Robot Expressive Motions: A Survey of Generation and Evaluation Methods

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20

Robots that have different forms and capabilities are used in a wide variety of situations; however, one common point to all robots interacting with humans is their ability to communicate with them. In addition to verbal communication or purely communicative movements, robots can also use their embodiment to generate expressive movements while achieving a task, to convey additional information to its human partner. This article surveys state-of-the-art techniques that generate whole-body expressive movements in robots and robot avatars. We consider different embodiments such as wheeled, legged, or flying systems and the different metrics used to evaluate the generated movements. Finally, we discuss future areas of improvement and the difficulties to overcome to develop truly expressive motions in artificial agents.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Computer systems organization** → **Robotics**; **Robotic control**; • **Human-centered computing** → *User models*; *User studies*;

Additional Key Words and Phrases: Robotics, expressive behavior, motion generation, motion control, affect

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1 INTRODUCTION

Robot motion generation is the focus of much research [14]. Most of the existing work develops trajectories and controllers that allow the robot to move in a fast and accurate fashion, with high repeatability in well-controlled environments. These approaches are targeted to industrial settings and fixed or mobile-base manipulators, where robots operate in isolation from humans. More recently, motion generation for humanoid robots has also been an active area of research [25]. With humanoid systems, the main focus of trajectory generation and control is to maintain postural balance and accomplish functional tasks.

However, robots are increasingly being deployed beyond isolated factory environments in places where they may interact directly with humans, even more, where they are expected to do so: interactive art [31, 49], companion robots [61, 72, 89], co-robots [82], and assistive robots [87]. These new applications introduce additional challenges to the motion generation problem, as the

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performance of the robot is not evaluated solely on objective criteria such as rapidity, precision, and repeatability but rather on more subjective criteria that depend on the perception of the user. Robot motions can be perceived to be calm, scary, efficient, unpredictable, legible, entertaining, healing, and so forth. These are no longer “robot motions” but rather *expressive motions*. To succeed in these new applications, the robot must accomplish more than functional tasks; it must also utilize movement to communicate with humans in their environment. Successful use of this communication channel enables the robot to convey its internal state(s) to nearby humans and has also been shown to improve team task performance in collaborative scenarios [9].

Expressive motions modulate the motion of biological systems and particularly humans. Human motion conveys information beyond achieving functional tasks while taking into account physical constraints such as joint limits or obstacles. Indeed, expressive motions can contain information about the affect, fatigue, intent, style, and personality of the mover. The information conveyed by the motion can be transmitted consciously or unconsciously. The degree to which expressive information is legible may depend on the type of motion executed: communicative, functional, artistic, or abstract [44]. Other parameters such as the social environment, presence of urgency, or presence of danger may affect the motion and its understanding significantly. When it comes to robots that can interact with humans, humans also interpret robot motion to be expressive, even when the robot structure is non-anthropomorphic [30, 42, 80], and social interaction can be improved when expressive motion is successfully utilized by the robot [10].

Concepts and principles of expressive motions were first formalized by animators [91] and inspired much of the early work on robot expressive motion [97]. Another important source of inspiration was notation systems for dance choreography, particularly the Laban system [6, 51]. More recent work has also explored the use of learning methods to characterize and generate expressive movement. In addition to generating expressive movements, researchers have explored how human observers perceive such movements and the impact it has on human robot interaction. Researchers have found that observers can reliably differentiate movements of different affect [37, 45, 81, 83, 99], intentionality [20, 87], and Laban efforts [48]. Furthermore, interactive user studies consistently indicate that participants prefer to interact with robots with expressive movement capabilities [34, 87, 88], modify their behaviors based on the expressive movement [21], achieve better team fluency during interaction [32], and have better retention of the interaction [26].

In this article, we review the state of the art in expressive motion generation for robots. Our review includes both physical and virtual robot structures, and extends to both anthropomorphic/biomimetic and non-biologically inspired morphologies as seen in Figure 1. Indeed, a large variety of robots has been considered in the literature: manipulators, small mobile robots, humanoids, or animated characters. A large variety of expressive content has also been considered: communicating affect [44, 46], conveying robot intentionality and thought [87, 88], and individual variations in style [58].

There is a large corpus of research in the field of facial expression and eye gaze [1] to convey expressiveness, which we do not consider in our review, focusing solely on whole body movements. Moreover, there exists a large corpus of expressive movement to support non-verbal and verbal interaction without a specific task [7]. In our review, we do not consider movement generation where the purpose of the movement is purely to convey the intended expression, and instead focus on methodologies that enable simultaneous generation of functional and expressive movement.

