Using Emotions to Complement Multi-Modal Human-Robot Interaction in Urban Search and Rescue Scenarios

Anonymous
Email
Anonymous
City, Country

Anonymous
Email
Anonymous
City, Country

Anonymous
Email
Anonymous
City, Country

Anonymous
Email
Anonymous
City, Country

ABSTRACT

In this study, we investigated if there is consensus in using emotions as an additional communication channel to support multi-modal Human-Robot Interactions (HRI) in urban search and rescue scenarios, in which effectiveness of interactions is the key to success. The natural mappings between specific situations that might happen during missions and the proper emotions for the robots to show in that situation were obtained through a Mturk study with 78 participants. Suggested mappings for a set of 10 common situations were provided, which can be used to improve HRI in urban search and rescue situations.

CCS CONCEPTS

• **Human-centered computing → Interaction design**; *Empirical studies in HCI*;

KEYWORDS

human-robot interaction, search and rescue, urban search and rescue, multi-modal communication, affective communication

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1 INTRODUCTION

Recent natural disasters such as the earthquakes in Peru, Nepal, Albania or volcano eruption in New Zealand emphasize the necessity of efficient search and rescue teams. In these situations, quick actions can be the key to save many lives. One of the factors that can help with accelerating the speed of Urban Search and Rescue (USAR) teams is efficient communication among team members.

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According to the Federal Emergency Management Agency (FEMA), USAR involves locating, rescuing, and initial medical stabilization of victims trapped in confined spaces following a structural collapse [1]. Search for the injured or/and trapped people is a crucial part of USAR missions[32]. One of the main challenges during USAR missions is racing with time since the chances of saving people decreases dramatically with time [37]. For example, 94% of people were rescued during the first 24 hours in the 1980 earthquake in southern Italy [18]. Earthquakes have usually been the reason for USAR missions, but USAR teams have also been deployed in other situations, such as extreme weather conditions (e.g., hurricanes and tornadoes) [33]. Note, it is also reasonable to expect that we will need USAR teams more often in the future due to extreme weather conditions resulting from global warming.

USAR teams can greatly benefit from the use of rescue robots in search and rescue teams for multiple reasons: (a) human rescuers may not be able to go to specific locations during USAR missions for many reasons including size [26], extreme heat [4], and toxicity of the environment [14], (b) areas that need to be searched are often not physically safe enough for the rescuers. For instance, more than 100 rescue workers were killed due to further building collapse during the search and rescue mission after the Mexico City earthquake of 1985 [39], (c) deploying robots to the target areas can be faster than deploying human teams [4], and (d) the number of individuals who are trained for search and rescue missions are limited and it takes many hours to train them properly [2].

Since the early 2000s, USAR teams have tried to employ rescue robots to improve their performance [4]. Although there might be some differences depending on countries, USAR teams in general consist of units which are specialized in search, rescue, and medical treatment [38]. According to differences in their operational work, USAR teams are divided into two. The command team is located at the specific location and has all the global information and tries to manage the other teams called field teams. Field teams are the teams that have the local information and mission. They follow the orders given by the command team, and they are responsible for physical search and rescue operation in the field.

While the rescue robots can significantly improve the speed and accuracy of search in USAR, they are not fully autonomous and they need help from human rescuers to be able to properly assist human members in the USAR missions. To the best of our knowledge, there are no fully autonomous teams of rescue robots to operate in highly cluttered, unstructured, and unpredictable urban disaster environments [8]. Hence, robots need to collaborate with humans to successfully perform USAR tasks. However, research related to rescue robotics has shown that Human-Robot Interaction (HRI) has been a bottleneck in USAR [4, 8]. The reason behind this bottleneck is a lack of transparency in rescue robots [22]. It is not always clear to the human rescuers what a robot is doing or why it is taking a specific action, as it may not be clear whether it thinks it has reached a goal or not. Therefore, developing alternative communication modalities between humans and robots to increase transparency of rescue robots would be essential to facilitate the communication between humans and robots.

