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SURVEY PAPER

Robots and emotion: a survey of trends, classifications, and forms of interaction

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ABSTRACT
The use of emotion to drive robotic interaction continues to grow across a range of use cases, from social robotics to increased survivability. Nevertheless, these efforts remain isolated from each other and are not easily compared between papers and projects. To this end an extensive survey of 1427 IEEE and ACM publications was conducted, covering robotics and emotion. The survey first resulted in broad categorizations of key trends covering emotional input and output. This was followed by an extended analysis on 232 papers that focused on the internal processing of emotion, where emotion was handled through some kind of algorithm and not just as an input or output. From this analysis, three broad categories were developed: emotional intelligence, emotional model, and implementation. Emotional intelligence captured the manner in which emotion was handled and included the subcategories: algorithm, mapping, and history. The emotional model category captured the emotion categories and number of emotions used, while the implementation category tracked the role, purpose, and platform. This paper concludes with a summary of key features discovered through the process, future opportunities, and a discussion of the intrinsic challenges emerging from the interaction of emotion and robotics.

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Robotics; emotion; survey; affective; interaction

1. Introduction

There is a long-established practice of using emotion in robotics, with a variety of approaches to the role of emotion. This can include use for improved social interaction [1], analyzing a human collaborator's emotion [2], or creating affective emotional displays [3]. The disparate range of methodologies for emotion in robotics leads to a vast set of approaches to emotion which are not easily classified, analyzed, or compared between projects. This forces new research in robotics and emotions to either draw on a small subset of past work in human–robot interaction (HRI) or to develop new choices, often based on psychology literature.

To address the lack of standard practice or any broader framework for robotics and emotion, we conduct an extensive survey of relevant literature. We chose to analyze any literature that involves robotics and emotion in the broadest sense, before narrowing our analysis to papers focusing on emotional interaction. We believe this survey constitutes a significant step towards developing unified categorization labels for emotion in robotics. We start by developing broad categories, diving each paper by the robot inputs and outputs. We then focus on robot systems that use emotion internally either mapping an input emotion to an action or mapping an internal emotion to an output. The mapping and use of emotion can be deeply varied, ranging from choosing emotions for better social interaction, to emotion for improved path planning for system performance.

We conducted our survey by collecting publications from IEEE XPlore digital library[1] and the ACM Full-Text Collection[2]. We found all publications that discuss emotion and robotics in either library. While IEEE and ACM are not comprehensive in the inclusion of all journals, book chapters and articles on robotics, they do contain four out of five of the robotics conferences and journals with the highest h-index. We believe that combined IEEE and ACM represent a sampling that shows the scope of research in robotics and emotion and allows for an analysis of the field as a whole. Overall our search resulted in 1427 publications found between both platforms. We then analyzed the abstracts of each of these papers, before focusing on 232 papers that feature emotional models with some use of input to output, and not only the perception or display of emotion.

In this paper, we first describe our collection and method for the survey and literature review. We then present the categories that emerged throughout the review process. This is followed by a result section, describing how many entries appeared in each category

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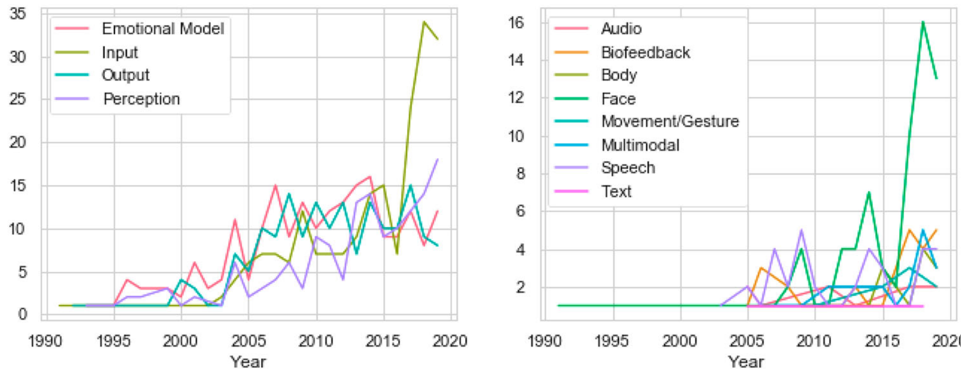

Figure 1. Emotional categorizations from abstracts and subcategories from inputs.

and comparing relations between different subcategories. We then present a discussion, proposing paradigm features of robotics and emotion, future opportunities, and intrinsic challenges. Finally, we use our categorization metrics to analyze a subset of papers from the *Advanced Robotics* and the *International Journal of Social Robotics*. Due to the quantity of publications analyzed, we only cite works that are specifically mentioned throughout the paper. A full list of analyzed publications is available online.[3]