To identify papers for inclusion into the survey, we used Google Scholar and keyword combinations of “affective/expressive/emotion/style,” “motion/movement/robot,” and “expression/generation/behaviour/design” to identify candidate papers. The candidate papers were then included if they: (1) included a motion generation aspect, either on a physical or simulated robot;

Fig. 1. An overview of the different platforms (virtual or physical) used in the papers surveyed, organized by degrees of freedom, degree of anthropomorphism, and physical reality. (1) [28], (2) [80], (3) [83, 87], (4) [11], (5) [48], (6) [80], (7) [40], (8) [45], (9) [105], (10) [33, 98], (11) [35], (12) [97], (13) [34], (14) [15, 21], (15) [38, 48, 55, 57, 85], (16) [29], (17) [16], (18) [29, 73], (19) [18, 20], (20) [40], (21) [5, 36], (22) [23, 24], (23) [95], (24) [69], (25) [69], (26) [70, 74, 94], (27) [64].

(2) incorporated both functional and expressive movements (generation papers focusing on only expressive gestures were excluded); and (3) generated movements of the entire body (papers focusing only on facial expression generation were excluded). A summary of the inclusion criteria and the papers selected can be found in Table 1.

The motion generation problem takes as input the functional objectives, robot and environment constraints, and outputs motor commands to the robot. When expressive motions are to be generated, there are additionally the expressive motion objectives. These could be the desired type and level of affect, personality, style, intent, or other. The methods proposed in the literature can be differentiated according to the following characteristics: (1) algorithm design (model, features, controller), (2) robot structure, and (3) evaluation approach. In Section 2, we first characterize the algorithms, considering the type of model, how the model features are formulated, the need for a reference trajectory, and the control structure. Then we discuss the robots on which the algorithms to date have been deployed, and differentiate between morphology-specific and morphology-generic algorithms. We then discuss how the quality and success of expressive motion generation is evaluated in Section 3. Finally, we conclude by discussing open problems and future areas of research.

Table 1. Summary of Papers Considered in the Survey Ordered by Feature, Use of Model, Reference Trajectory, and Method

Reference	Features	Model	Reference Trajectory	Control/Trajectory	Platform	Simulation and/or Real	Conveyed	Evaluation
[86]	Learned	Model free	No	Trajectory	Point, anthropomorphic	Both	Intent (legibility)	Physical interaction, measured task performance
[81, 92, 95, 103]	Learned	Model free	Yes	Trajectory	Anthropomorphic & other	Both/simulation/real	Affects/style	Questionnaire Ekman and Circumplex models/none
[100]	Learned	Model based	No	Trajectory	Anthropomorphic	Real	Intent	Physical interaction
[3, 34, 39, 53, 93]	Learned	Model based	Yes	Trajectory	Point & anthropomorphic	Real/simulation	Basic emotion/style/affect	Qualitative/screen based/error from human data/affect grid
[37, 38, 45, 87, 88, 99]	Hand crafted	Model free	Yes	Trajectory	Anthropomorphic/other/zoo	Simulation/both	Intent (forthought)/emotion (valence/arousal)/basic emotion	Screen based, open response/screen based, valence/arousal scale/discrete emotional categories/physical observation/real robot questionnaire on intent and preference for use/Likert scale of PAD
[11, 73]	Hand crafted	Model free	Yes	Control	Other/anthropomorphic	Both/real	Emotion (Ekman set)/dance movements	Screen and real robot
[98]	Hand crafted	Model free	No	Control	Anthropomorphic & other	Simulation	Expressivity	None
[23]	Hand crafted	Model based	No	Control	Anthropomorphic	Simulation	Emotion	Qualitative
[15, 26, 50, 58, 66]	Hand crafted	Model based	Yes	Control	Anthropomorphic	Simulation/real	Style/emotion/exaggeration/intent, incapacity	Qualitative/SAM/screen base/force questionnaire/physical interaction (storytelling), testing story retention and human eye gaze
[2, 5, 13, 18, 20, 27, 36, 41, 54, 57, 60, 62, 64, 65, 68, 71, 75, 105]	Hand crafted	Model based	Yes	Trajectory	Zoo/anthropomorphic/other/point	Real/simulation	Style/familiarity, harmony/emotions/personality/intent/personality/health/legibility/naturalness	Keyword questionnaire/on-screen, intent, success, avoidance pattern prediction/physical interaction/questionnaire task performance metrics
[83]	Expert	Model free	Yes	Trajectory	Other	Real	Affects	SAM, keyword questionnaire
[40, 104]	Expert	Model free	No	Trajectory	All/other	Real/simulation	Affect-personality/style-emotion	None/questionnaire and forced choice questionnaire
[59]	Expert	Model free	Yes	Control	Anthropomorphic	Simulation	Naturalness	None
[17, 19]	Expert	Model based	No	Trajectory	Point & anthropomorphic	Both	Intent deception/legibility	Screen based and real robot, questionnaire on deceptiveness/legibility
[47, 48, 96]	Expert	Model based	Yes	Trajectory	Zoo & anthropomorphic/other	Real	Laban efforts/lifelike/emotion, internal state, task state	Qualitative/screen based, video of a simulated trajectory