Different communication modalities such as voice, text, photos, videos, and GPS locations have been employed in SAR teams [19]. However, each method has its own advantages and disadvantages. For example, voice is not effective when the rescue scene is very noisy due to different machines operating [28]. Other modalities work well in noisy environments, but they require time to process and put extra mental workload on rescue workers [19]. Therefore, a combination of different communication modalities can improve success of current human-robot rescue teams. Using more than one communication modality adds redundancy and thus robustness to communication in human-robot teams. Specifically, in this research project, we hypothesize that a communication approach using emotions and other affective expressions can be effective and efficient in complementing existing communication methods in human-robot teams.

Although there has been an ongoing discussion for decades about the true nature of emotions [27], recent empirical findings suggest that basic emotions are intuitive, natural, and universal [24]. This is consistent with early work of Darwin where he claimed that certain emotions are expressed similarly in people around the world — including in isolated areas where there had been little contact with the outside world — showing that there is an inheritable component of emotions [23]. Hence, people do not require additional training to perceive basic emotions and their mental workload will not increase [47]. So emotions can be a good candidate for an additional modality for multi-modal interaction between humans and robots in USAR operations where the interaction itself is one of the main problems at present. Emotions can be particularly useful during co-located interactions, which happens so often during USAR missions [8]. Creating an additional modality can also reduce the cognitive load on human teammates, which is reported as a challenge in communications between humans and swarm robots [21].

As a first step towards enhancing communication in USAR human-robot teams, in this paper, we present a study into whether a natural and consistent mapping exists between specific messages/actions of robots — that might happen during USAR missions — and robots' emotions. The main motivation of this work is to understand how to use emotions as an alternative interaction modality between humans and robots in the USAR context, and to see if there is consensus in such mapping, which could potentially also be informative for contexts beyond USAR scenarios.

The rest of the paper is organized as follows. The related work is explained in Section 2. Section 3 presents research questions and the experimental design. Section 4 introduces results, and Section 5 discusses the results. Conclusions are presented in Section 6, followed by limitations and future work in Section 7.

2 RELATED WORK

Research on rescue robots in USAR environments started in the early 2000s [29]. From a control perspective, researchers have implemented various methods to control rescue robots. Since then, rescue robots have been effective in many situations. Human rescuers teleoperated robots to search for survivors after the great eastern Japan earthquake [30]. To reduce the human operators' workload, researchers started by designing low-level autonomous robot behaviors [34], e.g. where the operator navigates the robot to a stairway and it could then autonomously climb the stairs. Adding to this low-level autonomy, researchers implemented semi-autonomous control methods with adjustable autonomy levels in single robot-single operator teams [11] and single operator-multiple robot teams [48]. Rescue robots have also taken advantage of advancements in machine learning. For instance, [9] employed Hierarchical Reinforcement Learning (HRL) to develop learning-based semi-autonomous controllers for rescue robots in USAR contexts.

Recently, the concept of eXplainable Artificial Intelligence (XAI) has emerged with the targets of fostering transparency and trustworthiness [3]. This term does not only cover Artificial Intelligence (AI) algorithms, but also relates to autonomous agents and robots. Research on explainable agency is needed because humans attribute some mental states to agents/robots they are interacting with [16]. Hence. when an agent's or robot's behaviour is not explained, humans could either assume that there is a logic behind the observed robot behaviour (while in fact there might be an error), or they might assume that the robot is making a mistake (while it is in fact following its decision making processes). This directly affects the quality of interaction and users' trust in the agents or robots [36]. To address XAI problems for robots, researchers have implemented mental model architectures that use robots' sensors to observe the world and update robots' mental models [6].

On the other hand, rescue robots in USAR have not been widely studied from a human-robot interaction perspective. The work done in this field is quite limited and mostly focuses on enhancing teleoperation [8]. For example, research has studied the ratio of the number of human operators and robots in a team in the Robocup Rescue Real Robot League regarding operator's decision time and mental workload [41]. In another study, a simulation environment specific to the USAR context, called USARSim, was used to detect a human operator's mental workload and stress levels during different USAR scenarios [25]. Other studies used swarm robots for applications that required efficient human-robot team collaborations, with a focus on controlling human teammates' cognitive load due to interacting with a number of robots in the team [21].