2. Background and motivation

Emotion has received considerable attention in psychology with many different methods of classification emerging [4]. Most prominent amongst these is the discrete categorization by Ekman defining the six basic emotions, fear, anger, disgust, sadness, happiness and surprise [5]. Emotions are also often described through a continuous scale, with the most common being the circumplex model, mapping emotion on the two dimensions, valence and arousal [6]. Terms related to emotion include mood, which is usually described as emotion over a longer time span, with more gradual shifts than emotion [7]. Affect refers to the human experience of feeling emotion, as opposed to the emotion itself. Throughout this survey, we consider emotion in the broadest sense possible and include emotion, affect, and mood as well as other descriptions of emotion in the analysis. Likewise, for the term robot, we include all publications that mention possible implementation on a robot, such as virtual representations or digital agents that are intended as prior work to robotic implementation.

Emotion in robotics has seen dramatic increases in research over the last 30 years, spanning many applications and platforms (see Figure 1). This research can primarily be divided into two main categories, emotion for improved performance (called ‘survivability’) or emotion for social interaction [8]. Survivability invokes the belief that emotion is key to animals’ ability to survive and navigate the world and can likewise be used in robots. This includes situations such as an internal emotion based on external danger to a robot [9]. The second category – social interaction – includes anyway emotion is used to improve interaction, such as analyzing a human’s emotion, or portraying emotion to improve agent likeability and believability [10].

Despite the extensive work on emotion and robotics, there has been no specific survey or analysis to our knowledge. There are multiple surveys on HRI, such as an extensive 2008 survey conducted on HRI in general, however, this only contained a limited focus on emotion [11]. Other surveys have address specific aspects of robotics, such as social robotics, [12], robotic grasp [13], or empathy [14]. Due to the considerable growth in robotics and emotion, we believe a survey covering the related work and categories emerging across HRI literature and emotion is now due.

3. Method

Our survey review was split into three steps, based on the method described by Frich et al. [15]. The first step involved searching IEEE and ACM databases to gather all relevant articles and publications with our chosen keywords. The second step was to divide these papers into broad categories with a preliminary analysis, in our case based primarily on the abstract. The final step is to perform constant comparison analysis on selected papers and develop further classifications. Figure 2 shows an overview of the process, with the quantity of papers at each stage.

3.1. Step 1: Collecting publications

We built our paper collection method around inbuilt tools from the IEEE Digital Library and the ACM Digital Collection. Searching for papers with the keywords

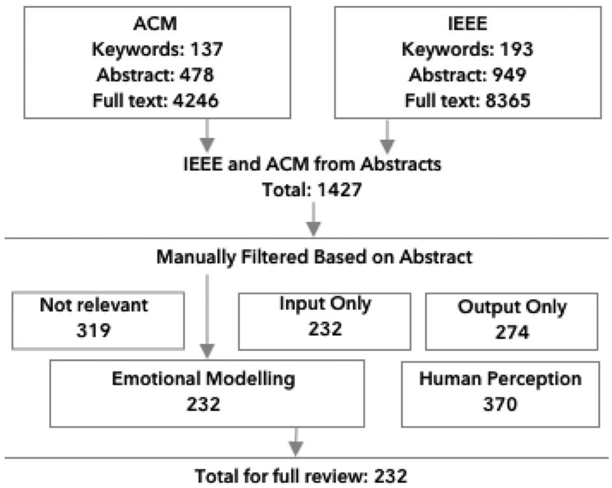

Figure 2. Flow chart of survey method.

Robot and Emotion showed a collection of only 330 publications. We then conducted a random sampling of abstracts of papers that were excluded, yet included the word emotion in the abstract or main text and realized that many of these papers should be included in the survey. We then expanded our search to include all papers that included the word emotion, affect, mood, or a variation (such as emotional) in our search. Our final paper collection included 1427 publications, referencing robotics and emotion ranging from 1986 to February 2020.

3.2. Step 2: Preliminary sorting

All abstracts of the 1427 papers were manually read by the first author. In cases where the abstract was not clear, the paper itself was checked. From this reading, the articles were split into four categories that emerged. The categories were input focus, output focus, emotional modeling, and perception. A separate list was also created of articles that were not relevant for the survey and only mentioned emotion in passing. Additionally, we filtered out duplicates that were published in both IEEE and ACM. Figure 2 shows the final number in each category, as well as duplicates and papers that were not used.