Fig. 2. Alternative controller structures for expressive movement generation.

2 EXPRESSIVE MOTION ALGORITHMS

In this section, we review the expressive motion generation methods proposed to date, summarized in Table 1. As shown in this table, algorithms can be differentiated along several characteristics: (1) the motion features used and how they are formulated, the model type or the absence of model (model free), and the need for a reference trajectory; (2) the control structure used to implement the developed system (Figure 2); (3) the robot structure(s) on which the algorithm is deployed; and (4) the expressive qualities conveyed.

2.1 Features

A key question when creating expressive trajectories is to determine which features of the trajectory are relevant for expressiveness and how they relate to the expressive qualities to be conveyed. A review of the features considered in the literature to date has been presented in Larboulette and Gibet [52]. One approach, inspired by animation [91, 96], is to rely on designer expertise to manually define the relevant features for each expressive class, manually specifying both the features and their mapping to the expression of interest.

Another source of relevant features is methodologies for annotating and describing expressive movement in the dance community, particularly the Laban system [6, 51] for dance choreography annotation. The Laban notation system consists of four components: Body, Space, Effort, and Shape. Body signifies the active body parts and the sequence of their engagement during a movement. Space defines the spatial locations and directions of the body parts engaged in the movement. Laban Effort and Shape components provide a set of descriptors for characterizing the expressive qualities of movement [6].

Finally, both the features and their mapping could be learned from exemplar movement data.

2.1.1 Manually Selected Features. Manually selected features are commonly used in conjunction with mimicking and retargeting approaches, where expressive movement generated by a human demonstrator is faithfully reproduced on the robot. Here, the features to be mapped consist

simply of the joint angle trajectories of the demonstrator. The human demonstration can be obtained by asking the demonstrator to move the robot through the desired trajectory (e.g. [83]) or teleoperating the robot (e.g. [40]). These two approaches facilitate mimicking, as the demonstrator is asked to demonstrate the movement directly on the robot's body, also known as *kinesthetic teaching* [4]. However, if the demonstrator uses its own body to demonstrate the movement, the system must *retarget* the demonstrated movement to its own morphology. The objective is to retain, as much as possible, the properties of the demonstrator's motion while making the motion feasible for the robot. This is typically done via optimization (e.g., [5, 36]) or dynamic filtering [59].

Manually selected features can also be abstracted from joint trajectories. For example, Inderbitzin et al. [37] studied the effect of several canonical parameters such as torso inclination and walking speed, which influence emotion recognition and behavior understanding. They concluded that body posture correlated significantly with valence while the velocities correlated with the arousal levels. These findings were echoed by Venture et al. [99] and used to manually craft robot affective gaits [38]. Karg et al. [45] propose to map hand-specified extracted features: step length, height, and time for a single swing step, from expressive human gait onto an hexapod robot. Bretan et al. [11] used hard-coded hand-designed postures and exaggerated gestures to generate emotional behaviors of their non-humanoid robot Shimi. Lim et al. [57] propose a framework using Speed, Intensity, Regularity, and Extent (SIRE) and formulate a direct empirical mapping from SIRE to emotion to generate affective movements for a humanoid robot NAO.

In addition to spatial and trajectory features, timing and coordination with other communication modalities can also influence expressiveness. Zhou et al. [105] investigate how robot motion timing influences human perceptions of robot characteristics, such as emotion and animacy, whereas Huang and Mutlu [34] investigate how contingencies between speech and gaze and gesture behaviors impact perceived expressiveness.

