

Using Affect as a Communication Modality to Improve Human-Robot Communication in Robot-Assisted Search and Rescue Scenarios

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Abstract—Emotions can provide a natural communication modality to complement the existing multi-modal capabilities of social robots, such as text and speech, in many domains. We conducted three online studies with 112, 223, and 151 participants, respectively, to investigate the benefits of using emotions as a communication modality for Search And Rescue (SAR) robots. In the first experiment, we investigated the feasibility of conveying information related to SAR situations through robots' emotions, resulting in mappings from SAR situations to emotions. The second study used Affect Control Theory as an alternative method for deriving such mappings. This method is more flexible, e.g. allows for such mappings to be adjusted for different emotion sets and different robots. In the third experiment, we created affective expressions for an appearance-constrained outdoor field research robot using LEDs as an expressive channel. Using these affective expressions in a variety of simulated SAR situations, we evaluated the effect of these expressions on participants' (in the role rescue workers) situational awareness. Our results and proposed methodologies (a) provide insights on how emotions could help conveying messages in the context of SAR, and (b) show evidence on the effectiveness of adding emotions as a communication modality in a (simulated) SAR communication context.

Index Terms—human-robot interaction, social robots, search and rescue, robot-assisted search and rescue, emotions, affective expressions, affective control theory, multi-modal communication, affective robots

1 INTRODUCTION

Emergency situations that require Search And Rescue (SAR) operations have been increasing on a yearly basis [1]. These situations may happen due to natural or man-made [2] causes and require an immediate response, as time is a key element for the success of SAR operations [3]. Therefore, improving communication efficiency in SAR teams can be beneficial for the success of time-critical rescue operations.

The member composition of SAR teams has been changing over the years. First, rescue dogs were included to help SAR teams by taking advantage of dogs' strong sense of smell, which can help find victims faster [4]. More recently, rescue robots have become a part of SAR teams. Various rescue robots have been successfully employed in real SAR operations depending on the SAR type (e.g. Urban Search and Rescue), such as snake robots [5], [6], shape-shifting robots [7], ground robots [8], [9], drones [10], [11], or underwater vehicles [12], [13]. There are many reasons behind the widespread use of rescue robots in real-life scenarios, such as (a) SAR areas being unreachable or not safe for

human rescuers due to various hazardous conditions such as extreme heat [14], the toxicity of the environment [15], or confined spaces [16]; (b) deploying robots to target SAR areas might be more time-efficient than deploying human rescue workers (thus increasing the operation's speed of progress); and (c) the limited number of human rescue workers since training human rescue workers requires significant time and effort [17].

Although rescue robots have been used in SAR operations since the early 2000s [14], they still need external help to operate appropriately. To the best of our knowledge, to date, there are no fully autonomous rescue robots or robot teams that can operate in unstructured and cluttered real-life SAR operations [18]. However, rescue robots can still act as teammates and improve human rescue workers' efficiency. To that end, a high level of collaboration between human-robot teammates should be achieved, which requires implementing clear and natural (i.e. intuitive) communication channels between the human and robot teammates. However, human-robot interaction has been identified as a *bottleneck* in robot-assisted SAR operations [14], [18]. In many situations, the intentions behind a robot's teammates' actions are not clear to the field workers, i.e., they do not know what the robot is doing or why it is behaving in a specific way. This lack of transparency in robot teammates' behavior has been identified as the main reason for inefficiency in SAR teams [19]. Therefore, using affective communication between human field workers and rescue robots by taking advantage of multi-modal communication, and developing alternative modalities for robot to human communication, might help overcome this bottleneck in robot-assisted SAR operations.

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Most of the rescue robots used today are already equipped with different communication modalities such as voice, text, photos, and videos [20]. Nonetheless, these modalities may not always be effective in providing efficient communication in human-robot SAR teams. Generally, the specific situation that initiates search and rescue efforts affects the selection of suitable communication modalities. Other factors such as network traffic and the number of people using a specified radio frequency can also cause delays and/or miscommunications between SAR team members (e.g., see [21]). Note, voice is often not effective in SAR operations because rescue scenes tend to be noisy [8], [22]. Modalities other than voice can work in noisy environments, but they put the extra mental workload on field workers, or these modalities do not work well depending on the search scene due to technical problems like delays (e.g., in understanding a message passed to rescue workers) and interferences (e.g., when a command does not contain the most recent information and inference needs to be made to predict the status) [20] (see [20] for more details on these situations and challenges). Hence, a combination of different communication modalities can help create a more robust communication in human-robot SAR teams, to ensure that if one of the modalities stops working accurately, the others can still be used as alternatives. In other words, using multiple channels for conveying the same message can ensure more effective operation. In this article, we propose using affective expressions including emotions and moods (collectively referred to as "emotions" in the remainder of the article) in a communicative way to complement existing communication modalities in human-robot SAR teams.

Many different theories exist that define emotions, such as Ekman's Psychoevolutionary Theory of Emotions [23], James-Lange Theory [24] or Cannon-Bard Thalamic Theory of Emotions [25], [26]. For example, based on Ekman's definition [23], emotions are caused by a specific event. Ekman argues that basic emotions (sadness, happiness, fear, surprise, disgust, anger) are innate, present from birth, and universally recognized. Darwin also agreed on the universality of emotions and claimed that even people in isolated areas have similar emotional expressions [27]. Therefore, people are believed to be skilled at perceiving basic emotions without any training, and this process is believed to be intuitive, so it does not require significant mental workload [28]. This makes using emotions an excellent modality to complement the existing multi-modal communication methods used in SAR robots. Employing this modality could contribute to overcoming the present problems in SAR robots related to interaction among teammates (humans and robots). It could offer a way to reduce the cognitive load of human teammates to understand robot teammates' behavior during SAR operations [29]. Providing a way for robots to express emotions will also give SAR robots an ability to interact socially with humans, which could help rescue teams to operate in a more natural and efficient way [8]. Moreover, this social ability of robots potentially can help victims in SAR situations who encounter robots, making them feel calmer until the medical treatment team arrives, e.g., by preventing a shock [8], [30], and is considered to be necessary for building affective robots that can communicate with humans more naturally [31].

Despite all the existing work on implementing affective expressions for social robots, to the best of our knowledge, only one study attempted to use affective expressions for rescue robots [32]. Bethel and Murphy suggested design guidelines to use body movements, postures, orientation, color, and sound to implement non-facial and non-verbal affective expressions on SAR robots, namely the iRobot Packbot Scout and Inuktun Extreme-VGTV. They simulated a disaster site to conduct a user study to test the effectiveness of those suggested guidelines [32]. While the guidelines were used to create a social robot (which was compared with a robot that did not have these capabilities) [32], a set of emotions which changed based on different SAR scenarios was not defined for the robot, which is the focus of our work. Unlike Bethel and Murphy's work, we propose to use affective expressions as a *complementary* communication modality to increase the efficiency of multi-modal human-robot communication in SAR teams. We believe such an approach can provide further insight into SAR robotics, also emphasizing the need for interdisciplinary approaches.

Prior to implementing emotions for SAR robots, it is important to study the feasibility of conveying SAR messages through emotions. Understanding whether there is a consensus in perception and expression of such emotions is necessary to verify whether communication through emotions would be possible and effective. Otherwise, it will not be clear what emotion a robot should show in a specific situation, and this might add to the risk of miscommunication. In addition, it is important to study which emotion should a robot show in a specific SAR situation, to be able to add emotions as an additional communication modality.

As our goal is to improve communication between robot-assisted SAR team members, this paper presents three online experiments that aim to understand (a) if affective expressions can be used for communicating SAR situations, (b) how a mapping between affective expressions and SAR situations can be obtained in a way that could potentially be generalized for different robots with different affective expression abilities, and (c) if affect, added as a complementary modality, can in fact improve understanding SAR situations when other modalities fail. The primary motivation of these studies is to understand how emotions can be used as a complementary communication modality for robot-to-human communication in SAR teams, alongside other existing multi-modal methods.

The remainder of the paper is organized as follows. Section II presents our research questions. Related work is discussed in Section III. Experiments 1, 2 and 3, alongside their corresponding results, are explained in Sections IV, V, and VI, respectively. Section VII presents a general discussion of the results, followed by concluding remarks in Section VIII and a discussion of limitations & future work in Section IX.

2 RESEARCH QUESTIONS AND HYPOTHESES

In this article, we address the following research questions.

- RQ1** Is there a consensus on what emotions should be used by Urban Search and Rescue (USAR) robots when they try to convey information to human team members

about situations commonly occurring during USAR operations?

RQ2 Is the mapping between emotions and USAR situations robust and not dependent on the wording of the sentences?

RQ3 How can a mapping between SAR related sentences and emotions be obtained, and is there a way to generalize such mapping without limiting it to a specific set of emotions?

RQ4 Can affective expressions complement and improve multi-modal communication in human-robot SAR teams?

H1 Affective expressions will increase participants' situational awareness (i.e. their perception of what is happening in the disaster area) when other communication modalities, such as text, fail.

3 RELATED WORK

In this section, we will first introduce SAR and then discuss the state of the art in the following areas that are relevant to our work: robots in SAR situations, research on Human-Robot Interaction (HRI) for existing SAR robots, using affective expressions in HRI, as well as some relevant work on sentiment analysis.