The primary goal of this survey was to improve understandings of how robots can interact emotionally, which we labeled emotional modeling. This includes a diverse range of approaches discussed in detail in Section 3.3 and compromises the papers we focus on for the rest of the paper. The other categories input only, and output only contained papers with a narrow focus on a specific robotic element. For input only this included systems such as facial recognition [16] or speech recognition[17]. The output only papers described methods to convey emotion, such as with audio [18] or robotic gait [19]. Papers that included both input and output were included in our primary category of emotional modeling.

Papers categorized as human perception focused on evaluating theories or ideas for HRI, or ways to alter the perception of a robot without developing a system. These were often 'wizard of oz' experiments, presenting a concept with no clear plan to implement [20]. Other papers in this category surveyed audience emotional attitudes to robots [21], or analyzed existing systems' emotional responses, among other metrics [22].

The list of papers removed as irrelevant generally included only a peripheral use of the word emotion. Other papers removed included an evaluation of a human's emotion when interacting with a system, such as to recognize if the system made the user happy [23]. Multiple duplicates were also removed that occurred and some extended abstracts that lacked sufficient detail were removed.

In our original method, we considered filtering publications by citation count or citation average by year. We, however, chose not to take this approach, with the aim of keeping as wide a range of approaches as possible in our classification. This allowed us to retain experimental approaches and the full spectrum of divergent emotional modeling techniques. With this central goal in mind, we did not impose any restrictions based on citation count or a paper's lack of general research visibility.

3.3. Step 3: Emotional coding

The final step of our review method utilizes Onwuegbuzie and Frels approach to constant comparison analysis [24]. Constant comparison analysis involves developing categories that are either explicitly described in a paper or categories that can be implicitly deemed significant across multiple papers. This form of analysis is iterative and involves consistently returning to each paper and identifying common trends, customs, and language between research that can allow areas of comparison to emerge.

Constant comparison analysis resulted in the development of three primary categories – emotional intelligence, emotional model, and implementation (see Figure 3). The first category, emotional intelligence, refers to the manner in which the system processes emotion. This can be considered which algorithm, such as what turns an emotion to a control method, or an action to an emotional output. Emotional intelligence also includes whether the algorithm maintains a history, and how the algorithm is mapped. The second category, emotional model, describes the classification method used by the research. The final category, implementation, captures

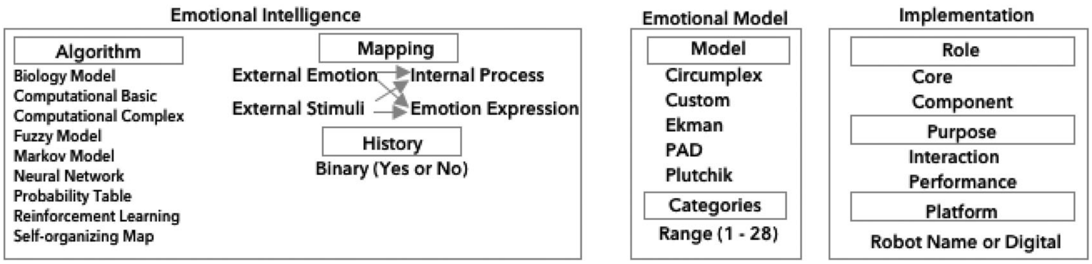

Figure 3. Categories developed with constant comparison analysis.

the role of emotion, the purpose of emotion, and the platform that is used.

3.3.1. Emotional intelligence – algorithm

Emotional intelligence classifies the algorithm used to control each robotic system. This category was by far the most diverse, with many algorithms not easily falling into discrete classes. Nevertheless, many trends did emerge across the papers. There were several reoccurring algorithms, including Fuzzy Models, Markov Models, Neural Networks, Probability Tables, Reinforcement Learning, and Self-Organizing Maps. Within each category, there was a large variety in implementation and complexity. Markov models, for example, could range from simple first-order implementations [25] to complex hidden Markov models [26].

We also found three separate broader categories emerge – computational models basic, computational models complex, and biology-inspired systems. Biology-inspired systems draw directly from comparisons to human or animal systems, such as imitating a homeostasis approach [27] or a neurocognitive affective system [28]. Computational basic included simple implementations, which used direct mappings, such as when something a user is correct being happy, or excited when asked for help [29] or systems with clear rules for responses based on different states [30]. Computational complex featured custom systems that did not fit in the other categories and had more detailed models of emotion, including complicated mappings between all inputs [31]. We did not attempt to apply any value on the algorithm used for any system, particularly the difference between computational basic and computational complex does not imply superiority for either version.

3.3.2. Emotional intelligence – history

History of emotional intelligence referred to whether the algorithm maintained some knowledge of a past state or choice. We kept this category binary, with even the most basic version of history being considered to contain past knowledge. An example of basic history may involve a system that maintains the single past emotion and incorporates this emotion into its updated emotion state [32]. Longer term history research often used the term mood, commonly combined with short-term emotion [33, 34].