Although mimicking and other approaches based on manually selected features allow the robot to reproduce the human-generated motion, the extent to which the intended expressivity is maintained will depend on how similar the robot is to the human embodiment, particularly when the demonstration and generation embodiments differ. In addition, with the mimicking approach, understanding what components of the motion contribute to expressiveness is lacking and cannot be used to generalize to new embodiments, tasks, or environments.

2.1.2 Expert Features. The two most common sources of expert features are animation principles and Laban features. Animation principles have been used to imbue robots with "lifelike" movements [96], forethought, and intelligence [88], and help the robot better express its "intent" [87]. One advantage of approaches based on animation principles is their applicability to humanoid [88], animal-like [96], and non-biological structures such as drones [87].

Another popular source of expert features are Laban descriptors [6]. Researchers have demonstrated that observers differentiate movements with different Laban efforts with both anthropomorphic [48, 92] and non-anthropomorphic [48, 83] robot structures, indicating that Laban features are a promising system for expressive motion abstraction.

2.1.3 Learned Features. The final set of methods seeks to learn both the relevant features and the mapping from a (large) corpus of labeled exemplar data. Several different techniques have been proposed, including dimensionality reduction techniques, such as principal component analysis (PCA) [95] or functional PCA [81], and spatio-temporal models such as factored conditional restricted Boltzmann machines (FCRBMs) [3], the Bayesian dynamic network (BDN) [53], factored Gaussian process dynamical models (GPDM) [100], and structured recurrent neural networks (S-RNN) [39]. Although the preceding works aim to automatically extract both the features and the mapping for generating expressive trajectories, and the learning approaches rely on large corpora

of human motion data, the majority of works remain focused on a single task (e.g., walking) and a specific robot structure, most commonly humanoid.

2.2 Model

Given a set of expressivity relevant features, the model describes how the features are mapped to the movement to vary the expressivity of the movement. The model type can vary depending on the types of features used, the type of expressions investigated, and the motion generation algorithm. A key distinguishing factor is whether the proposed approach starts from a default trajectory, which is then modified to achieve the desired expression, or whether the expressive trajectory is generated without access to a default (assumed to be an expression-free) trajectory. Approaches using hand-selected or expert features tend to use implicit models, where the mapping between features and motions is hand designed, whereas methods using learned features tend to use explicitly formulated models.

2.2.1 Implicit. Approaches using hand-crafted or animation-inspired features designed for specific movements (e.g., [11, 37, 88]) tend to also hand code the relationship between the features and the motion expressivity, without elucidating an explicit model for the mapping. Although these approaches take advantage of expert domain knowledge (e.g., animators) to generate expressive movements, the resulting system is difficult to generalize to other movements or embodiments.

2.2.2 Formulated. A more general approach is to explicitly formulate a model mapping the relationship between the features and the motion expressivity. The model may be fixed or learned.

A common way to formulate the expressivity model is within an optimization framework. In the optimization-based approach, the expressive objective is explicitly formulated as a cost function, which is then optimized to generate the most expressive trajectory. This approach has been applied to a variety of expressive styles, including legibility [20, 86], deception [19], emotion [23], style [58], and robot incapability [50].

The optimization cost function can be formulated in different ways. First, it can be defined or learned to directly generate expressive motion (e.g., [104]) or, second, defined as a measure of how well people understand the robot, using an explicitly defined model of user inferences. For example, in Dragan and Srinivasa [17], the authors propose a mathematical formulation of a legibility functional, which is optimized to generate legible trajectories. Third, it can be defined as a measure of how well users understand the robot, without an explicit model of how people make inferences. For example, Stulp et al. [86] optimize the robot trajectory by rewarding those trajectories that optimize successful task completion during human-robot collaboration, as those trajectories are hypothesized to be most legible.

An early example of a learned model is Ventrella [98], who proposed to generate autonomously expressive behaviors for animated systems using an animator-guided genetic algorithm. The algorithm produces gaits and movements of the system, and a user can “encourage an added level of humor and expressivity” by selecting some preferred gaits to pass on the future evolving generations. More recent examples include spatio-temporal models such as Factored Conditional RestrictedFBMs [3], the BDN [53], GPDMs [100], and S-RNNs [39], which simultaneously learn both the features and the mapping.