3.1 Search and Rescue

SAR is the general term for an operation that searches for people who are lost, trapped, and (might be) in danger. It is a broad term and has many sub-fields, usually depending on the search area, such as Mountain Rescue [33], Cave Rescue [34], Urban Search and Rescue (USAR) [35] and Wilderness Search and Rescue (WSAR) [36]. Regardless of the type of SAR, time is always a critical factor [3]. Thus, fast and efficient communication among SAR team members can be a deciding factor in whether or not the SAR team will succeed in saving people's lives.

3.2 Robots in SAR

The idea of using robots to assist SAR operations has been around since the early 2000s [37]. Initial research on SAR robots focused on the control of the robots, i.e., designing robust controllers to allow users to operate rescue robots easily [38], [39]. After successfully developing SAR robots, researchers shifted their focus to designing methods to reduce the human teleoperators' workload. Low-level autonomous robot behaviors in SAR operations (e.g., the ability to climb up/down stairs autonomously without explicit human input) were designed [40]. Semi-autonomous control methods were tested with adjustable autonomy levels in different scenarios, such as involving single robot-single operator [41] or single operator-multiple robot teams [42].

Machine learning (ML) techniques have been employed for robot-assisted SAR applications as well, e.g., to improve the efficiency of proposed controllers for SAR robots [43]. More recently, researchers started to take advantage of ML methods to process sensory data that allowed SAR robots to better understand the rescue environments [44], [45].

To overcome the black-box nature of the majority of the existing ML methods, researchers advocated eXplainable Artificial Intelligence (XAI) [46]. It has been argued that the explainability of robots is needed to foster natural interactions [47]. Otherwise, human users might (a) not trust the robot when it takes a correct action but does not justify it, thinking that the robot's action might be due to an error [48], or (b) assume that there is a logic behind every observed behavior of a robot while, in fact, there may not be a clear logic behind the robot's action, e.g. it may rather be a result of an internal error in the robot's decision-making processes [49], underlying reasons for which could range e.g. from sensor errors, faulty actuators, software bugs, to incomplete or contradictory knowledge.

3.3 Human-Robot Interaction in SAR

Most of the research in HRI related to robot-assisted SAR have focused on improving teleoperation of SAR robots rather than on investigating the interaction itself [50]. Some studies investigated swarm robots for SAR applications, but their focus was on how to reduce human teammates' cognitive load (e.g. [29]). To the best of our knowledge, only a few studies have focused on interactions between human and robot teammates in SAR. Researchers in [51] developed a virtual reality simulation for verbal communication in human multi-robot SAR teams, and they recorded data to create a better swarm emergency response where robots can clearly communicate with humans in the disaster area.

In another study, researchers analyzed the trade-off between the number of human operators and the number of rescue robots in a team for the Robocup rescue competition, taking operators' decision time and mental workload as optimization parameters [52]. Further, a specific simulation environment for USAR (USARSim) was proposed and employed to reduce human operators' mental workload and stress levels [53]. A few studies have also focused on interactions between human and robot teammates in SAR. For example, in [50], RFID tags in the SAR environment were used to exchange information between teammates to increase the mapping quality for gaining better team performance. Also, to simulate verbal communication in human multi-robot SAR teams, a virtual reality simulation was proposed in [51] to create a better swarm emergency response where robots can clearly communicate with humans in the disaster area [51]. Hada and Takizawa [54] also showed promising outcomes for remotely controlling rescue robots from a long distance (700m) using ad-hoc radio signals. Although it was not implemented, usage of gestures to communicate with search and rescue UAVs was proposed in [55].

While focusing on these different aspects of communication, research on the social side of HRI in robot-assisted SAR is quite limited. Fincannon et al. found out that rescue workers expect SAR robots to have social capabilities [56]. Furthermore, Murphy et al. surveyed 28 medical doctors and therapists who operated rescue robots to interact with victims [57]. They argued that it is important for rescue robots to have social capabilities to relieve victims until physical assistance arrives. They also stated that having social intelligence may contribute to building less "creepy" rescue robots [57].

3.4 Affective Expressions in HRI

Although integrating emotions into SAR robots has not seen much attention, emotions, in general, have been one of the popular topics in HRI. Many HRI researchers have focused on how to use the embodiment of robots to express emotions. Creating affective expressions in HRI has been investigated in multiple studies, e.g., using humanoid robots with a human-like embodiment (i.e. a head, face, arms, hands) [58], [59], or creating human-like expressions on non-human-like robots (e.g., using Action Units) [60], [61]. Many studies focused particularly on using facial expressions to implement expressive emotions for robots such as Kismet [58], iCub [59], and Probo [60]. Other research uses animal-like (zoomorphic) robots. A recent study described the design of affective expressions for the animal-like Miro robot, based on a diverse literature on animals' and humans' non-verbal expression of emotions through head, face, and body movements. The obtained mapping, between affective expressions and their recognition by human participants were found to be robust [62], even under visibility constraints [63], i.e., visibility situations similar to those that rescue workers also experience in SAR.

However, other, more machine-like and thus 'appearance-constrained' robots pose different challenges for creating affective expressions that are legible to human interaction partners [8]. Even for these types of robots, one of the few existing approaches suggested in the literature has been inspired by biological and ethological rules [64]. Related to SAR scenarios, in one study, researchers designed affective flight trajectories for drones to create expressive emotions for human users, taking inspiration from a performing arts method called the Laban Effort System [65]. In addition to employing motions to implement affective expressions, color [66], [67], [68], sound [69], or touch [31], [70] (either individually or in combinations) were used to create more affective robots.

3.5 Sentiment Analysis

Many previous studies on sentiment analysis have focused on mapping sentences with emotions, moods, or sentiments [71]. The classification of emotions in this process can be binary as in [72], where researchers categorized sentences as recommended (thumbs up) or not recommended (thumbs down) using unsupervised learning. Other work in this area goes beyond the mapping between sentences and emotions but tries to find the reason behind the predicted emotion (i.e., emotion stimuli). For example, in [73], researchers trained a model to detect the best-associated emotion and its stimuli for given sentences.

There has also been some work on the intersection of sentiment analysis and HRI. Russell et al. (2015) took advantage of speech-to-text technologies to apply sentiment analysis to the conversation between the humanoid robot MU-L8 and people interacting with it to improve the human-robot conversation [74]. Mishra et al. (2019) applied sentiment analysis methods to the feedback of customers interacting with the humanoid social robot called Nadine, to gain more insight on customers' expectations and how to use robots in real-world workplaces [75]. Despite all the success obtained so far, the most significant limitation is that

results highly depend on the context [76]. In other words, obtained mappings between text and emotions might differ drastically if the context of sentences changes (for example, a simple sentence like "I see someone" expressed by a rescue robot would be perceived differently in a search for survivors scenario, as compared with a domestic security robot operating in someone's home at night.). Hence, mappings between sentences and emotions in the context of SAR may also be different from those that are currently suggested for the other contexts.

3.6 Affect Control Theory

Emotion prediction and modeling have been studied extensively by different research communities so far. Theories were introduced to classify emotions along several dimensions. Two well-known examples are the PAD emotional state model [77] and Affect Control Theory (ACT) [78]. These models use three dimensions: Pleasure, Arousal, Dominance (PAD) or Evaluation, Potency, Activity (EPA) dimensions, respectively, to describe the emotional meanings of words. Such dimensional emotion models usually have mappings that consist of ratings for different words (e.g., gathered through extensive surveys for EPA). Our study uses this method to decide on the mappings between situations in SAR and emotional expressions of a robot.

4 EXPERIMENT 1

In this experiment, addressing **RQ1** and **RQ2**, we investigated if it would be feasible to use emotions in SAR robots. In other words, we asked if there would be consensus in the mapping of SAR-related sentences to affective expressions [79]. We also investigated whether such a mapping is robust to the wording of the sentences.

An online questionnaire was used where participants were asked to select one or multiple affective expressions from a set of 11 expressions (including emotions and moods)¹ that they believed could express a situation during USAR. The choices for the emotions were bored, sad, surprise, calm, disgust, angry, tired, annoyed, fear, happy, and excited. The situations were selected in a way that they represented ten common situations during USAR missions with two different wording styles (experimental conditions): *social and intelligent conversational agent style* and *system status report style* (see the first column in Table 1). This was to ensure that the obtained mappings are not dependent on the exact wording of sentences/situations. We used this emotion set as it includes both basic and complex emotions. Moreover, this set was previously designed, implemented, and evaluated on a zoomorphic social robot [62], which expressed emotions through body movements, including the head and face.

A questionnaire was used to gather participants' (a) demographics information, (b) SAR experience, (c) perception of robots, and (d) self-reported ability to understand and show emotions (see [79] for more details). Attention and consistency checks when showing situations (e.g., asking participants to select "happy") were included in the questionnaire.

1. in this paper, all of these affective expressions are referred to as "emotions"

The robot wants to communicate the following message:

I found an item that could belong to a person. Maybe the person is nearby.

