)-project presents an opportunity to easily replicate established workflow parameters inside a virtual simulation, in order to explore alternate routes, storage of goods, or construction methods, while still in the stages of production planning. A key component of the simulation is the consideration of emotional tendencies within an employee while performing a task. These emotional tendencies are used as a reward function of a reinforcement learning algorithm, which calculates the optimized order of a task selection while performing the task at hand.

Due to the fact, that robots and humans will be increasingly execute work tasks cooperatively as peers, forms of social interaction will be of significant importance [1]. To allow for an effective cooperative task, a robot has to understand people‘s specific knowledge, strengths and weaknesses [2] in order to estimate and react to the people‘s intentions and needs [3] as well as incorporate the dynamics of object interactions with fellow robots and humans [4].

Within this paper, we describe the interaction of our reinforcement learning algorithm and the emotional module, introducing a social-cognitive reasoning process whenever the robotic entity perceives a work task performed by human beings [5]. The entity is thereby enabled to conclude, whether or not an observed worker is performing within his or her physical limitations, abilities and previous experiences. Once the emotional state has been deduced, the robot might be able to offer assistance to the observed worker; within his own limitations of movement and interaction capabilities. This way, a machine could be enabled to adequately compute an emotional evaluation of a human‘s current state and thereby allowing it to follow rules of social behavior [6], [7]. In turn, the capability would also correspond with the human tendency and need to ascribe common social behavior upon machines [8].

II. Emotions within the working context

In our model, the genesis of emotions and their experience is linked to an individual‘s perception of affecting events like experiences in the past as well as unique physiological parameters, like strength and endurance [9]. These parameters have an essential influence since, for example, a strong person would not be affected as much by the task to carry a heavy object. On the other hand, an experienced person might know about certain unwanted aspects of a task, while an inexperienced person would be overwhelmed and therefore afflicted. In addition, the arousal-level is working as a form of emotion energy, therefore it directly affects the amplitude of an upcoming emotion (mimicking the interplay between cognitive system and hormonal influences of the human body), which can also lead to an emotional transaction [10], [11]. Meaning, an emotional event in the past is still visible in the form of lingering hormonal and cognitive reasoning effects which in turn affect the experience of a subsequent emotion by fueling the upcoming emotion.

Empirical research regarding emotions indicate a sufficient description of behavioral processes once reduced to a two dimensional scheme of emotional depiction [12], [13]. Furthermore, one of the established design guidelines for any implementation of an emotional module upon a robotic entity is to outline the need for an emotional module and to limit the module to the requirements of an attempted system environment interaction [14], [15]. Once condensed down into a positive and a negative valence [16] the meaningfulness of an emotion can be used to describe either a tendency of being in a state one would want to maintain or in a situation which one would want to change. Our paper describes the

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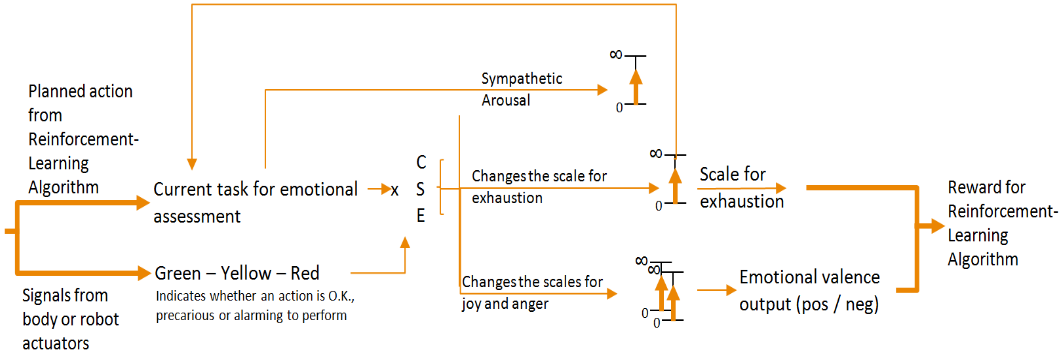

Fig. 1. The Emotion Model: From left to right (upper path) two main values (Movement and Ergonomic) are computed against the CSE preferences of the Agent. At the same time, the proposed action is valued on the arousal scale, where after the changes for fatigue and success are calculated, alongside the values for joy and anger. In the end, the values are prepared as output variables for the reinforcement learning algorithm.

beneficial aspects of including an emotional framework [17] as a computational support structure for robotic entities inside a production environment. Since the goal of the Smart Virtual Worker project is focused on depicting a specific work context, we looked for scientifically established models, for an overview see [18]. However, in the case of a worker simulation, we have to include multiple agent‘s physical abilities, experiences and physiological reactions. Additionally, the agent‘s constitution has to be simulated, affected by the aforementioned abilities. This led us to the represented robust models from the empirical psychological research.