2.3 Robot Morphology

The developed approaches also cover a broad range of robot morphologies, as illustrated in Figure 1. The platforms range from simple, low degree of freedom (DoF) systems, where control is simplified but the range of attainable expressivity may be limited (e.g., [11, 40, 48, 65]), to complex full-body robots with a large number of DoFs where control challenges play a key role during

motion generation (e.g., [36, 64, 73]). Most approaches consider humanoid embodiments (e.g., [23, 37, 58]); a few consider animal-like systems (e.g., [65, 96]); and a small minority consider non-biologically inspired morphologies, such as mobile robots, quadcopters (e.g., [83, 87]). Although the majority of approaches developed in the literature are designed and tested with a single embodiment, a small number of methods are formulated to be agnostic to embodiment and are explicitly validated on multiple embodiments, such as both point and articulated robots (e.g., [19, 20, 86]).

2.4 Control Structure

When generating expressive robot motions, two types of control architecture are commonly used, as illustrated in Figure 2. In the first type, in the upper part of the figure, the motion generation problem is separated into two sub-problems: trajectory generation and control. Within the trajectory generation module, given the objectives and constraints, an expressive reference trajectory for the controller is generated. This trajectory is then followed by the controller to achieve the desired motion. This type of architecture is commonly used with robots that have closed architecture controllers or with animation characters using kinematic animation. With the second type of architecture, in the bottom part of the figure, the objectives and constraints are considered directly by the controller, which generates the appropriate expressive behavior and motor commands without intermediate trajectory generation.

With trajectory-based methods, expressive movement is generated at the trajectory level, and the designed trajectory is then provided as input into the robot controller. The role of the controller is then to generate motor commands for the robot to follow the specified trajectory as closely as possible. If the trajectory does not satisfy the robot's dynamics constraints, there is a possibility of control failure. This is particularly an issue for humanoid robots, where the balancing and the related constraints may limit the ability of the robot to execute a task with the desired expressivity. Ramos et al. [73] proposed to use operational space inverse dynamics to generate and control expressive movements. Each task to be executed is defined in terms of reference movement in a designated operational space, then projected back in the state space of the robot. Tasks are prioritized via a stack of tasks to avoid conflicting tasks.

In Claret et al. [15], the authors proposed to generate feasible affective behaviors via null-space decomposition, with the affective components being a lower-priority task compared to the reference task.

2.5 Reference Trajectory

Another differentiation between the way movements are generated concerns the requirement for a reference trajectory. As shown in Table 1, expressive movements may be generated by the modification of a reference trajectory, where the reference is modified either by the planner or by the controller. Alternatively, expressive movements can be generated “from scratch,” where the trajectory is directly generated as in other works [20, 40, 86, 100] or the control input to the robot is directly generated, as in Felix et al. [23] and Ventrella [98].

3 EVALUATION OF EXPRESSIVE MOTIONS

Once generated, expressive motions must be evaluated. In this section, we review the methodologies and metrics used for evaluations. There are two types of methodologies for the evaluation of the generated behaviors: real environment methods and screen-based methods, both based on user studies. In real environment methods, the observers are faced directly with the real system to evaluate in a real environment, they can observe the dimensions of the system and the sounds it makes. These evaluation methods require extensive experimental setup, time, and there may be variations in each repetition of the experiment due to the system hardware. However, they offer

Fig. 3. The self-assessment manikins [8] used often in evaluation of expressive movements.

an evaluation closer to the target application and environment, and are more likely to provide an accurate evaluation of the system [15, 21, 38].

Within real environment methods, we can also differentiate between observational and interactive studies. In observational studies (e.g., [38]), participants observe the physical robot performing movements and then rate their impressions. However, in interaction studies (e.g., [26, 86]), the participant and robot collaborate on a task, and task-relevant performance criteria are measured.

However, screen-based methods primarily use a video of the system or of an avatar of the system, the former allowing for not yet prototyped systems to be tested. When conducted in a controlled environment, the observers see exactly the same stimulus in the same conditions (e.g., [43]). However, they may not be able to assess the real size of the system or the sound it makes. Screen-based evaluations can also be conducted in uncontrolled environments, where the benefit is to allow for large-scale samples of observers recruited widely through various means (Amazon Turk, Internet survey, etc.). However, in that case, it is impossible to control the environment in which the survey is administered—the size of the viewing screen, the speed of the video playback, and the settings of the sounds—and therefore it is more difficult to obtain a fair unbiased evaluation.