Which emotion(s) do you think the robot should use for this situation?
(select multiple if you cannot decide on one. If you select 'not sure', you must select another answer as well)

- | | | | |
|------------------------------------|------------------------------------|----------------------------------|-----------------------------------|
| <input type="checkbox"/> Angry | <input type="checkbox"/> Annoyed | <input type="checkbox"/> Bored | <input type="checkbox"/> Calm |
| <input type="checkbox"/> Disgusted | <input type="checkbox"/> Excited | <input type="checkbox"/> Fearful | <input type="checkbox"/> Happy |
| <input type="checkbox"/> Sad | <input type="checkbox"/> Surprised | <input type="checkbox"/> Tired | <input type="checkbox"/> Not sure |

Fig. 1: Interface Used in Experiment 1

4.1 Procedure

First, participants reviewed and accepted the consent form and read the study instructions. Then, they read an example of an USAR scenario and were shown five different images of USAR robots in various shapes (machine-like, animal-like, or human-like). This was intended to help participants envisage the provided USAR scenario while not being biased by the appearance of a specific robot. All images of the USAR robots were represented as black and white line drawings (see [79] for an example of these images).

After reading the example USAR scenario and getting familiar with the concept, participants saw the USAR related statements in random order, and they were asked to select one or multiple emotions that they thought would be appropriate for a robot to exhibit in that situation (see Figure 1). After the completion of mapping all ten sentences to emotions, participants answered the above mentioned questionnaire.

4.2 Participants

112 participants from North America (Canada and the USA) were recruited on Amazon Mechanical Turk for this study. Inclusion criteria for recruitment were having an approval rate of at least 97% based on at least 100 HITS on Mturk. Data from the participants who failed the attention or consistency check questions were removed. We had a total of 78 participants (48 male, 29 female, 1 other; ages 20–72, avg: 35.7) who passed all the checks. 40 of them were in group A (they saw the sentences shown in the social and intelligent conversational agent style). The remaining 38 were in group B (they saw the sentences shown in the system status report style). Participants received \$2 upon completion of the study and a pro-rated amount based on the number of questions participants answered when they did not complete the study. This study received ethics clearance from the University of Waterloo's Human Research Ethics Board.

4.3 Results

4.3.1 Wording Style Results

To analyze whether the change in the wording of the sentences affected the obtained mappings between situations and emotions, we compared the selected emotions for each sentence pair (condition A versus B) using Pearson's correlation coefficient [80]. All sentence pairs (e.g., "I am stuck and might need help to proceed" and "stuck here") were significantly correlated ($0.78 \leq r \leq 0.99$). This suggested that the obtained mappings were robust and do not seem to be affected by the wording of the sentences.

4.3.2 Mapping Results

Table 1 presents emotions that were selected significantly more than random or/and more than the other emotions in each situation. We also provide suggestions for emotions to be used in each of these situations. Emotions shown in green are our first suggested choice for the mapping, emotions shown in orange are the second suggested choice, as alternative mappings (e.g., in case a robot is not capable of showing a specific emotion). These suggestions are (a) based on the agreement between two conditions and (b) significance levels.

4.3.3 Questionnaire Results

Results indicated that the majority of the participants believed that rescue robots are necessary and useful. Most of the participants stated that they were good at understanding and showing emotions. On the other hand, they were not entirely familiar with USAR or/and rescue robots (see [79] for more details).

5 EXPERIMENT 2

This experiment addresses RQ3. Since Experiment 1 suggested that mapping emotions to situations in SAR is feasible, we now investigated if there is a method to obtain these mappings in a way that (a) the mappings would not solely depend on a set of emotions (e.g., the 11 emotions shown to the participants in the previous study), and (b) the mapping process would have the potential to be automated in the future. Therefore, in this experiment, we study whether it is possible to use the three dimensions associated with emotions in the PAD emotional state model [77] or ACT [78] (EPA). As these three dimensions are very similar in the two models, we decided to use the EPA dimensions (i.e., Evaluation, Potency, and Activity) of the ACT, as datasets exist, mapping emotions and EPA dimensions, which were gathered through large surveys and have been updated over the years to account for possible changes over time, as well as including different countries, to account for potential cultural differences.

While the Evaluation (E) dimension in ACT shows how "good" an emotion, identity, action, etc., is, the Potency (P) dimension shows how "powerful" something is, and the Activity dimension (A) shows how "active" it is. For example, the EPA value for the emotion "happy" is [3.44, 2.93, 0.92]², based on the U.S.A. 2015 Dataset [81], which is used in this experiment. This suggests that "happy" is believed to be quite good, somehow powerful, and slightly active.

For the sentence/word below:

I am stuck and might need help to proceed.

How would you rate it on the three aspects below?



Fig. 2: Interface Used in Experiment 2

2. Note that EPA values are commonly rated in a range between -4.3 and 4.3

TABLE 1: Findings of the first experiment. Only emotions that were selected significantly more than random are included (***: $p < .001$, **: $p < .01$, and *: $p < .05$). Two suggested mappings are shown in green and orange respectively. Cond. A: Condition Social and Intelligent Conversational Agent Style, Cond. B: Condition System Status Report Style

Sentence	Cond.	Significant Expressions		
		Suggested Mappings		2 nd Mapping
		1 st Mapping		
I can again communicate with our team outside of the building. Communication with external team restored.	A	excited*	happy***	calm***
	B	excited*	happy***	calm**
I lost communication with our team outside of the building so we are on our own now. Communication with external team lost.	A	NA	fear***	annoyed*
	B	sad*	fear**	annoyed*
I am stuck and might need help to proceed. Stuck here.	A	fear**	annoyed***	NA
	B	NA	annoyed***	NA
I detected dangerous material here, let's proceed carefully. Dangerous material detected here.	A	NA	fear***	NA
	B	surprise*	fear***	NA
I believe we are behind schedule. I also noticed it is getting dark and there is not much time left. Behind schedule. It is getting dark.	A	NA	annoyed***	fear***
	B	tired**	annoyed***	fear**
I found an item that could belong to a person. Maybe the person is nearby. An object that might belong to a person was found.	A	happy**	excited***	calm**
	B	surprise**	excited***	calm***
My battery is running low and I will stop working soon. Battery is running low.	A	sad**	tired***	fear**
	B	NA	tired***	fear*
I think I found a surviving person. Possible living person detected.	A	surprise*	excited***, happy***	NA
	B	calm*	excited***, happy***	NA
I detected that there might be a risk of further collapse so we should only proceed with caution. Further risk of collapse detected.	A	NA	fear***	NA
	B	NA	fear***	NA
I think I heard someone is calling for help, we might have found a survivor. Possible call for help detected.	A	surprise*	excited***	happy***
	B	NA	excited***	happy*

To study whether using the EPA dimension can lead to similar mappings, instead of directly mapping sentences to a set of emotions (as in Experiment 1), we asked participants to rate the sentences used in Experiment 1 on the EPA dimensions (see Figure 2). Afterwards, we calculated the emotion, from the set of 11 emotions used in Experiment 1, that was the closest to the EPA rating for each sentence. **Selection of additional sentences:** Also, compared to Experiment 1, we included more sentences related specifically to different types of SAR, in addition to the sentences related to USAR used in the first experiment, to get insights on the potential validity of such mappings (i.e., to see if meaningful mappings can be obtained) for an extended set of situations (see sentences in row 11 to 16 in Table 2). Since Experiment 1 suggested that the mappings were consistent and not affected by different wording styles, we only focused on sentences conveyed in the more expressive social and intelligent conversational agent style.

Table 2 shows the different sentences used in this study. Sentences (11) and (12) were included since generally more than one field team operates in a search area, and the need for additional members might change dynamically depending on the current task [20]. Sentences (13) and (14) were included because detecting the environment's temperature is crucial for SAR sub-types involving extreme environments such as deserts, in water, or in very cold climates. The survival rate of victims decreases significantly both in cold water during maritime search and rescue [82], and in hot weather due to dehydration during WSAR [83]. Furthermore, sentence (15) was added since there is a chance to encounter an injured victim in SAR operations [20], [33], [84], [85]. Lastly, sentence (16) represents another scenario that is common during almost all SAR operations since it is usually impossible to directly reach some area of interest in the rescue field [34], [36], [82], [86].

Rating the sentences: Participants were shown all the sentences used in Experiment 1 and the additional sentences as in Table 2 in a random order, and they were asked to rate

these sentences according to the EPA dimensions [78]. In other words, participants were asked to rate, on a continuous scale, how good, how powerful, and how active each sentence (and the corresponding situation it conveys) was (see Figure 2).

As a consistency check, we asked participants to rate the words "angry", "good," "infant," and "boss" in addition to the sentences to compare these ratings with the original EPA values obtained from the U.S.A. 2015 Dataset [81]. These words were selected as they cover a range of different values on each of the E, P, and A dimensions and could help ensure consistency between participants' ratings and the reference ratings in the dataset (used to find the closest emotion). In addition to these sentences and words, attention checks were included that instructed participants to select a specific answer (e.g., "I found that for this sentence you have to select the leftmost option on all bars.").

Obtaining the associated mappings: Obtained EPA ratings were used to identify the corresponding emotion among the list of 11 affective expressions used in Experiment 1. The EPA ratings of the 11 emotions (from the most recent, U.S.A. 2015 Dataset [81]) were compared with the obtained EPA values for each sentence. Euclidean distance [87] was used to find the closest mapping. As an example, for the sentence "I think we need additional team members", we compared the distances between participants' EPA ratings for this sentence (e.g., [0.83, 0.77, 0.71]) and EPA values of all 11 emotions. We found that the closest distance (1.68) corresponded to the emotion "surprised" ([1.42, 1.35, 2.17]).