Nonetheless, studies exploring interaction between humans and robots in USAR context or/and from XAI perspective are very limited. Kleiner et al. [20] found that RFID tags placed in the environment to exchange information between humans and robots increases team performance. In another study, a simulation environment was developed to simulate verbal communication between multiple robots and humans in SAR scenarios [5]. In another study, ad-hoc radio signals were used for communication between human teleoperators and rescue robots and achieved long distance (700m) remote control of rescue robots [15]. Furthermore , it was proposed to use gestures to communicate search and rescue drones, but it was not implemented in the study of Mayer et al. [31]. In general, rescue robots in today's world use voice, text, photos, and video streams to provide useful information to rescue workers [19].

A related research field is sentiment analysis, i.e. extraction of sentiment-related information from text [45]. For instance, classification of review sentences as recommended (thumbs up) or not recommended (thumbs down) using unsupervised learning has achieved an average accuracy of 74% [46]. Others, Ghazi et al. [13] built a new dataset to detect both the emotion and emotion stimuli (i.e., cause) in emotion-bearing sentences. A supervised information extraction model was trained on this dataset to extract Ekman's six emotions (happiness, sadness, surprise, disgust, anger, fear) [10], in addition to shame. The sentiment analysis approach has been also applied to extract emotions from sentences obtained from social websites. In this regard, an algorithm called SentiStrength 2 to detect sentiment strength of text from six social websites (MySpace, Twitter, YouTube, Digg, RunnersWorld, and BBC Forums). SentiStrength 2 algorithm performed better than a baseline approach for different datasets in both supervised and unsupervised methods [45]. Sixty-four common emojis were used to map extracted emotions from 1246 million tweets. An increase in accuracy was achieved in different baseline datasets, as compared with distant supervision approaches. Nevertheless, accuracy in sentiment analysis is still highly context dependent [35]. In our work, the aim is to complement human-robot communication using affective expressions of the robot to accompany verbal communication, as an additional channel of (non-verbal) communication. Multi-modal communication, and redundancy of communication channels, verbal and non-verbal, will benefit situations where communication accuracy is not guaranteed in noisy and unpredictable environments. Our goal is to use affective expressions to convey messages e.g. in USAR scenarios, therefore, it is important to use affective expressions that are intuitive to people and can as accurately as possible reflect a specific message.

Complementing the communication modalities in human-robot teams discussed above, our work provides further insight into the interaction between humans and robots in USAR contexts and proposes using emotions as complementary, non-verbal communication modality for co-located interaction during USAR missions. To the best of our knowledge, this is the first study to suggest using emotions in search and rescue applications to increase efficiency of interactions among team members.

3 EXPERIMENT

Through a user study on Amazon Mechanical Turk, we investigated whether a natural and consistent mapping exists between a robot's communications/messages in USAR missions and robots' emotions.

3.1 Method

In this experiment, participants first read about different USAR situations and messages and then were asked to map them to an emotion. To ensure that the wording of the messages would not affect the mappings, participants were divided into two conditions. Depending on the condition, robots' messages were conveyed in either system status report style (e.g., "Dangerous material detected here") or social and intelligent conversational agent style (e.g., "I detected dangerous material here, let's proceed carefully"). Note that the social, conversational agent style also had additional information (e.g., "let's proceed carefully") that is intuitive and does not exist in the other style. Note, the messages in each condition were not meant to be identical in content. If great differences are observed in how participants map a robot's communication with emotions in these two conditions than this would indicate that a mapping will depend heavily on the style of the communications, which could make such a mapping less useful. On the other hand, if in both conditions we find similar mappings then this would suggest that such a mapping can be used across different robot communication styles. The messages are shown in Table 1.