A second important design choice for evaluation is the evaluation metric(s). Evaluation metrics are commonly inspired by human expressive movement evaluation methods. Kleinsmith and Bianchi-Berthouze [46] provide a review of the important features and parameters that can be used to evaluate a wide range of affective behaviors in humans, and most of them have also been applied for evaluating perceived affect in animated systems and robots. In many of the works discussed earlier, the evaluation of the generated expressive motions is purely qualitative: researchers rate or evaluate themselves with regard to the motions and behaviors generated using some criteria described in Kleinsmith and Bianchi-Berthouze [46].

The next most commonly used metrics are observer-based evaluations using semantic questionnaires or expressive model questionnaires. Mehrabian and Russell [63] proposed standard semantic questionnaires for human emotion evaluation that have also been applied to robot studies [44]. Yumer and Mitra [102] used several parameters such as recognition of the style and realism in their questionnaire. Most of the semantic questionnaires used in the literature are usually crafted for the very specific experiment and expressiveness to be measured and are not standardized [43]. Affective model questionnaires consist mainly of five different tests: the pleasure-arousal-dominance “Self-assessment manikins” (SAM) [8] 3, the positive (PA) and negative (NA) affect scale (PANAS) [101], Russell’s circumplex model [77], the Ekman model of basic emotions [22], and the Tellegen-Watson-Clark model [90]. They provide standardized metrics to assess chiefly affective behaviors. These tests are subjective evaluations and must be processed with statistical analysis with a sufficient number of observers [15, 84]. Few studies have compared the validity of the different tests; for example, Saerbeck et al. [80] evaluated the impression of the affective behavior of two robots—iCat

and Roomba—using both the PANAS and the SAM. They concluded that both tests led to similar results with regard to the manipulated variables. In Sial et al. [84], a panel of 18 participants was asked to rate movements of a non-anthropomorphic “mechanoid robot” with the SAM, Russel’s circumplex model, and the Tellegen-Watson-Clark model. Results were shown to be equivalent between the different ratings instruments for the exaggerated motions they displayed. However, Ross and Keyson [76] stressed the importance of considering the subjective nature both of expression and of understanding of affective behaviors when designing expressive systems. Indeed, each user of the system, despite having the same experience, may have a totally different interpretation of its expressiveness, making none of the previously cited evaluation methods necessarily reliable.

Quantitative measures could provide a significant advantage and enable objective evaluation. There exist some automated affect recognition systems for human motions [44]; however, for robotics systems, there are still very few because it is still unclear which variable would be of interest to evaluate the expressiveness of the motion [46] or how to measure such variables reliably. Burton et al. [12] generated affective movements of a full-body system and then used classification methods to discriminate between the different affect categories generated. Dubois et al. [21] showed that proxemics could be used as a quantitative measure as it correlates with the robot’s behaviors and how observers perceived it.

4 DISCUSSION AND CONCLUSIONS

As overviewed in the preceding sections, a wide variety of techniques for expressive motion generation have been proposed in the literature, considering a broad variety of expressive content, including affect, legibility and intent, a broad variety of functional tasks, and a variety of robot morphologies as can be seen in Figure 1.

A key commonality of all of the approaches to date is the difficulty in evaluation. The majority of the works considered use user-study based evaluation, which is subjective and influenced by the choice of the questionnaire instrument; the stimulus presentation; and cultural, contextual, and other individual factors.

Guidelines for designers. Given the broad variety of techniques proposed in the literature and the lack of comparative studies, it can be difficult for designers to choose the appropriate methodology when implementing expressive movement. There does not appear to be a single best method; rather, different methods are appropriate depending on the desired expressivity and robot morphology. From the survey, the following broad guidelines can be extracted. When the desired movement is

- fine and detailed, and the platform has a high-DoF anthropomorphic shape, and platform-specific methodologies are recommended;
- highly variable, using learned mapping is recommended, and otherwise direct mapping should be used; and
- must be morphology independent, and then control-based techniques or optimization-based techniques are recommended.

Table 2 summarizes the methodologies depending on the desired movement and the morphology of the system. The great majority of proposed methods are designed for anthropomorphic systems. For non-anthropomorphic systems, hand-crafted and expert features are mostly used. Optimization and control methods can generate movements for a variety of morphologies, yet a universal method is still to be proposed.

Several significant open challenges remain.