5.1 Procedure

Participants first read the consent form and the instructions for the study. Next, they rated sentences (along with consistency and attention checks) on the EPA dimensions in a random order (see Figure 2). Finally, they received an end code for the completion of the study.

5.2 Participants

We recruited 223 participants (79 from Canada and 144 from the USA) on Mechanical Turk for this study. We started with the same recruitment criteria as in Experiment 1, namely having an approval rate of at least 97% based on at least 100 HITS on Mturk. However, we later changed the criteria to an approval rate of 96% based on at least 50 HITS on Mturk for participants who were from Canada³. After filtering, based on the attention check questions, 133 participants remained (72 from Canada and 61 from USA). Participants were paid \$0.3 for participation in this study. This study received ethics clearance from the University of Waterloo's Human Research Ethics Board.

5.3 Results

In this section, we will first discuss how consistency checks were applied and will then present the results for the ratings and the obtained mapping between situations and emotions.

5.3.1 Consistency Checks

Despite having a high approval rate criteria for recruitment on MTurk, 90 participants failed either or both of the attention check questions. Since attention check questions were related to selecting the right or left-most part of the continuous bars, we included an error margin during the filtering. We accepted a range of answers that were not too far from the correct answer on the continuous scale (i.e., a 10% error margin for both left and rightmost part of the continuous scale).

3. None of the participants from Canada failed any of the attention checks, so we changed the criteria to be able to recruit more participants

TABLE 2: Predicted emotions based on the distance between average EPA ratings of participants' EPA scores and EPA ratings of the 11 emotions from the U.S.A 2015 dataset [81]. Dist. refers to the calculated Euclidean distance [87] between EPA values of the predicted emotions and participants' ratings. The last column shows the mappings obtained in Experiment 1 for comparison.

No	Sentences	Average			1 st Prediction		2 nd Prediction		From Exp. 1
		E	P	A	Dist.	Emotion	Dist.	Emotion	
1	I can again communicate with our team outside of the building	2.55	1.73	0.93	1.39	Excited	1.49	Happy	excited, happy, calm
2	I lost communication with our team outside of the building so we are on our own now.	-2.00	-1.35	-0.42	0.56	Fearful	1.23	Annoyed	fearful, annoyed
3	I am stuck and might need help to proceed	-1.08	-1.46	-0.13	1.48	Fearful	1.49	Annoyed	fearful, annoyed
4	I detected dangerous material here, let's proceed carefully	-1.03	0.98	-0.56	1.76	Disgusted	2.17, 2.43	Annoyed, Fearful	fearful
5	I believe we are behind schedule. I also noticed it is getting dark and there is not much time left	-1.72	-0.98	0.12	0.68	Annoyed	1.06	Fearful	fearful, annoyed
6	I found an item that could belong to a person. Maybe the person is nearby	2.16	1.23	0.38	1.94	Surprised	2.16	Excited	happy, excited, calm
7	My battery is running low and I will stop working soon	-1.80	-1.73	-0.82	0.90	Fearful	1.35	Sad	sad, tired, fearful
8	I think I found a surviving person	3.00	2.63	1.70	0.77	Excited	0.94	Happy	surprised, excited, happy
9	I detected that there might be a risk of further collapse so we should only proceed with caution	-0.99	0.37	-0.47	1.57	Disgusted	1.75, 1.99	Annoyed, Fearful	fearful
10	I think I heard someone is calling for help, we might have found a survivor	2.81	2.32	2.32	0.20	Excited	1.65	Happy	surprised, excited, happy
11	I think we need additional team members	0.83	0.77	0.71	1.68	Surprised	2.79	Excited	NA
12	I think we have more team members than we need. One of us should join the other team	0.65	0.88	0.83	1.61	Surprised	2.62	Angry	NA
13	I detected that the temperature of the environment is too cold for a person	-1.25	-0.30	-0.52	1.35	Fearful	1.36	Annoyed	NA
14	I detected that the temperature of the environment is too hot for a person	-1.45	0.14	0.36	0.83	Disgusted	0.97	Annoyed	NA
15	I found a victim that requires medical attention	0.06	1.42	1.88	1.39	Surprised	2.02	Angry	NA
16	I detected that this rescue route requires obstacle clearance	-0.25	0.49	0.54	1.98	Angry	2.04	Disgusted	NA



Fig. 3: Examples of the designed light patterns

average EPA ratings of participants was calculated to be "Excited" with a distance of 1.39, compared to EPA ratings in the dataset, and the second closest emotion was "Happy" with a distance of 1.49. These results were consistent with the mappings obtained from Experiment 1 (i.e., Excited, Happy, and Calm). Only for two sentences the two closest emotions did not match with the ones obtained through the first experiment, however the third closest emotion matched. The third closest distance for these two sentences is shown in pink colour in Table 2.

6 EXPERIMENT 3

Experiments 1 and 2 supported the feasibility of using affective expressions with SAR robots. In this experiment we explored the effect of affective expressions on robot-to-human communication in the context of SAR teams to address research question RQ4 and our hypothesis H1. In other words, we asked if affective expressions, used as an additional communication modality, can improve accuracy of communication in situations where other modalities may fail.

6.1 The Husky Robot and Affective Expressions

To be able to use affective expressions in scenarios with a robot that might realistically be used in SAR scenarios, we designed and implemented the expressions on Clearpath's Husky robot⁴, an appearance-constrained robot. Affective cues were displayed using light signals (LED strips), based on EPA dimensions of ACT [78]. A series of informal pilot studies were conducted with recorded videos of Husky's affective expressions, and with lab members who were not involved in this research and who were not part of the participants that were subsequently recruited for the experiment. In each pilot, different parameters of these expressions (e.g., light intensity, frequency, patterns, etc.) were used. After analyzing the results of the pilot studies, we decided to continue with a full light pattern (i.e., turning on/off all the LEDs on a strip around the robot) since in this case the light patterns can more easily be observed from all viewing angles. In addition, we decided to use the *color* of the lights for the Evaluation dimension (how good the emotion is), while using the *brightness* of the lights to represent how powerful the emotion is (Potency), and the frequency of the light changes to represent the Activity dimension (see Figure 3). These design suggestions were also inspired by the work of Collins et al. (2015) [68].

After implementing affective light displays, noisy text messages were created to mimic a situation when the robot-to-human text communication modality fails during the

4. <https://clearpathrobotics.com/husky-unmanned-ground-vehicle-robot>

SAR mission. Zalgo text with different chaos levels was used to distort the text messages and make them difficult to read [88]. Here, again, a pilot study with different noise levels was conducted with lab members to decide on the noise level (one that would not be too easy to read/understand). The noisy text messages were presented to participants of the study as displayed on a radio transmitter device (Motorola XPR 7550e), which is widely used during real SAR missions [89]. Figure 4 shows an example of the noisy text message shown to participants.

The experiment had a between-participant design where participants were randomly assigned to two conditions: *Emotion* condition and *No emotion* condition. While Husky expressed emotions using lights in the Emotion condition, it did not use emotions as a communication modality in the No Emotion condition (i.e. when no lights, and thus affective expressions, were displayed).

6.2 Procedure

The study consisted of three steps as below:

Step 1: Participants first completed an initial training step to learn the affective expressions of Husky. The training was similar to the training in [63]. Participants first watched a training video showing emotional displays along with a text indicating the corresponding emotion (this video could be played as many times as participants chose to). Then participants were tested on their recall abilities of these emotions, to see how well they learned the meaning of each of these emotional displays. Five emotions were used in this study: happy, excited, tired, annoyed, fear. This step was added to make sure that the participants in the emotion



Fig. 4: The main task in Experiment 3 where participants were shown two videos for each scenario and then asked to guess what message Husky wants to convey.

condition will know the meaning of emotional displays of Husky. This is also an expected step if emotions might in future be used in SAR robots as a communication modality, since, in practice, SAR workers get training regularly, including on how to use new tools. For such high-risk tasks such as SAR, one cannot rely on SAR team members being able to 'intuitively' recognize the affective expression that they encounter for the first time, they would rather expect to be trained, to be able to operate and interact with the robot reliably. Thus, adding this step to SAR workers' regular training routine might actually be feasible in future applications.

Step 2: Each participant watched 20 videos for 10 different SAR scenarios (two videos for each scenario) and were asked to select what message they thought the robot was communicating to them. Each scenario consisted of two videos (one providing the SAR context and one showing the message rescuers would receive as described below). The scenarios were shown to participants in random order. After watching the two videos for each scenario, participants were asked to select the message that they believed the robot wanted to convey to them. The list of messages to select from included all 10 different messages. It was a multiple choice option, so participants could select more than one message from the list. They could replay the videos as many times as they wished, before making a decision. The videos were automatically paused if they switched the interface tab or opened another application to measure their response time accurately (and to ensure participants paid sufficient attention to the videos).