3.3.3. Emotional intelligence – mapping

We describe the method of converting input to output, as the mapping used by the system. For our mapping class we use two potential inputs with two potential outputs, with the system possible of using any combination, such as one input to both outputs. The input categories were external stimuli and external emotion, while the output categories were internal process and emotion expression. External stimuli included responding to any input that was not emotional in nature, such as the distance from a wall [35]. External stimuli also include programmed goals and tasks, such as a robot's list of objectives [36]. The second input was external emotion, which primarily involved recognition of a human participant's emotion, such as through voice [37]. This category also contained content that had been preassigned an emotion externally before use with the robot, such as emotionally tagged images [30]. The first output method, emotional expression, references any occasion where the robot displayed emotion, such as through facial expressions [38]. The second output method, internal process, referred to use of an emotion internally by a robot to alter its decision making process. This was widely used for environmental navigation or path planning [39].

3.3.4. Emotional model – model and categories

We considered emotional models purely from the point of view of occurrences in the reviewed publications. This implied that we purposefully did not draw on psychology literature to use established common classes, instead aiming to analyze how classification models are used in robotics. Our final categorization included the standard emotional models, Circumplex (Valence/Arousal), Ekman's six categorizations, Plutchik's Wheel of Emotions, [40], and PAD (3-dimensional model) [41]. This list of emotions is certainly not all-encompassing and leaves out many common models in emotion literature, however, we found this represented all emotions used in the papers analyzed.

The most common category for emotions, however, was custom definitions. Custom models ranged from subsets and subjective variations of Ekman's six classes, to single binary emotions, to custom sets that do not reference any literature, such as happy, hungry and tired [42]. Custom models were often tailored to fit specific robot tasks, such as frustration for mistakes [43] or combinations such as tired, tension and happiness [44].

We also included the number of labeled emotions that were used for each model. These ranged from 1 emotion up to 24 emotions, with a wide range of emotions used at each level. For example, systems that used only two emotions were not restricted to a positive and negative emotion (such as happy and sad), but instead could use complementary emotions such as courage and fear [45]. For systems with a single emotion, many variations were represented, such as guilt in a military application [8] or regret for optimal task queuing [46].

Emotional model explicitly focused on categorizing emotions that were used in the implemented model in each paper. It was common for papers to have an extensive background section that referenced models such as Plutchik, Ekman, or the Circumplex, but created a new variation that we then referred to as custom. For the quantity of emotions used we always labeled the system by the minimum number of emotions. For example, if a system was able to detect eight emotions from a voice source, but only processed and used four emotions in its algorithm, this would be labeled as four categories. This rarely occurred, however, with the vast majority of models maintaining the same emotion categories throughout.

3.3.5. Implementation – role, purpose, and platform

Implementation was split into three subcategories; the role of emotion, the purpose of emotion and the robotic platform used. The role of emotion could either be core or component, with core implying the system was built around the role of emotion. Component implied that emotion was only part of a much broader system. The next subcategory, purpose of emotion, labeled how emotion functioned within the system. Throughout our literature review, we arrived at two distinct labels, interaction and performance. These labels match those described by Arkin, who describes the purpose of emotions in robotics as interaction and 'survivability', which allows the robot to better interact with the world [47]. The final implementation category, robot platform, considers which robot was used for implementation. These ranged from standard HRI robots such as NAO [48], to custom designs [49] or digital interfaces [50].

3.3.6. Unused categories

The previous categories all emerged through constant comparison analysis, with many changes and developments occurring through the process. Two categories that were eventually discarded were perceived or evoked emotion, and the project stage. It was sometimes possible to understand whether authors believed the robot is attempting to evoke an emotional reaction from a human or have a user just perceive the emotion that is displayed, however, the vast majority of papers did not explicitly emphasize either alternate. Additionally, we considered project stage as whether a project was a theoretical model, a demo system, a studied experiment, or a system with regular use, however, the boundaries between each stage was not always clear. We ultimately decided that both unused categories also did not offer any strong findings that could contribute to our overall research.

4. Results

4.1. Broad categories

The results from our broad initial categorization of abstracts show a continual expansion in publications on robotics and emotion across all categories. These trends are shown in Figure 1, as well as a breakdown of the subcategories used for input. We categorized input types as these were commonly a single feature that were easily split apart. We found output, however, was almost always multi-modal, and usually considered the robot as a whole, without a clear emphasis on a certain robotic feature. This reflects the nature of robotic interaction, where isolating the effect of individual output features is often not possible.