The module, based on two forms of input, calculates, based on three physiological variables for individualizations (strength, experience and sensibility), a level of arousal and a corresponding emotional valence. All while checking for an emotional transaction and, if necessary, applying the corresponding emotional energy to the experienced emotion. In addition, the level of endurance of the human is adjusted in accordance with exhaustion of the performed tasks.

III. Reinforcement Learning Agent

We chose a well-known actor-critic learning agent, which is comprised of “actor” and “critic” components [19]. The objective for the learning algorithm is to establish a policy deducing from given states (s) into actions (a)), which maximizes the accumulation of rewards in the long-term. The actor selects actions according to the established policy, while the critic maintains a value function, associating each state with an estimate of the expected return value. Once learning commences, the actor‘s action strengths are initialized with zero, and the agent is placed in an initial state (e. g. the corner of his working place). At each step, the δ value, a temporal-difference prediction error (TD) is computed to determine if the simulated action led to a better reward than expected:

$$\delta = r + \gamma * V_{t+1} - V_t \tag{1}$$

whereas r is the observed reward for the transition from current to next state and γ serves as discount factor. The values V_{t+1} and V_t are computed initially as state evaluations of the emotional model. The prediction error updates the preference p of the selected state-action pair:

$$\Delta p(s, a) = \alpha\delta \tag{2}$$

where α is a positive learning rate. The critic function in our system is not monotonic, even if a high V_{t+1} is observed in the beginning, this transition does not necessarily lead to an ideal solution. To overcome this issue, we use an exploration phase with random policy and eligibility traces [19]. The critic is updated in each step:

$$\forall s \in S : \Delta V = \beta\delta e(s) \tag{3}$$

$$e(s) = \gamma\lambda e(s) \tag{4}$$

Where $e(s)$ represents the time when the state s was visited. The parameter β, another learning parameter, and the discount factor γ controls the influence of the trace. The value of λ influences the number of preceding states updated in each step. If there are not enough trials to explore the state continuum or if λ was too high, this approach might lead to a suboptimal solution.

As described earlier, the agent has a set of possible actions, in fact only small subsets of them are possible in one state. To avoid exploring unnecessary state-action pairs we use task-specific conditions [20]. These conditions reduce the high extent of general rules, e.g. the agent is able to reach an item only if the item is located within its proximity. Instead of defining these rules inside the agent module, they could also be learned from the environment. But this would only increase the needed exploration and therefore is not our goal. Secondly the SVW project aims at finding optimal action sequences for working tasks not gaining basic environmental knowledge.

IV. Elements of the Model

The module is based on two forms of input parameters (see Fig. 1). The input is generated by the reinforcement learning algorithm which suggests a work task to the motion generation (which is not a part of this paper). This in turn impacts the emotional model in that way that the ergonomic actuator assessment is deemed as being feasible, precarious or alarming. Afterwards, due to the strong individual basis of emotion generation, while confronted with circumstances from the environment, the emotional model individualizes its computational routines. The changes of the valence scale is thereby dependent regarding three factors of a worker's physiology: constitution (C), sensitivity (S) and experience (E).

The emotional state is modeled as a pure valence-based differentiation, which basically leads to the agent liking or disliking the current situation. Furthermore, the model adjusts a scale, a sympathetic arousal, meaning the likeness that the worker is going to change its valence scoring. This enables the model to be able to transfer emotional 'energy' between the implemented emotional states, in accordance with the theory of emotional transaction by Zillmann [11], [10]. The output of the model therefore are, based on the current emotional appraisal, the values for V_{t+1} and V_t influencing the critic function of the reinforcement learning algorithm.

A. The Agent

The simulated human being, the virtual worker, is characterized by additional attributes like sex, weight, height and a resulting BMI score. In addition, we differentiate possible fitness-levels (well-trained, normal strength and disadvantaged), given work-experience, age and a score for sensitivity. Thereby defining attributes which describe the required internal state and calculate an unique emotional valence.