For each scenario, participants were shown 2 videos. The first video showed movements of Husky in a 3D simulated disaster environment and the second one showed the message that Husky intended to send to the participants, i.e., it showed the noisy message with/without affective light displays on the robot (depending on the condition) for each scenario. Participants were then asked to select the message that they thought Husky wanted to convey to them (see Figure 4). The emotions displayed in each situation were chosen according to the results of Experiments 1 and 2.

The experimental setup shown in Figure 5 was used to simulate common scenarios happening during SAR operations and to give participants an illustration of the context that search and rescue robots may encounter in SAR operations. In this setup, Husky starts from a particular point depending on the scenario and follows a specific route.

TABLE 4: Different routes were followed by Husky for each scenario indicated by a number (names for corresponding scenarios are given in Table 2). Please see Figure 5 for experimental setup and locations of labelled points (a_{Right} , a_{Left} , b , c , d , e_{Right} , e_{Left}). Matched emotions for each scenario can be found in Table 1.

No	Path Followed
1	$a_{Right} \rightarrow b \rightarrow c \rightarrow d$
2	$b \rightarrow d \rightarrow e_{Right} \rightarrow e_{Left} \rightarrow d$
3	$b \rightarrow c \rightarrow d \rightarrow c \rightarrow d \rightarrow c \rightarrow d$
4	$b - a_{Left} \rightarrow b \rightarrow c \rightarrow d$
5	$b \rightarrow c \rightarrow d$
6	$b \rightarrow a_{Right} \rightarrow b \rightarrow c \rightarrow d$
7	$a_{Left} \rightarrow b \rightarrow c \rightarrow d$ (decrease speed gradually)
8	$b \rightarrow a_{Right} \rightarrow d$ (use curvy path from a to d)
9	$b \rightarrow a_{Left} \rightarrow d$ (use curvy path from a to d)
10	$a_{Right} \rightarrow d$ (use curvy path from a to d)

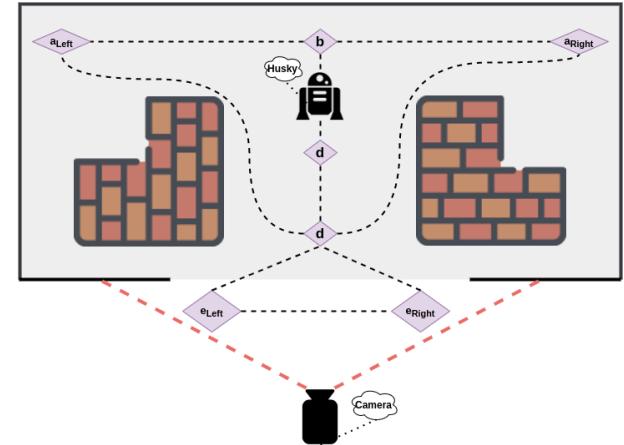


Fig. 5: Illustrating the experimental setup used to mimic common scenarios happening during SAR missions in Experiment 3. Different locations are shown with pink rhombuses and labeled with letters. Possible routes between these points are shown with dashed lines. For each scenario, Husky starts its movement from one of these points and visits particular points using dashed routes. Note, this setup was not shown to participants.

TABLE 5: Description of parameters to transform EPA ratings into corresponding LED attributes. We determined the range of LED parameters based on the feedback through previous pilot studies.

LED Parameters				
Name	Description	Description	Min	Max
Evaluation (E)	Goodness	Color	Red	Green
Potency (P)	Powerfulness	Intensity	0	255
Activity (A)	Activeness	Duration	4300 ms	300 ms

For example, for the scenario "I think I found a surviving person", Husky starts from point b in Figure 5, then goes to point a_{Right} . During this movement, Husky slowly goes out of the view for the observing participant. Then, it appears again and moves toward point d by taking the curvy path (a shorter path compared to going first point b and then point d).

At some point during these movements, participants were also notified that they got a text message from Husky, both visually (by seeing a text saying that they have received a message), and through sounds (a beeping sound similar to the receipt of a text message). The message itself was not shown to them at this point to make sure that they will focus on the movements of the robot and will consider the context. The timing of receiving this text notification was controlled and differed in each scenario, to make it realistic. The different paths taken by Husky in each scenario are summarized in Table 4.

Step 3: participants were asked questions regarding their opinions about search and rescue robots, emotions in SAR, and how difficult they found the noise levels of the displayed text. These questions asked: (1) how useful they thought rescue robots are, (2) how familiar they were with rescue robots, (3) whether they had seen a SAR robot before, (4) how necessary they thought rescue robots are, (5) how much they believed rescue robots could be better than rescue dogs in the future⁵, (along with 3 additional consistency and sanity checks). Next, participants answered

5. Note, in our research we do not intend to suggest that robots might be better than rescue dogs (which probably they cannot, in many ways), but included this question to provide participants with a more familiar reference point for comparison.

TABLE 6: Values of parameters to transform EPA ratings (min -4.3 and max 4.3) into corresponding LED attributes for each emotion used in the study. EPA values for the emotions were obtained from the USA Student 2015 dictionary [81].

Emotion	EPA Values [81]			LED Parameter Values			
	E	P	A	R	G	B	Duration(ms)
tired	-1.58	-1.28	-2.28	31	0	0	4154
happy	3.54	2.85	0.85	0	255	0	1609
fear	-2.41	-1.07	-0.81	54	0	0	2958
excited	2.77	2.13	2.46	0	174	0	300
annoyed	-2.13	-0.47	0.58	64	0	0	1828

a question depending on the condition they were assigned. Participants in the emotion condition were asked to report on (9) how much they thought the robot’s use of lights in order to convey emotions was helpful to understand messages sent by the robot, while the participants in the no emotion condition had to state (9) if they preferred the robot to use lights/emotions and thought that could be helpful for understanding the messages sent by the robot. All questions in this section were rated on a continuous scale, and participants had an option of “prefer not to share” if they wished not to provide answers (as requested by our ethics committee).

6.3 Apparatus and Simulations

6.3.1 Husky Robot

Husky is an Unmanned Ground Vehicle (UGV) designed by Clearpath Robotics⁶ to be used as outdoor field research robot. It fully supports Robot Operating System (ROS).

6.3.2 Emotional Expressions Using Lights

A NeoPixel RGB LED strip was used. All emotions that were used in the experiment were programmed on an Arduino micro-controller in C++ using libraries Adafruit NeoPixel and FastLED. Each emotion was given a function in which the period, wavelength, and color of the wave could be altered based on the design. For the experiment, EPA dimensions were transformed to represent different parameters of LED lights (see Table 5 for description of parameters and Table 6 for parameter values).⁷

For recording the videos of Husky showing affective expressions using LEDs, we attached two LED strips to the Husky robot’s top and side (360°) to provide better perception of light from various viewing angles, e.g. Figure 4. We normalized the range of LED parameter values based on the EPA range of emotions under consideration. For example, emotion “happy” has the largest P value (2.85), so it was converted to 255 (max LED value for RGB parameters). We took the possible risk for participants into account that lights might possibly trigger a seizure while selecting the minimum duration [90].

6.3.3 Gazebo Simulation

The Gazebo simulator was used with ROS to create a realistic SAR simulation [91]. To construct the SAR disaster environment, various 3D models provided by Open Robotics⁸

6. <https://clearpathrobotics.com/husky-unmanned-ground-vehicle-robot/>

7. The related code is made open-source to provide a starting point for other researchers who are interested in implementing affective expressions based on ACT. www.github.com/samialperen/epaLights

8. https://github.com/osrf/gazebo_models

were combined. The resulting simulation environment in Gazebo will be made publicly available upon acceptance of this article so that other researchers could use it for their own research.

6.4 Participants

We recruited 151 participants on Amazon Mechanical Turk. Only participants whose approval rate was higher than 97% based on at least 100 HITS were allowed to join the study to increase the quality of the obtained data. Recruited participants were located either in the USA or in Canada. Participants who completed the study were paid \$3 for compensation, while a pro-rated amount was paid to those who did not finish the task. This study received full ethics clearance from the University of Waterloo’s Human Research Ethics Board.

16 of the participants failed an attention check question (i.e., “I think drinking water is liquid”). Also, data of 33 participants who gave inconsistent responses were discarded. After filtering, data from 102 participants (37 female, 65 male; ages 22-69, avg: 38.9, std: 11.1) were left for the analysis where 53 were in the emotion condition and 49 were in the no emotion condition.

6.5 Statistical Analysis

In this experiment, we investigated two factors: perception accuracy and response time. Perception accuracy was investigated to address our fourth research question (RQ4). Response time provided us with information on how fast participants responded to the questions (to see if showing emotions affected response times, and also as a way to check how response times differed for those who passed and failed the emotion training, which could provide some insight on whether failure in training was due to participants’ level of attention to the task, or due to other factors).

The perception accuracy of participants was calculated by measuring their success in selecting the correct SAR-related messages. Response time was reported by measuring how fast they selected the messages.

Further, the independent measures considered in this study were: (a) participants’ responses to the questions in the survey, (b) the order of messages seen by the participants, (c) the total number of times they switched away from the main task, (d) the total inactive time not spent on the task, and (e) the experimental condition participants were assigned to (emotion vs. no emotion). To investigate the relationships between the independent and dependent measures, Linear Mixed Effect Models (LMMs) [92] were employed and the factors in the model were decided based on minimizing Akaike’s Information Criterion (AIC) [93]. One-way binomial tests were applied, assuming uniform probability distribution as the null hypothesis, to determine whether participants selected a specific scenario (or emotion in the training step) significantly more than another option [60].