For our categorization of input, we separate movement to encompass cases where the emphasis is on a specific gesture or motion type, such as gait. Further analysis of input showed expected trends, such as a clear spike in the use of facial detection, pertaining to broader computer science advances in deep learning [51], that began with the then state of the art paper DeepFace in 2014 [52].

4.2. Emotional intelligence – algorithm

Our most common classification for algorithm was computational complex. Figure 4 shows the variety of algorithms used across all systems. We did not find any unifying trends amongst algorithm choice, instead we believe that algorithms are generally chosen specifically for the robot implementation, more than based on any robotic common approach. As with the increase of facial recognition due to deep learning, we saw a recent emergence

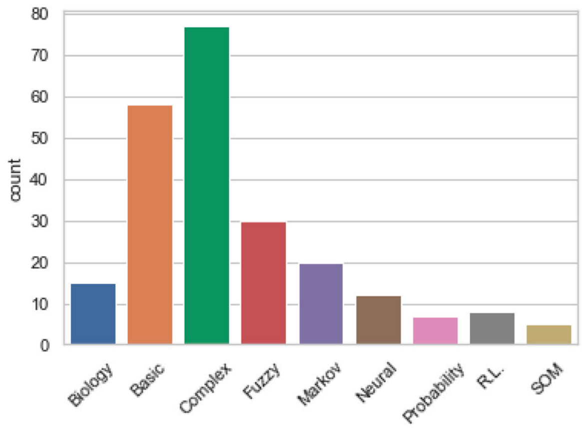

Figure 4. Algorithm use count.

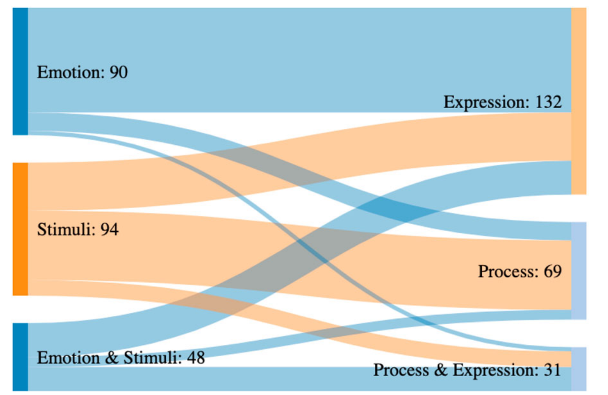

Figure 5. Sankey diagram of input to output.

of neural networks, with 11 of their 12 uses happening after 2012, and showing demonstrated growth through this time period.

4.3. Emotional intelligence – history

Across each paper analyzed, 27.16% included some form of history. During the time period of 1990–2000 only one paper occurred that included history, however, from 2000 onwards the use of history fit in the range of 27% to 35% as shown in Table 1.

4.4. Emotional intelligence – mapping

All possible combinations of input to output occurred at least three times in the dataset, shown in Figure 5 and Table 2. Table 2 shows for either performance or interaction the frequency of each mapping, converting the same data presented in Figure 5 into numerical form. For example, in the first row it shows that there were five occurrences of performance focused systems with emotional stimuli mapped to internal process. The least common mappings were Emotion to Process & Expression, and Emotion & Stimuli, which only appeared in three and seven papers respectively. The most common mapping Emotion to Expression was appeared 74 times, while Stimuli to Process was the second most common with 49 uses.

Table 2. Input and output mapping by system purpose.

	Stimuli	Emotion	Expression	Process	Freq
Performance	No	Yes	No	Yes	5
Performance	Yes	No	No	Yes	40
Performance	Yes	No	Yes	No	2
Performance	Yes	No	Yes	Yes	3
Performance	Yes	Yes	No	Yes	4
Performance	Yes	Yes	Yes	Yes	2
Interaction	No	Yes	No	Yes	8
Interaction	No	Yes	Yes	No	74
Interaction	No	Yes	Yes	Yes	3
Interaction	Yes	No	No	Yes	9
Interaction	Yes	No	Yes	No	32
Interaction	Yes	No	Yes	Yes	8
Interaction	Yes	Yes	No	Yes	3
Interaction	Yes	Yes	Yes	No	24
Interaction	Yes	Yes	Yes	Yes	15

4.5. Emotional model – model and categories

The majority of papers used custom emotional models ($n = 154$) accounting for 67% of the papers. This was followed by the use of Ekman's discrete classes ($n = 45$), accounting for 19% of the papers. Circumplex ($n = 20$), PAD ($n = 8$), and Plutchik ($n = 5$) each occurred in less than 10% of the publications. Figure 6 shows the range of emotional models used across all publications. Figure 7 shows how many emotion categories were used by all publications with custom emotion models; a paper that uses anger and fear would show two emotions. The mean number of emotions used across all categories was 4.10 with a median of 4. Publications with a purpose of

Table 1. Percentage breakdown of history, the role, purpose and implementation.