1) The physiological attributes: Based on the given attributes for weight, height, BMI score, fitness and age our model computes the virtual strength of the agent. All differences between possible agent types are calculated as a value of capability, based on the described computational algorithm. In practical terms, the model of a normal human possesses a capability value of 0, which translates to having 100% of the strength of a standard human. The chosen disadvantaged person has less strength than an assumed normal person, which calculates to a capability value of -20 meaning 80% from an assumed standard human. A stronger person on the other hand has a capability value of $+20$, meaning he yields 20% more strength than our assumed normal person.

2) The experiences: We assume a person gains knowledge over time regarding the tasks performed, which in turn leads to an increased experience value. Basically, it defines the familiarity with any given, processed task. The model itself is based on an experience value which is, again, set to 0 for a normal human. A rather inexperienced and insecure person is scored with a value of -0.5, while an extremely experienced person is calculated on the basis of a 5.0, which indicates that he is very familiar with the task and thereby infers his own chances for success.

3) The sensitivity: People, influenced by environmental effects, differ in their affections. To incorporate this behavior, a sensitivity value is defined, which allows the model to compute an affected state. A worker with a lower threshold reacts more intensely to strenuous tasks while workers with a higher score of sensitivity are not affected to a lower degree or even not at all. The sensitivity value is hereby set to 0 for a standard person, to 5.0 for a very thick-skinned human and -0.5 for a very sensitive worker.

B. The Internal Emotional State

Based on the described psychological and physiological attributes, an internal state is computed. The resulting value represents an individualized appraisal of task performance. The parameterization was approached on a case-by-case analysis of actually carried objects by humans. The mathematical formulas were thereby generated by deducing visible changes during the task. Afterwards the model will be evaluated by psychological methods where simulation and the real-world experiment consists of the same experimental setup.

1) The input parameter: Once all previously described input values and object parameters are present inside the simulated environment, the currently performed action, including physical properties (e.g. the weight of an object in kg), the time (in seconds), how long the task needs to be performed and an ergonomic value from the actuator module, serve as the basis for the emotional assessment. The variables in question are either present from the start as database entries, or will be calculated on the fly by other modules of the project. The ergonomic value ranks the physiological stress of a task-necessary movement on the body. Currently, its assessment is based on the RULA-system [21].

The ergonomic output labeled as "Level of workload" incorporates four distinct values: carried weight, covered distance, action time, and a separate ergonomic assessment based on RULA. The possible results are:

1: low level of workload, no handicap, and no overload
2: increased level of workload, impairment by weaker persons is possible
3: severe level of workload, impairment, and overload of normal persons is possible
4: overload of normal people

Based on these levels of workload, the module calculates the internal states of emotional valence, sympathetic arousal, a positive valence (labeled for convenience as joy), and a negative valence (labeled as anger).

2) General functionality: Our model consists of four scales, arousal, exhaustion, joy and anger. Within the exception of exhaustion all scales are limited to 100. The exhaustion scale is limited by the strength of the simulated worker. A strong worker has an exhaustion limit of 120 and a weak worker of 80 compared to a normal worker with the usual limit of 100. Going forward, these scales will be update, whenever something influences the worker emotionally. The basic increase is growing following a logarithmic function (see equ. 5). This means, the next update is based on the current value and the change depending of the remaining unaffected part of the scale. For example if the current value is 10, the unaffected part is 90. The current value is calculated by the remaining unaffected part divided by a factor q_v (see equ. 5). The value $v_{curr}(t)$ is weighted by our parameters (e.g. sensitivity), in a way that if high parameters are used as the quotient results in a smaller increase of the subsequent value.

$$\triangle v_{curr}(t) = \frac{100 - v_{curr}(t-1)}{q_v} \tag{5}$$

$$v_{sub}(t) = v_{curr}(t-1) + \triangle v_{curr}(t) \tag{6}$$

3) The sympathetic arousal: The change value of the arousal $\triangle a$ is influenced by the exhaustion X, the sensitivity S, the arousal increase value r_a, the level of workload W and the time rate of an action τ. The quotient q_{al} of the logarithmic function in the case of a lower workload ($W = 1$) is $2 + r_a$ and in the case of greater workload ($W > 1$) the quotient q_{ag} is $2 + r_a + X + S$.