6.6 Results

Through LMM, it was found that participants in the emotion condition had a significantly higher perception accuracy

than participants in no emotion condition ($se = 0.04, t = 2.287, p = .024$). On the other hand, no significant correlation was found between the condition participants were assigned to and their response times ($se = 6.06, t = -0.05, p = .960$). These results are shown in Tables 7 and 8.

LMM results also revealed other significant findings. As suggested in Table 7, participants who thought rescue robots were not useful or who were familiar with SAR had a significantly lower perception accuracy. Furthermore, Table 8 shows that while there was no significant differences between the conditions, participants familiar with SAR, participants who think rescue robots are useful, or those who had a higher inactive time spent more time predicting the messages in the scenarios. On the other hand, participants who had seen a rescue robot before were faster to respond. We also detected that participants got faster in providing the response as they see more videos (shown as order effect in the table).

6.6.1 Training Success

Training success is important specifically in the emotion condition, as emotions might not have provided a beneficial additional communication modality for those who did not pass the training.

41 participants failed to learn all five emotions during training. They were labeled as "failed" to investigate their results separately. Table 9 shows only incorrect responses of these 41 participants. Among the mis-recognized emotion pairs, fear-tired and annoyed-fear were the ones that got confused the most, while the happy-excited pair was the least confused. All emotions were perceived with an accuracy more than the chance (20%), while "happy" was perceived with the best accuracy ($\approx 91\%$), and "annoyed" with the worst accuracy ($\approx 59\%$).

6.6.2 Perception Accuracy - Training Success

As mentioned previously, the participants in the emotion condition had a significantly higher accuracy than participants in the no emotion condition. The average perception accuracies of participants in both conditions is shown in

TABLE 7: Linear Mixed-effects predicting participants' perception accuracy

Covariate	Perception Accuracy			
	Estimate	SE	t	Pr (> t)
Condition				
No Emotion ^b				
Emotion	0.09	0.04	2.287	0.024 *
Familiar with SAR	-1.64e-04	6.78e-05	-2.417	0.017 *
SAR Robots Not Useful	-2.59e-04	8.02e-05	-3.234	0.002 **

* = $p < .05$; ** = $p < .01$; *** = $p < .001$; ^b = baseline level

TABLE 8: Linear Mixed-effects prediction participants' response times

Covariate	Response Time			
	Estimate	SE	t	Pr (> t)
Condition				
No Emotion ^b				
Emotion	-0.3	6.06	-0.05	0.960
Inactive Time	0.11	0.03	3.273	0.001 **
SAR Robots Useful	0.04	0.02	2.012	0.047 *
Familiar with SAR	0.06	0.01	4.355	0.000 ***
Seen SAR Robot Before	-0.04	0.01	-2.865	0.005 **
SAR Robots Necessary	-0.03	0.02	-1.543	0.126
Order Number	-6.1	2.45	-2.487	0.013 *

* = $p < .05$; ** = $p < .01$; *** = $p < .001$; ^b = baseline level

TABLE 9: The table shows participants' incorrect guesses to recognize the affective expressions implemented on Husky. Rows show emotions expressed by Husky, and columns show participants' corresponding responses to these expressions. Since only incorrect responses of participants who failed to learn all emotions in the training step are included (41 participants failed in total; 22 in emotion condition, 19 in no emotion condition), all diagonal entries have zero, i.e., a non-zero diagonal entry means that the emotion was perceived correctly.

Responses	Tired	Fear	Excited	Happy	Annoyed	
Emotions	Tired	0	7	4	4	10
	Fear	26	0	4	4	14
	Excited	0	1	0	20	1
	Happy	2	1	5	0	1
	Annoyed	14	27	7	4	0

Figure 6. Participants in the emotion condition were also divided into two groups depending on their success during the training. Those who passed in the training step had a significantly higher accuracy than those who failed based on LMM ($t=2.425, se=0.054, p=0.019$). We did not find a significant difference between perception accuracies of participants who passed and failed attention checks in the no emotion condition.

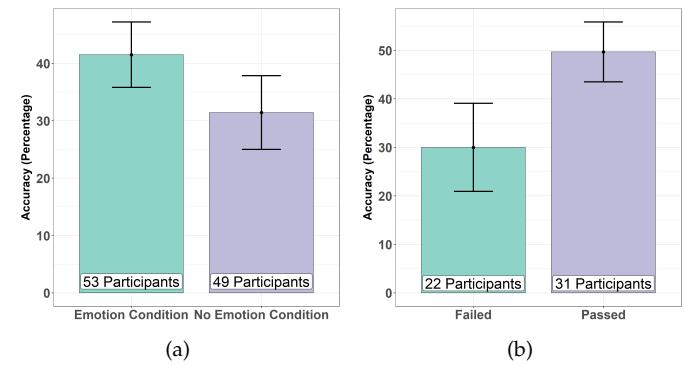


Fig. 6: (a) Average perception accuracy of participants for each condition given (the difference is significant; $t = 2.357, df = 97.623, p = 0.020$). (b) Average perception accuracy of participants in the emotion condition compared based on their success in the emotion training step (the difference is significant; $t = 2.425, se = 0.054, p = 0.019$).

The success of recognizing individual SAR scenarios in terms of robot-to-human communication was also analyzed for three groups: (a) participants in the emotion condition who passed the training, (b) participants in the emotion condition who failed the training, and (c) participants in the no emotion condition, including those who failed and passed in the training step (see Figure 7). Overall, those who were assigned to the emotion condition and passed the emotion training had a significantly higher accuracy as compared with both those who failed in the emotion condition ($se=0.057, t=-2.273, p=0.025$), and those in the no emotion condition ($se=0.045, t=-3.211, p=0.002$), according to a LMM. Note, none of the scenarios were recognized with more than 60% accuracy.

The success in recognizing individual SAR scenarios regarding their type (positive vs. negative sentiment, based on the Evaluation dimension of the existing EPA values) was also examined for the same three participant groups (see Figure 7). Participants who passed the training in the emotion condition, shown in Figure 7 (a), had the highest accuracy in understanding whether the scenario was positive or negative (over 90% accuracy). In contrast, participants

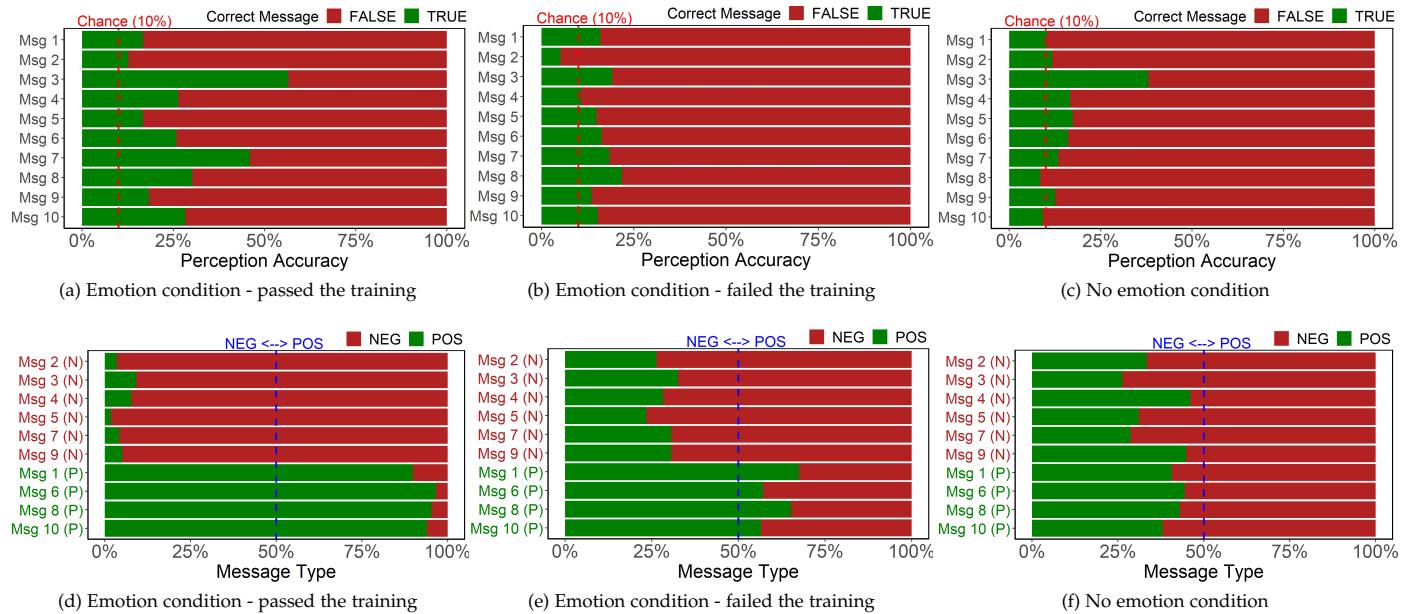


Fig. 7: Perception accuracy of the messages shown to participants during the experiment 3. Individual accuracies of the messages are shown at the top and accuracies regarding the type of the messages (positivity/negativity) shown at the bottom. See Table 4 for the scenario names.

in the no emotion condition, shown in Figure 7(c), had the lowest accuracy (for some scenarios, their accuracy was even less than the chance level, i.e., 50%).