For each message, participants could choose one or multiple options from a list of 11 affective expressions (including emotions and moods): Bored, Sad, Surprise, Calm, Disgust, Angry, Tired, Annoyed, Fear, Happy, and Excited. This set was selected because (a) it covers a wide range of affective expressions, including simple and complex emotions, as well as different moods, and (b) these affective expressions have been designed and evaluated on a social robot called Miro [7] in a recent study [CITATION REMOVED FOR ANONYMITY], which can facilitate implementing them on a selected USAR robot.

All situations seen in Table 1 were selected carefully after analyzing common situations occurring during SAR missions. For example, the command team, which is considered to be the main control unit, is responsible for gathering all the global information and sharing it with field teams. There are regions where the field teams cannot make a contact with the command team, which are called dead zones. It is quite critical for field workers to be aware of whether they are in the dead zone or not [19]. That is why situations (1) and (2) were included.

Introducing robot teammates creates some problems for field workers as well. They need to know whenever robot teammate(s) need help. Common problems that robots in the field have is being stuck in an area and having low battery [8]. These problems were included as situations (3) and (7). Information about these situations would help to increase transparency of robot teammates' actions [22].

Situation (5) was included as timing is critical in SAR missions and field workers need to know and take active or proactive actions when their performance slows down [37]. The probabilities of further collapse in the searched area [39] or encountering hazardous material [14] are high for USAR missions. Therefore, situations (4) and (9) were included. Situations (6), (8), and (10) were considered since they represent the most positive scenarios that might happen during a SAR mission and all the field workers need to be aware of these situations whenever they happen [19]. Lastly, an additional message was added as an attention check, where we instructed participants to 'select happy as the answer'.

Different communication styles used for the statements were inspired by research in human-computer Interaction (HCI) and human-robot interaction (HRI), where agents/robots are attributed human-like traits based on their behaviour [12], and their communication may differ and be closer to humans (human-like) or

Table 1: Situations/Messages that rescue robot(s) wants to convey

No.	Social and Intelligent Conversational Agent Style	System Status Report Style
(1)	I can again communicate with our team outside of the building	Communication with external team restored
(2)	I lost communication with our team outside of the building	Communication with external team lost
(3)	I am stuck and might need help to proceed	Stuck here
(4)	I detected dangerous material here, let's proceed carefully	Dangerous material detected here
(5)	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
(6)	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
(7)	My battery is running low and I will stop working soon	Battery is running low
(8)	I think I found a surviving person	Possible living person detected
(9)	I detected that there might be a risk of further collapse so we should only proceed with caution	Further risk of collapse detected
(10)	I think I heard someone is calling for help, we might have found a survivor	Possible call for help detected

machines (machine-like) [17, 40, 44] (i.e., social and intelligent conversational agent style and system status report style, respectively, in our case).

Furthermore, participants were asked to respond to a questionnaire. The questionnaire was composed of two sections: demographic questions (i.e., about age, gender, education level, and ethnicity) and questions related to emotions and SAR experience, which contained the following questions (all answered on a continuous Likert scale from completely disagree to completely agree)[1]:

- I think rescue robots are useful. (Robots-useful)
- I was familiar with rescue robots before this study. (Familiar-SAR)
- I think rescuing people can save their lives. (Attention check question)
- I had seen an example of rescue robot before this study. (Seen-SAR-Robots)
- I think rescue robots are necessary. (Robots-necessary)
- I believe in future rescue robots can become better than rescue dogs.
- I think rescue robots are not useful.
- I believe in the future we will not need rescue robots.
- I am good at showing proper emotions in real life situations. (Good-show-emotions)
- I have difficulty understanding others' emotions.
- I have difficulty showing proper emotions.
- I think when people are happy, they mostly express happy emotions. (Attention check question)
- I think I have a good understanding of people's emotional states/moods. (Good-understand-emotions)

3.2 Procedure

Participants first accepted the consent form and read the instructions. They then read a short example of an urban search and rescue scenario and saw various images of rescue robots to get a better understanding of the concept (and also to ensure that their assumption of the robot would not affect their responses). In order to give participants examples of rescue robots and prime them towards considering in the study USAR scenarios in general, and communication situations with USAR robots in particular, we showed a variety of different existing USAR robot designs. But in order to limit the information provided, trying to avoid the elicitation of answers regarding any detailed features of specific robots, we presented the examples of USAR robots as black and white line drawings.