$$W = 1 \quad : \quad \triangle a(t) = -\frac{a(t-1)}{q_{al}} \cdot \tau \tag{7}$$

$$W > 1 \quad : \quad \triangle a(t) = \frac{100 - a(t-1)}{q_{ag}} \cdot \tau \tag{8}$$

The equation shows a logarithmic decrease, if the level of workload is 1. In this situation the agent is currently relaxing or takes a rest to calm down. If the level of workload is higher than 1 the arousal will be increased logarithmically. The arousal increase value is one of the initialized vector $\{1.5, 1.5, 1.0, 0.0\}$ whereas the index is equal to level of workload. For example, the level of workload is 3, the increase value of arousal is 1.0. The worst case occurs if the level of workload is 4, at which point the decrease would be half of the current difference of arousal when compared to the maximum value of 100. In other cases, the increase of the value wont be as dramatically. The values for sensitivity and exhaustion increase (if they are less than 0) or decrease the growth (if they are greater than 0) of the arousal. The time rate controls how fast or slow the arousal is increasing. The exhaustion factor X is the current value of exhaustion $x_{curr}(t-1)$ relative to its maximum (see equ. 14 ff.). Due to the fact that a greater value decreases the growth we have to calculate:

$$X = 1 - \frac{x_{curr}(t-1)}{x_{max}} \tag{9}$$

4) The values of emotion: The calculated values of emotions are labeled as either joy (j) or anger (n) (since the foremost interesting aspects of a worker simulation is to decide whether or not the work is capable while maintaining a positive or negative emotional valence) and are influenced by the change value of the arousal $\triangle a$, the value of experience E, the value of sensitivity S, the time rate τ and the emotional increase value r_{em}, depending on the level of workload W. The quotient q_{el} and q_{eg} of the logarithmic functions of joy and anger are the same and are calculated by $q_{el} = 2 + r_{em}$ and $q_{eg} = 2 + r_{em} + E + S$.
The value of anger is increased whenever the workload level is 3 or 4 and the exhaustion is very high. In the other case, if the workload is 2, joy is increased. If the level of workload is 1 the emotional values are decreased. In this case we calculate the values of emotion as follows:

$$W = 1 \quad : \quad \triangle n(t) = -\frac{n(t-1)}{q_{el}} \cdot \tau \tag{10}$$

$$\triangle j(t) = -\frac{j(t-1)}{q_{el}} \cdot \tau \tag{11}$$

$$W = 2 \quad : \quad \triangle j(t) = \frac{100 - j(t-1)}{q_{eg}} \cdot \tau \tag{12}$$

$$W > 2 \quad : \quad \triangle n(t) = \frac{(100 - n(t-1))}{q_{eg}} \cdot \tau \tag{13}$$

To limit the values for anger and joy, we are using the same logarithmic mechanism as in equation (7) where we have to replace the $a(t-1)$-term with $n(t-1)$ or $j(t-1)$. We also rely on the same mechanism to decrease the emotional valence if the level of workload is 1, because this indicates that the task is deemed to be easy. The emotional increase value is one of the initialized vector $\{1.5, 1.5, 1.0, 0.0\}$ whereas the index is equal to the level of workload.

5) The exhaustion: The current value of exhaustion $x(t)$ is dependent on the level of workload W, the exhaustion increase value r_x, the value of experience E and the time rate τ. The quotients of the logarithmic functions of exhaustion are $q_{xg} = 2 + r_x$ and $q_{xl} = 2 + r_x + E$.

$$W = 1 \quad : \quad \triangle x(t) = -\frac{x(t-1)}{q_{xl}} \cdot \tau \tag{14}$$

$$W > 1 \quad : \quad \triangle x(t) = \frac{100 - x(t-1)}{q_{xg}} \cdot \tau \tag{15}$$

As before, we use a logarithmic function to calculate the increase and decrease of exhaustion. The exhaustion increase value is one of the initialized vector $\{1.5, 5.0, 2.0, 0.0\}$ whereas the index is equal to the level of workload.