	1990–2000	2001–2005	2006–2010	2011–2015	2016–2019	Total
Quantity	16	29	61	72	52	230
History	6.67%	27.59%	32.79%	22.22%	34.62%	27.16%
Emotion Core	68.75%	31.03%	72.13%	70.83%	69.23%	65.95%
Emotion Comp	31.25%	68.97%	27.87%	29.17%	30.77%	34.05%
Interaction	62.50%	65.52%	80.33%	76.39%	80.77%	75.86%
Performance	37.50%	34.48%	19.67%	23.61%	19.23%	24.14%
Digital	37.50%	44.83%	39.34%	31.94%	50.00%	40.09%
Robot	62.50%	55.17%	60.66%	68.06%	50.00%	59.91%

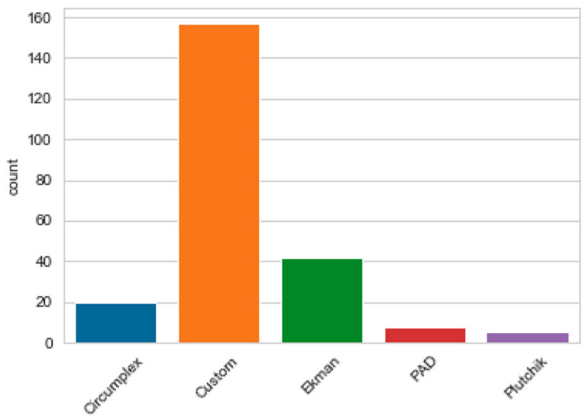

Figure 6. Emotional models count.

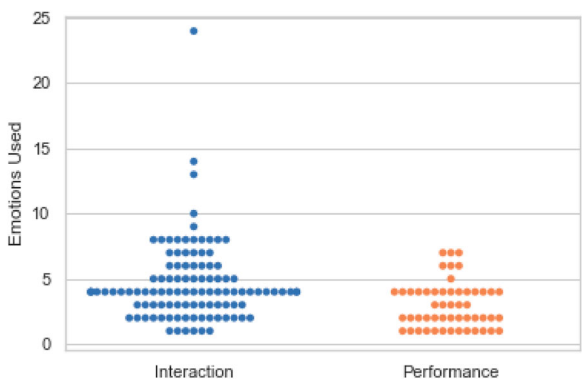

Figure 7. Quantity of emotions used in custom emotion models.

interaction had a mean of 4.66 and median 4, while performance publications had a mean of 2.97 and median of 2.

4.6. Implementation – role, purpose, and platform

There has been only limited variation in how often papers used the role of emotion as either the core question or a component of the research. There was a jump between 2001 and 2005, however, outside of this change the range has remained close to the combined average of 66% as core and 34% as a component. There has been a gradual shift towards focus on interaction. From 2016 to 2019, 81% of emotion related papers used emotion for interactions. Across all publications interaction was the focus of 76% of papers. The purpose of emotion and its relation to other categories is discussed further in Section 4.7.

Table 1 shows the variation between robot and digital implementations. There were no significant trends with physical robots occurring slightly more. The relatively high use of digital interfaces (40%) is worth noting, considering the ability to replicate studies between physical and digital agents is not established [53]. SoftBank Robotics Nao was the most common robot appearing 14

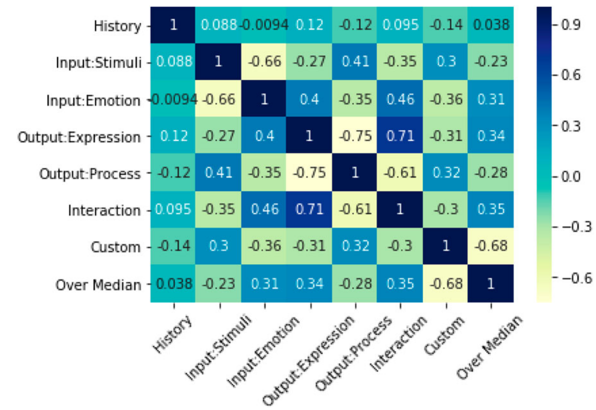

Figure 8. Correlation and log-linear analysis.

Table 3. Use of emotional models by role of system.

	Custom	Over	Freq
Performance	Yes	Yes	7
	Yes	No	45
	No	Yes	4
Interaction	Yes	Yes	36
	Yes	No	69
	No	Yes	71

uses. Other robots used were a mix of commercial and research robots like SoftBank Robotics Pepper [54] and many custom designs. The mean usage of each robot platform was 1.44 times with a median of a single use. We found no paper where a custom designed robot was used by more than one research team.