Afterwards, participants were shown the statements one by one, in a random order, and were asked to provide their mappings by selecting one or multiple affective expression/emotion. Upon completion of the mappings, participants completed the questionnaire.

3.3 Participants

We recruited a total of 112 participants on Mechanical Turk. All participants had an approval rate higher than 97% based on at least 100 HITS. Fifteen participants failed the attention check questions and 19 participants provided inconsistent answers to the questionnaire at the end of the study. This left 78 participants (48 male, 29 female, 1 other; ages 20-72, avg: 35.7). Out of the remaining 78, 40 saw messages in the social and intelligent conversational agent style and 38 saw them in the system status report style. Participants were paid $2 if they completed the task. Otherwise, they were paid a pro-rated amount based on the number of questions they completed. This study received ethics clearance from [REMOVED FOR ANONYMITY].

4 RESULTS

In this section, we present the obtained results related to mappings of statements to emotions for different styles of statements, as well as the questionnaire results.

4.1 Communication Style Effect

We first checked how different wording of the sentences (i.e., social intelligent conversational agent style vs. system status report style) affected the responses. All pairs of corresponding sentences in each condition were significantly correlated ($0.78 \leq r \leq 0.99$), suggesting that the selected mappings were robust and wording did not affect the selected emotion.

[1] note that some questions are repeated in different ways, which acted as sanity checks

4.2 Mapping Results

Table 2 shows the results for the selected emotions for each sentence and each wording style. Each cell in this table shows how many participants chose the corresponding emotion. Significance of the selected responses was calculated using one-way binomial test, assuming uniform probability distribution as null hypothesis, and significant responses were shown in bold with corresponding significance levels represented in the Table. Furthermore, one-way binomial tests were also employed to check whether a specific response was selected significantly more than the all the other options for a specific emotion (shown with pink). For example, happy was selected significantly more than the other emotions for the statement "Communication with external team restored". In some cases, we could not find a specific emotion that was selected significantly more than others, rather we found a set of 2 or 3 emotions that were selected significantly more than random. For example, in the statement "Possible living person detected." both happy and excited were preferred, i.e. they were selected significantly more often than random. Regardless, the results show that the participants clearly have preferences for specific emotions for each statement, and that such a mapping is significant and consistent.

Table 3 summarizes the results shown in Table 2. It contains the set of emotions that were selected significantly more than random for each statement. Our suggestions for final mappings are shown in green and possible alternative mappings are shown in orange.

4.3 Questionnaire Results

As mentioned above, we asked participants about their familiarly with USAR situations and robots used in USAR, as well as their perception of necessity and usefulness of robots (to understand their general attitude toward robots). Participants were also asked to self-evaluate their ability to understand and show emotions. This was mostly to understand our participant group better and to identify if any of these factors have affected ratings. Figure 1 shows the obtained results. The majority of the participants believed that the robots are necessary and useful in USAR situations, and indicated that they are good in understanding and showing emotions. However, a majority of participants were not familiar with USAR scenarios, neither had they seen a USAR robot before. We did not find any effect of these factors on participants' mappings.