6) The output parameter: At the moment, the output of our model, the emotional valence of an action, is dependent on the dominating emotion and the level of arousal. This dominating emotion is labeled as "joy" if $j > n$ causes a positive algebraic sign of the emotional valence or is labeled as"anger" if $n > j$ yield to a negative algebraic sign of the emotional valence. In this case the value of the emotional valence is defined by the calculated arousal of an action:

$$n > j \quad : \quad emo_{val} = -\frac{n(t) - j(t)}{100} \cdot a(t) \tag{16}$$

$$j > n \quad : \quad emo_{val} = \frac{j(t) - n(t)}{100} \cdot a(t) \tag{17}$$

$$j = n \quad : \quad 0 \tag{18}$$

This calculated emotional valence represents the interpretation of the current emotional state of the agent. If the values of joy and anger differ greatly, the emotional output is increased compared to a smaller difference, because in this case, the resulting positive or negative emotional valence would be too narrow to adequately distinguish between them.

V. Results

The model, using the previously explained equations, simulates different worker types within a predefined work

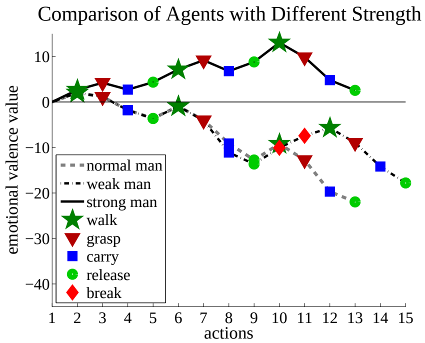

Fig. 2. The emotional values of a normal, strong and weak worker. The strong worker executes the tasks with a positive valence whereas the weak worker needs a break in step 11 and 12 to finish the work episode.

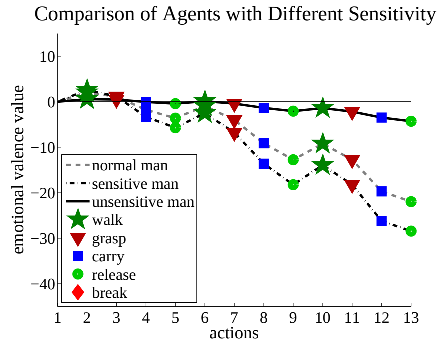

Fig. 3. The emotional valence values for a sensitive and unsensitive worker compared to the normal worker. The sensitive agent is more affected as a normal agent. Contrary to this, the unsensitive agent is not affected.

task. In our example, every agent type has to carry three boxes, two boxes with $20kg$ and one box with $30kg$. The emotion model calculates the internal emotional state and sends this value to the reinforcement learning algorithm, which uses this signal to maintain the critic function. The calculated state transition reward is used as reward by the reinforcement learning algorithm. Additionally, the emotion model possesses the capability to trigger a break, whenever the exhaustion level of the simulated worker is getting too high. In this case, the reinforcement learning algorithm halts the current action selection and inserts an idle action. Based on this value, the reinforcement learning algorithm explores the different actions and chooses an emotionally best-case scenario. In our work set, we defined seven different worker types to demonstrate the model:

Worker type	Properties
Normal	$80kg, 1.85m, C = 0, E = 1, S = 1$
Strong	$90kg, 1.90m, C = 20, E = 0, S = 0$
Weak	$60kg, 1.80m, C = -20, E = 0, S = 0$
Sensitive	$80kg, 1.85m, C = 0, E = 0, S = -0.5$
Unsensitive	$80kg, 1.85m, C = 0, E = 0, S = 5$
Experienced	$80kg, 1.85m, C = 0, E = 5.0, S = 0$
Unexperienced	$80kg, 1.85m, C = 0, E = -0.5, S = 0$

We compared the simulated working tasks for different agents, where each has one parameter changed: Sensitivity (S), Constitution (C) or Experience (E), with assumed standard properties of a normal human being. We change only one parameter in our setting, as the influences of the parameter within the work task is superficially shown.

In the following figures we will show comparisons of the different worker types. Figure 2 shows a strong, a weak and a normal worker type. The strong worker shows no adverse effects from the work task. He carries the boxes with ease. Therefore, the emotional valence is positive, which means that the emotional state manifests in a positive emotional state. In contrast, the weak worker interprets carrying the boxes as very hard, thus the emotional state manifests in the negative spectrum. Additionally, the weak worker needs a break in step 11 and 12 due to the raised exhaustion levels. In the end, due to the much more strenuous workload for the weak worker, the time to completion is increased, compared to the strong worker.