Morphology invariance. Although several different robot morphologies have been considered in the literature (Figure 1), including anthropomorphic, mobile, and flying platforms, separate

Table 2. Expressive Movement Guidelines for Designers

Morphology Movement	Anthropomorphic	Zoomorphic	Other or Unspecified
Fine and detailed	Platform-specific methods	Hand-crafted animation	Hand-crafted animation
Highly variable	Direct mapping or learned features or control or optimization	Hand crafted or control or optimization	Control or optimization

methods have been developed for each type of structure, where the expressive affordance for each structure is manually designed. Approaches that allow for changes in the robot morphology, or transfer between morphologies, remain an open challenge.

Degree of automation. The objective with many of the works to date is to automate expressive movement generation, or learn an appropriate mapping from offline collected data, so that the robot can autonomously generate expressive and functional movements. However, in many applications, full autonomy may not be desired; rather, some degree of human guidance or tele-operation may be preferred. In such cases, the ability to direct the robot to convey expressiveness interactively may be desired. Currently, this can be achieved through direct tele-operation, which may not be feasible for more complex or higher DoF structures. Systems that enable interactive expressive content generation from spoken or other abstract instructions [67] may be a promising step in this direction.

Features and notation systems. An important direction of existing research has been the identification of relevant motion features that convey expressive content. Three classes of approaches can be distinguished: features that are manually designed, features that are based on existing notation systems (e.g., Laban), and features that are learned from data. The first two approaches have the advantage that they are more easily interpretable and, in the case of existing notation systems, facilitate shared understanding with interdisciplinary communities. However, the hand-selected features may not result in the best-performing systems, especially when the morphology of the robot differs significantly from the human form, making it difficult for human designers to predict the best features.

Lack of context. Although the existing systems enable robots to generate expressive motions, the robot still lacks the cognitive abilities or states that accompany those expressions in humans. Unlike human movers, robots are unable to incorporate context into the generation of their movement, leading to stereotypical and potentially inappropriate movement. For example, different levels and types of expressivity may be appropriate in different cultural and social (i.e., work vs. home) contexts, and without this knowledge the robot's behaviors will be perceived as inappropriate.

Effectiveness. Given the lack of cognitive ability underlying the movement generation, it is questionable whether expressive movement will be effective during long-term human-robot interaction, or whether the initial expectations raised by such expressive movements may lead to subsequent disappointment. Long-term studies in the wild are highly required. Examples of such studies, which do not necessarily include expressive movement per se, can be found in Leite et al. [56].

Better measures and long-term evaluation. Finally, to develop truly interactive systems and to control these systems in real time, better and more more automated measures of expressiveness and user perceptions are mandatory. With the progress in sensing technology and data processing—IoT, human sensing, and big data—the development of new and more easily and automatically obtained metrics are still to be expected. Of particular interest would be measures that can be obtained by non-intrusive observation that do not require users to respond to questionnaires that disrupt the interaction.

To fully understand the impact and utility of expressive motion in context, interactive studies that consider not just human observers' ability to differentiate expressive movements but also the impact of expressive movement on robot and joint task performance and acceptability are needed. Some works [18, 26, 86] provide promising examples, where task performance is evaluated as a function of robot movement expressivity. However, most studies to date consider only short-term interactions in laboratory settings. Future work should consider long-term interactions in situated contexts such as home or work environments. Approaches from the broader field of social human-robot interaction can be used as templates for this approach by considering ethnographic approaches [78, 79] for understanding human perceptions and acceptance of robots during long-term interaction.

Multi-modal expressivity. Although this survey focuses on bodily expressions, there may be tasks and/or expressions that cannot be successfully conveyed with this modality. Expressivity might be richer and more flexible if multiple modalities (e.g., facial expression, speech, affective gestures) are used in combination with expressive functional movements. To date, only a few works (e.g., [34, 60]) consider multi-modal expressions; this is an important direction for future work.

In our contemporary society where emotional intelligence is becoming more and more valued, the expressiveness of the robot could result in an increased perceived intelligence of the robot. Such expressiveness, if appropriately used, could lead to improved communication and better human-robot interaction. However, if the expressiveness is not dynamically modified and only operates in stereotypical patterns, users may experience disappointment or deception when discovering the pattern. It could also cause the robot to behave out of context since the robot does not actually have the cognitive ability to incorporate context in its expressive movements. This might cause loss of trust or engagement in the interaction. Therefore, expressive motion generation is an emerging field of research with high potential, but additional work and care during deployment are needed before the communication modality can be fully exploited in applications. This potential could be expanded when the different modalities are all taken into account together.

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