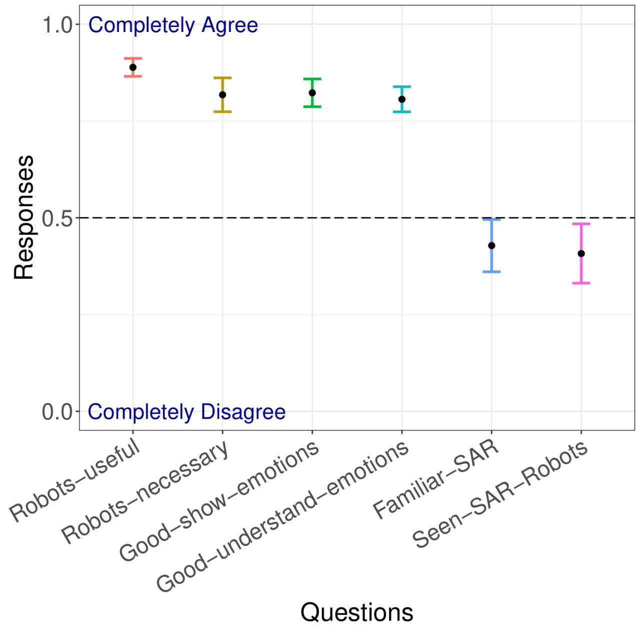

Figure 1: Participants' responses to the questionnaire

5 DISCUSSION

Using emotions as an additional communication channel for multimodal interaction can improve interactions between humans and robots, as perceiving emotions is considered to be natural for people [24]. In this paper, we investigated the feasibility of using emotions in urban search and rescue scenarios, for conveying a robot's messages. Through a study on Mechanical Turk, mappings between 10 common situations in urban search and rescue scenarios and the associated affective expressions (11 options in total) were investigated.

The results suggested that reaching consensus on specific mappings between messages in USAR situations and emotions is feasible and the mappings can be significant and consistent, as the majority of the participants agreed on the same emotions. Further, the mappings seemed to be robust, as they were not affected by the wording of the sentences, i.e. the robot's communication style. In other words, conveying statements in social and intelligent conversational agent style or system status report style did not affect the selected mappings between emotions and statements.

Another interesting point to discuss about the obtained mapping is the range of selected emotions. Despite providing 11 different emotions/affective states to the participants, three of these emotions (bored, disgusted and angry) were not preferred by the majority for any message. We can only speculate at this point but the reason behind this might be the fact that the total number of statements during the study was limited, and participants could not find a proper sentence to match these emotions. This suggests that a subset of emotions might be sufficient to convey information from robots to humans, as they will be complement other types of multimodal communication. Furthermore , while 'happy' and 'excited' were selected together in many situations, we noticed a preference towards one of them depending on the statement.

It is important to highlight that we propose to use emotions as an additional modality to convey information from robots to humans to complement current multi-modal communication methods rather than replacing them. As a result, robots will be able to communicate with human teammates through emotions in addition to current modalities such as voice, text, video streams [19], motions [42], touch [49], sound and color [43]. An additional modality might help to design more robust and fail-safe human-robot communication systems. This can be particularly useful for high-risk real life applications like USAR and firefighting.

Ultimately, the idea of using emotions as an additional communication modality to convey information about robots' internal state could be generalizable to various types of robots. Although the way robots express the emotions might change, the mapping between

Table 2: Number of responses for each emotion and statement for both wording styles. Emotions selected significantly more than random are shown: ***: $p < .001$, **: $p < .01$, and *: $p < .05$ (significance was calculated through binomial tests). Emotions selected significantly more than all other options for each statement are shown in pink