Also the other worker types and tasks show very different results within their episode chronology. While the strong worker appraises the episode carrying 3 boxes to a goal with values of +2.55 and -15.50 the weak worker produces results between -16.9 and -24,73 with at least one necessary break in between his episodes. In comparison, a normal worker, who needs no break, evaluates the tasks between -21.96 and -31.84. Both worker types, the strong and the weak worker, prefer to carry the heaviest box after carrying the two $20kg$ boxes. In contrast the normal worker prefers to carry the heaviest box halfway through the task. This is because the exhaustion level heavily influences the emotional values, so they try to avoid this emotionally negatively connoted action until the end.

The sensitivity value in our model affects the emotional experience in a way which alleviates the emotional peak by either smoothing it over in the case of an insensitive worker or is raised in the case of a sensitive worker (see fig. 3). The emotional valence of the sensitive worker decreases rapidly towards -40, while the insensitive worker stays close to 0 for a long time and finishes the episodes with a mere -4.29. Interestingly enough, the insensitive worker carries the boxes with alternating sequences finally resulting in a value of -4.02 and -6.70. This is possible due to the fact, that the carried order of the boxes is rather unimportant due to the comparable small changes in the emotional state. The sensitive worker on the other hand produces emotional states between -28.43 and -39.88. Thus the emotional worker prefers carrying the heaviest $30kg$ box in between to balance the emotional scales of anger and joy.

The experience of the worker possesses the ability to compensate or boost the exhaustion levels. (see fig. 4). The emotional valence of the experienced worker after carrying the first box is around zero while carrying the heavy box. But once this action is completed, he slowly becomes manifested in a negative value, due to the rapidly increasing exhaustion. The inexperienced worker shows a higher decrease of the emotional value to -20 leading up to a break at step 10, which leads to a negative computed emotion due to the higher affection.

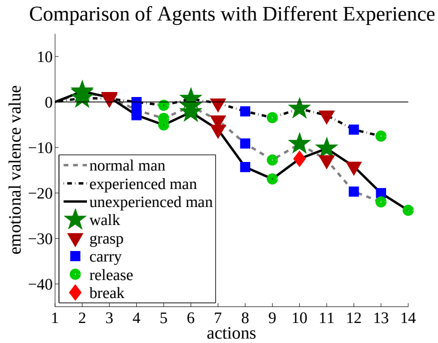

Fig. 4. The emotional valence values of an experienced, unexperienced and normal worker. The experienced worker values are close to 0 thus the worker is not affected during the task. In contrast, the unexperienced worker needs breaks and appraise the task with a high negative value.

VI. Discussion and Future Work

The demonstration of our model, which is able to evaluate the emotional valence during a basic work task depending on the properties of the agent, showed that the preferred sequence of carried boxes depends on the aforementioned properties, such as experience, constitution and sensitivity. Furthermore we were able to predict, which worker type needs a break at what time in the sequence. We also showed which sequence of boxes resulted in an emotionally balanced worker type.

Although the combination of emotional rewards and a reinforcement learning algorithm is not new [22], our module is not primarily focused on the satisfaction of human needs. Instead, our reinforcement learning algorithm uses our emotion model based on human experiences, strength and weaknesses. As a result, the reinforcement learning algorithm is able to compute and plan different actions and sequences, according to an emotionally stable activity. Therefore, if this cognitive model would be implemented as a robotic extension, it would enable the robot to adequately understand and predict emotional reactions of a human co-worker and anticipate associated behaviors, thereby suggesting less emotionally stressed action to its human counterpart during upcoming tasks.

In turn our model entails the necessary requirements of a sociological cognitive computational routine for a robot. With the help of the predicted and evaluated emotions it is possible to compare these with the anticipated results in the real world. Afterwards, following a learning period and an adjustment of the agent preferences, which have to be individually assessed during the learning process, a robot could adequately decide at what point during a task process to offer assistance and to whom. Thus leading to a more productive work environment.

Within the scientific discourse, the upmost criticism of computational emotional architectures is that their computed outcomes are virtually impossible to be evaluated in the real world [23]. Nevertheless, since the goal of the presented model is to simulate the emotional valence while performing a task, we have concrete evidence which can be compared to results in the real world. The results of this upcoming study will be published shortly.

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