6.6.3 Questionnaire Results

Participants in both conditions were asked to report how hard it was for them to read the distorted text messages. As it can be seen in Figure 8, the majority of the participants found the shown text messages very difficult to read, with 45 of them stating that they could not read the text. To test the relation between their responses to this question and their performance during the main task, reported noise levels were factorized into five, with noise level 1 representing their responses between 0 and 250, and level 5 representing that they could not read the text at all. We did not observe an effect of the reported noise level on perception accuracy ($se = 0.018, t = -0.520, p = 0.604$) & response time ($se = 2.818, t = -1.204, p = 0.231$).

Participants' responses to the two statements about the usage of affective lights during the experiment are shown in Figure 9. For both statements (one for each condition), the mean value is around 750 (1000 corresponding to 'I totally agree' and 0 indicating 'I totally disagree'), showing that most of the participants in the no emotion condition indicated that they would prefer to see the robot's emotions, and those in the emotion condition found the robot's emotions to be helpful in understanding the situation.

A linear mixed-effect model was fit for participants in the emotion condition to predict response time and perception accuracy based on their ratings of how helpful they found the lights. While there was no significant effect of ratings on perception accuracy ($se = 0.000, t = 0.819, p = 0.413$), there was a significant negative effect of how helpful they found the lights on their response times ($se = 0.000, t = -2.479, p = 0.016$), indicating that the more useful the

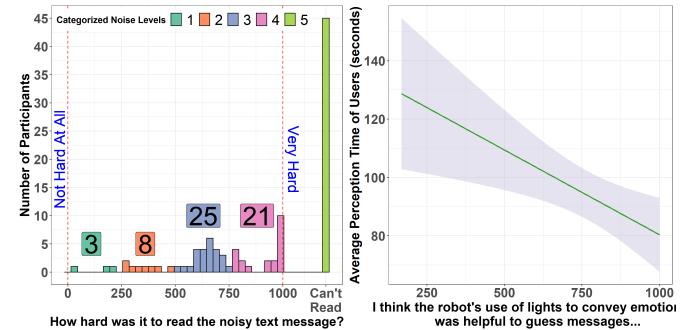


Fig. 8: On the left: Participants' responses to the survey question "How hard was it to read the noisy text messages?" and on the right: average response time of each participant vs how useful they found lights to guess messages sent by the robot

participants rated the emotions, the less time they spent on guessing the messages (see the plot on right in Figure 8).

7 DISCUSSION

In this paper we studied the feasibility of using emotions as a communication modality in SAR robots. Through three online experiments, considering a range of different scenarios that could occur in search and rescue situations, we provided evidence that suggests that emotions might in fact be useful as an additional communication channel in SAR robots – to complement the existing communication modalities and to improve the success and efficiency of robot to human communication. As an additional benefit, this ability might also help victims since it has been suggested that social SAR robots can contribute to the reduction of stress levels of victims and prevent shock [8]. However, as using emotions in SAR robots for communication purposes is a

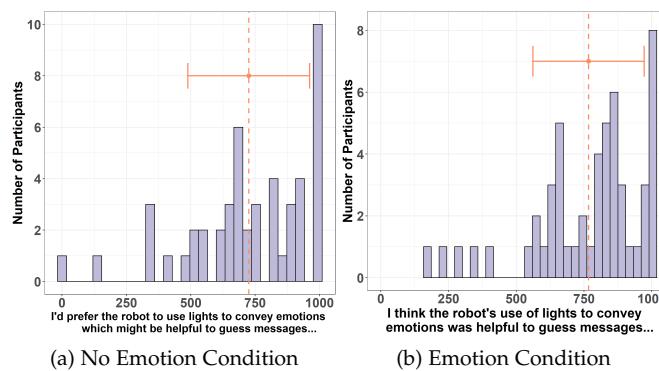


Fig. 9: Response of participants in both conditions. Mean and standard deviation were shown with orange dashed and solid lines respectively.

novel research direction, we carried out three experiments into understanding (a) the feasibility of using emotions in SAR robots (Experiment 1), (b) different approaches that can be used to decide on an emotion that a SAR robot should show in a specific situation for communicating a specific message (Experiment 2), and (c) whether emotions can improve communications between SAR robots and humans when other modalities fail (Experiment 3).

In Experiment 1, we asked whether there would be consensus in mapping emotions to SAR situations (**RQ1**), and if such a mapping would be robust, and not be affected by the wording of sentences in those situations (**RQ2**). Results showed that participants agree on a particular mapping between described SAR situations and emotions of a SAR robot to convey that situation, which was not affected by the wording style. These results were promising and encouraged us to further pursue the use of emotions as an additional communication channel for SAR robots.

As these mappings might be affected by the selected set of emotions (e.g., a specific SAR robot may not be capable of showing specific emotions due to its embodiment), we asked if it is possible to use a method to get the mappings in a way that would be flexible and independent of the selected set of emotions, to address **RQ3**. This led to the design of Experiment 2, where Affect Control Theory (ACT) was used and mappings were measured along three different dimensions: Evaluation, Activity, and Potency (EPA). We then used the EPA values associated with the set of 11 emotions (used in Experiment 1) to check whether the mappings would be consistent between the two experiments. Results suggested that similar mappings can be obtained when participants are asked to rate SAR situations on the EPA dimensions, as opposed to directly mapping to emotion words. Therefore, our results suggest that mappings using EPA ratings can be used in the SAR domain in the future, which can flexibly be used with different emotion sets.

Dimensional emotion models are usually not used to understand emotions of sentences. Rather, they are often used to describe emotions (as well as identities and behaviours in ACT). That is because it is difficult to obtain ratings for these dimensions for sentences due to multiple challenges. For example, the mappings will be highly context-dependent, and it would be hard (if not impossible) to conduct extensive surveys to gather ratings for all combinations of sentences,

in all contexts, in a similar manner that the other EPA values are collected (as a large number of sentences can be created with the combination of the related words). Further, there is currently limited literature available on mapping sentences to emotions or dimensional emotion values, most of which can only evaluate sentences on the Evaluation dimension (i.e., regarding a sentence's sentiment, positive or negative). Since automated methods for inferring emotions from sentences are still not reliable, in Experiment 2 we presented a set of context-dependent (i.e., SAR related) EPA values. Note, different robots have different capabilities and limitations regarding affective expressiveness. However, with the proposed method we developed in Experiment 2, depending on the robot's expressive capabilities (e.g. it might not be able to display certain emotions), the set of emotions can be adjusted by identifying the "next best" emotions. Thus, this method allows us to find mappings according to the robots' capabilities. However, it is important to emphasize that, regardless of the robots' expressive capabilities, we still need to decide on a reasonable set of emotions that are being considered for the mappings. The ACT datasets include a large set of emotions, many of which may not be relevant in some specific contexts. For example, if we had used the complete set, instead of limiting it to our set of 11 emotions, the two closest affective expressions for the sentence "I detected dangerous material here, let's proceed carefully" would have been "obligated" and "aggrieved", which (a) does not seem appropriate for the context of SAR, and (b) cannot be expressed easily on a social robot.

An approach similar to ours might be used in other application domains beyond search and rescue, however, future work is needed to study generalizability of our approach to other domains, as this work was the first attempt in using Affect Control Theory for designing affective lights for appearance constrained robots (cf. Akgun's Master thesis [94]). Also, as emotions are context dependent [95], [96], while a similar method could be used in other domains to obtain mappings between situations/messages and emotional displays of a robot, it is reasonable to expect that the mappings might not be exactly the same.

When analyzing data in Experiment 2, we came across an incidental finding, i.e. we observed differences between ratings of participants from Canada and the USA for a few of the sentences. Cultural differences in EPA ratings, while not relevant for answering our research questions, are indeed well supported by research related to Affect Control Theory (e.g., see [97], [98], [99]), and some of the differences in EPA ratings that we observed might indeed be due to cultural differences. For example, in Experiment 2, participants from the USA rated the sentence "I think we need additional team members" as *better, more powerful, and more active*, as compared to the participants in Canada, who rated this sentence closer to neutral in all dimensions. We saw a similar tendency for the sentence "I think we have more team members than we need. One of us should join the other team". In both cases, the situation involved a change in the structure of teams. While future work is needed to study why the ratings were different for these situations, and whether cultural differences were in fact the reason for observing this result, if this is the case, it may emphasize that cultural differences should also be considered when

designing emotions for robot-to-human communication of SAR robots (similar to the way different EPA ratings are obtained in different countries for emotions, identities, and behaviours in ACT). These differences may be important considerations for the future design of robots' emotional displays in different application domains [96].