4.7. Correlations and contingency tables

After examining each category individually we created a correlation matrix using the Pearson product-moment correlation coefficients to establish pair-wise correlation (Figure 8). In Figure 8, Custom refers to whether the system used a custom model of emotion, while over median refers to using above the median number of emotion categories (such as happy and sad). We found the strongest correlation between input use including emotion stimuli and whether the system was performance or interaction based. We also used contingency tables to compare the system purpose and emotion model (see Table 3) and the purpose with input mapping (see Table 2). These tables show the frequency of custom emotions and each possible mapping in relation to the purpose of emotion in the system. Table 3 shows that the vast majority of performance systems (45 out of 56) use custom emotion models, with less than 6 emotions.

5. Discussion

We identified various trends through the development of our method and results for further analysis and discussion. In this section, we cover both clear findings from our survey, as well as our opinions on potential future directions and areas requiring refinement of approaches. We split these points into three sections, first paradigm features, which are clear trends that emerged across all papers. Our second area is intrinsic challenges, which highlights key issues that appeared across all areas. Finally, we discuss future opportunities based on our subjective views of possible future work extending directions in the current literature.

5.1. Paradigm features

5.1.1. The interaction or performance approach

Our survey displays the two separate methodologies associated with the role of emotion for either interaction or performance. These two roles are clearly associated with different approaches in each category. The emotional models and number of categories are greatly varied, with interaction systems much more likely to use larger numbers of emotion. The mapping system between interaction and performance also consistently showed contrasting results. Tables 2 and 3 show the variations in approaches. While this distinction was somewhat to be expected it is clear that future research should considered the goals of either improved interaction or improved performance through two separate frameworks.

5.1.2. Diverse approaches shaped by current trends

There was extensive variety in the approaches to the algorithm used and emotional models. Combined computational basic and computational complex represented over 60% of the algorithms used. While this shows a broad range of approaches, there is a clear parallel in emotion algorithms to wider computer science and engineering trends. This is most apparent in the growing use of facial analysis driven by deep learning for input, but also present in the increasing transition to neural networks for internal algorithms, with 11 out of the 12 neural networks used in emotional models occurring since 2012.

5.2. Future opportunities

5.2.1. Limited long term interaction and history

In categorizing history, we allowed for the most general, easiest to attain category, which would include a single previous step or first order Markov model. Even with this consideration, only 27% of papers had some form of history. The majority of these papers only included a single previous step, with the inclusion of longer form extremely rare. There is a significant opportunity to pursue longer term emotions, including simple additions of knowledge of past short-term interactions. We believe there is much unaddressed potential in considering a longer history of emotion in robot models, that could carry across conversations, and even extend over day-to-day interactions.

5.2.2. Signaling is the current paradigm for interaction

Signaling in HRI refers to the concept that the internal emotion used by a robot is also the emotion externally shown by a robot. The counter approach to this would be using an internal emotion, such as sadness, based on performance, but displaying a happy gesture to improve the interaction. Signaling is by far the dominant paradigm for emotion in robotics, however, comes with significant limitations for future work, such as an assumption that an outwardly shown state is always an internal emotion. The emphasis on signaling also distances emotion in robotics from emotion in humans, where people rarely display their full emotion [55]. In our review, we found alternates to signaling was overlooked unanimously by every publication.

5.2.3. The social aspect of emotions

Emotions are inherently social, with humans expressing emotion towards others and emotion shaped through our interactions [56]. For humans this occurs through direct contact as well as wider social expectations and norms [57, 58]. The majority of papers used emotion at most at a dyadic occurrence (one human and one robot), and often as a solitary experience functioning internally within the robot. Omitting social aspects from robotics prevents the use of many psychology based possibilities that draw on group dynamics, and has the added risk of ignoring a crucial aspect of human emotion. In our review some papers did address group dynamics with promising results [59], but overall had a very limited representation in the publications analyzed.

5.3. Intrinsic challenges

5.3.1. Anthropomorphism

Anthropomorphic language was very commonly deployed in each paper, and to a reasonable extent was expected. We believe, however, that extra consideration should be given to describing a robot as having a 'feeling', when a single emotion is mapped to a trivial input. Overuse of anthropomorphic language has the potential to inaccurately describe the actual role of emotion in a robot system, trivialising not only human emotion but also the reducing the real potential and methodology that artificial emotion can have in robotic systems.