statement	cond.	bored	surprised	disgusted	tired	fearful	excited	happy	annoyed	angry	calm	sad
I am stuck and might need help to proceed.	A	1	8	1	3	**14****	1	0	**22*****	2	2	8
Stuck here.	B	6	1	4	4	8	2	1	**14*****	7	4	7
I believe we are behind schedule. I also noticed it is getting dark and there is not much time left.	A	0	4	1	7	**19*****	3	0	**15*****	5	3	4
Behind schedule. It is getting dark.	B	2	1	2	**11****	**11****	1	0	**15*****	2	4	5
I can again communicate with our team outside of the building.	A	1	4	0	0	0	**11***	**27*****	2	0	**15*****	0
Communication with external team restored.	B	0	1	1	0	0	**10***	**27*****	0	0	**12****	0
I detected dangerous material here, let's proceed carefully.	A	0	6	0	0	**35*****	3	0	1	1	7	0
Dangerous material detected here.	B	0	**10***	3	0	**29*****	4	0	0	3	2	2
I detected that there might be a risk of further collapse so we should only proceed with caution.	A	1	2	0	0	**33*****	1	0	3	1	6	0
Further risk of collapse detected.	B	0	2	2	0	**27*****	5	0	2	4	2	4
I found an item that could belong to a person. Maybe the person is nearby.	A	1	7	0	0	0	**24*****	**11****	1	0	**11****	0
An object that might belong to a person was found.	B	1	**11****	0	0	1	**17*****	7	2	0	**13*****	2
I lost communication with our team outside of the building so we are on our own now.	A	1	3	0	0	**23*****	2	0	**11***	4	6	8
Communication with external team lost.	B	2	2	1	1	**12****	0	0	**12****	5	5	**10***
I think I found a surviving person.	A	1	**12***	0	0	0	**33*****	**22*****	1	0	3	0
Possible living person detected.	B	0	7	0	0	1	**22*****	**15*****	1	0	**10***	0
I think I heard someone is calling for help, we might have found a survivor.	A	0	**12***	0	0	2	**31*****	**21*****	0	0	4	0
Possible call for help detected.	B	0	9	0	0	8	**19*****	**10***	0	0	8	1
My battery is running low and I will stop working soon.	A	0	2	0	**23*****	**13****	0	0	7	1	2	**14****
Battery is running low.	B	0	1	1	**16*****	**9***	0	0	7	1	5	8

Table 3: Statements and the affective expressions that were selected significantly more than random (*: $p < .001$, **: $p < .01$, and *: $p < .05$). Our suggested first choice for the mapping is shown in Green (which is also consistent with the ones shown as pink in Table 2). The second, alternative, suggestion is shown in Orange. Cond. stands for condition.**

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

emotions and messages might stay the same for the USAR context. In addition, one can employ the same idea to create a primitive alternative communication channel for other application scenarios that require human-robot teamwork such as firefighting, military activities, warehouse applications etc. In this way, we might be able to overcome the bottleneck of HRI in these areas by mapping the most critical and repetitive situations happening during the missions to emotions.

6 CONCLUSION

In this paper, we conducted a MTurk study to investigate the idea of using emotions as an additional communication modality in human-robot interaction. USAR was selected as a possible real-life application area, and the natural mappings between specific messages or situations that might happen during USAR missions and emotions were obtained. The type of message conveyed by the robot was also altered to investigate differences between messages conveyed in the intelligent agent style and in system status report style. This distinction did not affect the resulting mappings of the majority, but we found minor differences. In conclusion, using emotions to communicate may complement existing multi-modal interaction schemes and enable more robust and fail-safe human-robot teams in the future.

7 LIMITATIONS & FUTURE WORK

Our study had several limitations. First, many of our participants were not familiar with USAR scenarios or the robots used in those scenarios (see Figure 1). They were also asked to imagine the situations, as opposed to interacting with a real robot. While we tried to reduce this effect by showing participants examples of such robots and providing information about USAR, their responses might have been affected. Future work needs to investigate these mappings in real USAR situations and when rescuers are interacting with actual robots. Further, if these mappings are validated, it should also be investigated whether the emotions would benefit communication in real scenarios.

Secondly, while we selected a subset of affective expressions that covered the primary emotions and additional, more complex emotions as well as moods, the choice of this set might have affected participants' responses and different mappings might have been obtained with other sets. Also, only a small set of emotions were selected by participants in the end. Future study is needed to further analyze the efficiency of the smaller subset.

Additional studies using the idea of mapping between specific messages and emotions for different application scenarios could also solidify the generalizability of the idea of conveying information via emotions as a complementary communication modality.

Lastly, future work can consider the applicability of this approach to other related application areas such as using huamn-robot teams in firefighting.

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