As discussed above, the first two studies supported the feasibility of bringing emotions into the SAR context. Therefore, in Experiment 3 we investigated the effectiveness of using emotions as an additional communication channel (e.g., video streams, voice, and text [20]). Our intention is to propose an additional interaction modality to complement existing multi-modal channels. In this way, we would be able to employ SAR robots with more robust and failure-safe communication abilities that might help to improve field workers' shared mental models and situational awareness [100]. To that end, we first proposed a method to show affective expressions on an appearance constrained robot, Husky, using light displays that were designed based on ACT and EPA dimensions. The proposed method was inspired by earlier work [68]. Employing EPA dimensions allowed us to implement affective expressions quantitatively on appearance-constrained robots. Using these implemented emotional displays and the mappings obtained from the first two studies, as well as through simulations of SAR scenarios (which were designed in a way to also convey the context that the SAR workers would get from SAR robots' movements, locations, etc.), we investigated whether the usage of emotions can improve communication in robot-assisted SAR teams (**RQ4**) in Experiment 3. Results suggested that a rescue robot that uses emotions can increase the accuracy of understanding the messages when other communication modalities (i.e., text in our experiment) fail, supporting **H1**. It is important to emphasize that, in our work, the effect of emotional displays on improving the accuracy of understanding robots' messages was studied in the specific context of search and rescue, and for a range of common situations that often occur in SAR. Future work will benefit from studying how emotional displays can complement multi-modal communications between humans and robots in other domains, especially in similar situations where other communication modalities may fail. This includes robots operating in noisy environments, or robots interacting with persons who have hearing impairments.

While it was not the focus of this study, we found many challenges with conveying emotions through lights. Even though participants were trained at the beginning about the meaning of each emotional display (a step expected to be part of future training of human team members in future SAR applications), we had participants who failed the training. Fear was the most commonly confused emotion among the negative emotions, which was confused with either annoyed or tired. The reason behind this misrecognition may be that EPA values for our negative emotions were close to each other, which makes them less distinguishable through lights only, especially when captured through videos and displayed on computer screens. Under these conditions, e.g., the difference in the Potency (P) dimension may not be recognized well solely based on changes in light intensity. Therefore, improvement of emotional displays may further improve communications. In our experiment, emo-

tion training accuracy increased participants' accuracy in understanding the SAR situations. Those who successfully passed the emotion training step had a significantly higher accuracy in recognizing the SAR situations. However, even those who failed to distinguish the emotions in the training step still benefitted from the affective expressions by understanding the sentiment (positive or negative Evaluation) of the messages (because sentiment was clearly distinguished by showing green or red lights), leading to less confusion as compared to the no-emotion condition. This suggests that while a larger range of emotions can be helpful in increasing perception accuracy in SAR situations, conveying the sentiment can still be beneficial, limiting the potential SAR messages that a robot may convey.

While it was reasonable to assume that the perceived noise level may also affect accuracy (therefore was controlled for in the analyses), we did not find an effect of the reported noise level on perception accuracy (similar to what was previously seen in [63]). One explanation could be that the participants judged the difficulty based on how they assumed they understood the text messages (e.g., thinking that they recognized a message while they did not).

To summarize, while future work is needed to better understand the benefits of using affective expressions with SAR robots (e.g., studies in real world situations and recruiting experienced rescue workers), this article provided a first step towards using affective expressions in SAR robots with the goal of increasing efficiency in SAR. We provided evidence on the feasibility and effectiveness of using emotions as an additional communication modality in search and rescue teams, to increase efficiency and robustness of communications, which is a key in success of SAR operations. The idea of using emotions to complement multi-modal human-robot interaction, as well as the proposed methodology for obtaining the mappings and applying them to a specific context, in our case SAR, has the potential to be applied to other real-world applications that require efficient human-robot teamwork such as in other rescue contexts (e.g., firefighting), as long as proper mappings between common situations happening in these contexts and emotions exist.

8 LIMITATIONS & FUTURE WORK

Our study had several limitations. Due to the online nature of the studies, participants did not have a chance to interact with real SAR robots (we had planned such in-person experiments but then COVID-19 restrictions made those impossible). The participants also did not experience a real SAR scenario, which could help with understanding the situations and might affect the mappings. While illustrating possible SAR operations using several pictures of SAR robots as well as simulated and real videos of the Husky robot, the obtained results might differ in real-life scenarios. Mappings are also likely to differ if they were obtained from participants who had experience with SAR situations themselves. However, the online approach reduced biasing participants with the appearance of a particular robot, and it also helped with reducing the experimenter bias for the first and second experiment [101]. This approach has been shown to be effective in many HCI and HRI studies and

has gained more attention when COVID-19 has affected the feasibility of conducting in-person HRI studies, as a safe method for data collection [102]. Nonetheless, future work is needed to investigate if and how obtained mappings would translate to real-life situations and with ratings by participants who have experience with SAR situations. In-person interaction of rescue workers with the Husky robot displaying affective expressions should also be investigated in a field study, e.g. simulating a real disaster area.

Although participation was limited to the USA and Canada, participants' level of English was not assessed during any of the studies. Yet, based on their answers to attention check questions, it is reasonable to assume that they understood the task and the sentences. Also, While Experiment 2 created ratings that can be used with different emotion sets, we did not examine how the mappings change based on different emotion sets. This can be investigated using different emotion subsets in the future, e.g., using those that can be shown by a specific robot.

In Experiment 3, the first limitation concerns the design of emotional expressions using affective lights. Generally, there are many challenges in designing emotional displays for appearance constraint robots. Emotional expressions have been mostly designed for human-like or zoomorphic robots which are not common in search and rescue scenarios. These challenges could limit the range of emotions that can be shown by appearance constraint robots. In our study, we limited the range of emotions to those that have been previously designed for other types of robots. As an example, we used 'calm' as an emotion representing a 'near neutral' state, because a neutral state could not be properly designed with lights. Although we do not expect that this has affected the outcome of our study, as all of our messages notified users about an event that was either positive or negative, it could be considered a limitation of our approach. Also, in our study, participants could not distinguish between the different negative emotions as well as they did for the positive emotions. Although positive and negative affective lights' visibly differ in real life, this difference is not that clear in the recorded videos due to the technical difficulties of recording high-speed, low/high brightness of LED lights. An additional study with real human-robot interaction might in fact improve the accuracy of users' emotion recognition. Alternative LED designs could also be investigated to improve the recognition of the robots' emotions shown through lights. Moreover, longer-term, repeated interaction with SAR robots and a better recognition of emotional displays of robots can be expected to improve human-robot communication, since our findings showed that participants' success in perceiving SAR scenarios increased as their training success increased (see Figure 6). Similarly, the selected robot, as well as the specific design of the scenarios, might have affected the findings. Studies that involve SAR robots capable of showing a smaller or larger range of emotions, as well as including other scenarios or different designs for scenarios can complement and verify the findings of the third experiment in the future studies.

When affective rescue robots are used in real SAR missions, there might be other challenges regarding the usage of affective expressions in a disaster area. For example, perception of affective expressions might differ in environments

with varying visibility conditions such as smoke, rain, or darkness as we investigated in [63]. While this previous study showed that recognition of affective expressions conveyed through a robot's body and head gestures could be robust, to a reasonable extent, under different visibility constraints [63], future work is needed to examine the effects of visibility conditions on the accuracy of recognition of SAR robots' robot-to-human communications through emotions. Also, while we provided a first step towards implementing emotions on appearance-constrained robots, future work needs to investigate how to improve affective expressions of SAR robots using in-person experiments as well as field studies. For example, employing a different way of matching light parameters with EPA dimensions and/or having additional parameters (like using different patterns for each emotion) could be investigated.

Furthermore, our study was designed in a way that the majority of the participants could not read the noisy text messages that accompanied the emotional displays. This was because we wanted to study the benefits of using emotions as a communication modality in situations when the other modalities fail. Future studies can investigate the impact of emotions in other situations, e.g., when other modalities are less noisy, to study if using emotions can lead to a faster recognition of the situation.

Lastly, studies that employ emotions to convey information from robots to humans in different application areas, such as firefighting and service robotics, can help support generalizability of using emotions as a communication channel to complement multi-modal human-robot interaction in other similar contexts.

9 CONCLUSION

In this article, we presented three online studies to investigate the possibility and benefits of using emotions as a complementary communication modality in robot-assisted Search and Rescue (SAR) to improve communication between rescue workers and SAR robots. Mappings between situations commonly occurring during SAR operations and emotions were obtained in the first Experiment, and a different method was investigated for obtaining the mappings in the second Experiment. Results of the first two studies confirmed the feasibility of using emotions in specific SAR contexts. The mappings were also robust to the wording of the sentences. Employing a dimensional emotion model was investigated and proposed as a practical approach for gathering mappings that are not dependent on a specific emotion set, which could make mappings more generalizable to different SAR robots. In the third Experiment, affective expressions obtained from the mappings in the previous studies were implemented on an appearance-constrained rescue robot (Clearpath Robotics Husky) using affect control theory and lights, and were used in simulated SAR situations to study the benefits of using emotions as a communication modality in a situation when other modalities may fail. Results of the third experiment suggested that participants who saw a rescue robot with an ability to express emotions had a better situational awareness. To conclude, this article presented a first step towards using emotions in SAR robots as an additional communication modality and provided

insights and approaches that might help with the design and employment of emotions in SAR robots. This is hoped to increase the efficiency of (affective) SAR robots' robot-to-human communications and improve participants' situational awareness of the disaster area, which could ultimately lead to more successful SAR missions.

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