5.3.2. Custom emotional models

Psychology research has developed many categorization and models, with a wide range of reviewed and accepted models. For robotics research, there are many times where custom subsets of emotions certainly make sense for a task specific response. We believe, however, that many papers chose to create slight variations from establish models, without a clear rationale. This variation then imposes future difficulty in comparison to other approaches. While we do not suggest that all papers should use existing models, we propose that when possible using existing emotion categories allows for better depth and comparison across the field. This challenge is not isolated to robotics, with affective computing also primarily using custom emotion models [60].

5.3.3. Project isolation

The challenges from using many different models for emotion carries over to the relative isolation between each robotic system and emotion. It is generally not possible to compare approaches from separate publications beyond anything other than what is mentioned in the paper itself. In our review only a single paper compared an emotional model with a baseline emotional model [61], with other publications occasionally comparing their emotional model to a system with no emotion.

Multiple papers did compare a digital implementation with an implementation in a robot, however, it was very rare for a paper to compare across robot platforms.

We recognize that testing a system on multiple robots requires extensive additional work, however, believe at times this would greatly help with understanding the possibilities of a system. A single paper in our review did compare the same emotional model on multiple robots [62]. Issues of comparison are further compounded when considering that the average use of each robot was 1.44 times, indicating that comparing the role of emotion even on a single platform could be significantly expanded. An immediate answer to this problem could come through an encouragement of replication studies that allow for further exploration of algorithms and methodologies across platforms.

6. Analysis of additional papers

After completing the above analysis we chose to demonstrate our classification system on publications outside of ACM and IEEE. Our aim was not to conduct a thorough literature review on additional papers, instead it was designed to analyze if our categorization methods easily carried to new papers or if external publications presented ideas outside our categories. We choose to analyze papers from *Advanced Robotics* and the *International Journal of Social Robotics*. From *Advanced Robotics*, we selected eight papers with the keyword emotion from 2005 to 2021. From the *International Journal of Social Robotics*, we chose the top eight papers from 2010 to 2021, that were associated with word emotion, after discarding surveys.

Table 4 shows a summary of the broad categories for each paper. Hashimoto et al. [63] present an example of our perception category, as although it is showing facial expression the emphasis is understanding how varied facial expression alters human perception of the robot. In our previous broader analysis, we did not include types of output, but found for this subset of papers this was more easily achieved.

Table 5 shows the papers analyzed that fell into our primary emotional modeling category. This collection all fell well within our expected results from previous literature review. The primary contrast was more common use of physical and custom robots, with only one digital version. As these were all journal articles it seems

Table 4. Advanced robotics and social robotics broad categories.

Paper	Journal	Year	Type	Notes
Hashimoto et al. [63]	AR	2009	Perception	
Kuhnlenz et al. [64]	AR	2010	Output	Face
Hyun et al. [65]	AR	2010	Input	Speech
Van de Perre et al. [66]	AR	2015	Output	Gesture
Ajibo et al. [67]	AR	2020	Output	Gesture
Li et al. [68]	SR	2011	Output	Movement/Gesture
Venture et al. [69]	SR	2014	Input	Body
Claret et al. [70]	SR	2017	Output	Movement/Gesture
Andreasson et al. [71]	SR	2018	Output	Touch
Striepe et al. [72]	SR	2019	Output	Movement/Gesture

Table 5. Advanced robotics and social robotics interaction papers.

Paper	Jour	Year	Algo	Mapping	H	Model	No	Pur	Platform
Kim et al. [73]	AR	2009	CB	ES to EE	Y	Custom	2	I	Mung
Gruebler et al. [74]	AR	2012	NN	EE to IP	Y	Custom	2	P	Nao
Li et al. [75]	AR	2019	CB	EE to EE	N	CP	NA	I	Digital
Hirth et al. [76]	SR	2010	CC	All	N	Ekman	6	I	ROMAN
Chen et al. [77]	SR	2015	FM	EE to IP	N	CP	NA	I	MRS
Bagheri et al. [78]	SR	2020	RL	EE to EE	Y	Custom	4	I	Pepper

reasonable to assume that they would be more likely include a physical implementation. We found that this additional analysis supported our categorization methods, with each previously categorized paper easily falling into our method.

7. Conclusion

In this survey, we have presented a comprehensive categorization method for emotion in robotics. Through these categories we were able to identify common trends and patterns in the functionality of emotion in robotics literature. As emotion continues to expand in robotics we believe there are many unexplored future opportunities, as well as intrinsic challenges to be addressed. Overall, our results indicated a diverse field, primarily split up by the underlying goal of the system for either interaction or improved performance.

Notes

1. https://ieeexplore.ieee.org/Xplore/home.jsp
2. https://dl.acm.org/
3. https://github.com/richardsavery/robot-emotions-survey

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