Cross Validation of Emotional Features with a non-Anthropomorphic Platform

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Abstract— **Robots should be able to express emotional states to interact with people as social agents. Emotions are a peculiar characterization of humans and usually conveyed through face expression, body language and voice. However, there are cases where robots cannot have any anthropomorphic shape, for example when they have to perform tasks that require a specific structure. This is the case of home cleaners, package carriers, and many others platforms. Therefore, emotional states need to be represented by exploiting non-anthropomorphic features, such as movements and shape changes. This paper presents a case study concerning emotion expression in non-anthropomorphic platform and how it is perceived by humans. This case study was designed basing on results obtained from a previous experiment, done to assess precise values for linear velocity, angular velocity, oscillation angle, direction, and orientation that could be used to express happiness, anger, fear, and sadness. Results of this case study show that people can recognize some emotional expressions better than others and that additional features should be added to differentiate some emotions. Additionally, a simple scene was played to verify whether people prefer actions including emotional expression.**

I. Introduction

Emotions and mental states are not just expressed through facial expression and voice, but also by body postures and other features [1]. Many psychological studies have focused their attention on how emotions are conveyed through the face [2]. Similarly, the robotics community uses anthropomorphic faces (e.g. [3]) and bodies (e.g. [4]) to convey emotions. In many situations, the presence of anthropomorphic elements would be out of place and not justified by the main robot's functionalities. Most of the current and future robotics platforms on the market will not require anthropomorphic faces [3] or limbs [5]. For instance, floor cleaning robots are robots that do not have any anthropomorphic characteristics and still they accomplish their task. This generates the necessity to study other mechanisms that could help to convey emotions, which could give people an idea about the robot's state, and engage the user in long term relations.

However,the amount of works studying non-anthropomorphic features in robotics (e.g., [6]) remains still small in comparison to those exploiting anthropomorphic features. Moreover, these works do not provide specific range of values for the characteristics used to express the implemented emotions. For example Suk and collaborators [7] in their study give specific values for acceleration and curvature, but their connection to specific emotions is not described. Rather, they established a relationship between their values and pleasure/arousal dimensions. This could help to select specific features to convey certain emotions, but it would be better to know the precise range of values to be assigned to each characteristic to avoid misinterpretation with wrong emotions. These values could be used in social robotics to show emotions and, as consequence, increase their acceptance.

This paper is organized as follows. Section II introduces some previous works done in conveying emotion. Section III presents the platform used in the case study and the Emotional Enrichment System. Finally, sections IV and V present case study's design and results.

II. Related Work

Some researchers in Human-Robot Interaction (HRI) use videos to evaluate their implementations of emotions. One of the most well-known expressive robots is Kismet [3], a robotic face able to interact with people and show emotions. The face had enough degrees of freedom to portray the emotions suggested by Ekman [8] (*Happiness*, *Surprise*, *Anger*, *Disgust*, *Fear*, and *Sadness*), plus *Interest*. Despite the complex system behind Kismet, the emotion's projection evaluation was done using videos with a very limited number of participants. A similar approach was followed by Li and Chignell [5], who used videos of a teddy bear robot to study the contribution of arms and head movement to express emotions. In the same direction Destephe and collaborators [9] studied the attribution of emotion to a robot's gait using a virtual representation of the platform WABIAN-2R. Knight and Simmons [10] used two platforms (i.e., Keepon and NAO) with different degrees of freedom to study the possibility to project inner states with just head movements. Although the use of videos has the advantage to cover a major number of participants, they miss the impact created from the physical interaction between the participant and the platform.

The use of real platforms to study emotion projection follows two paths, using both anthropomorphic and non-anthropomorphic platforms.

The first path is characterized by the use of cue positions to project emotions [11]. In some cases, special attention has been taken to determine head's angle and arms' position contribution to specific emotion expressions [12]. Nevertheless, current humanoid platforms cannot generate

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smooth gaits, and this limits the quality of body movements. To overcome this limitation, some researchers have reduced the human resemblance (e.g., eliminating limbs and facial expressions) to increase platform mobility and study new mechanisms to project emotions [13]. Reducing even more the anthropomorphism, Saerbeck and Christoph used a Roomba platform to study the contribution of curvature in a trajectory to conceive emotional states [6]. Similarly Lourens and Barakova [14] implemented a set of behaviors to determine the emotion perceived from diverse movements, which were selected from the work done by Camurri et al. [15]. Similarly, Barakova and collaborators [16] created a closet in which lights could be manipulated to convey predefined behaviours. The robot's behaviours were defined using the Interpersonal Behaviour Circle (ICB). Their findings suggest that electronic systems can elicit a type of reactions different from the one expected by theories of interpersonal communication. Despite the type of platform used, these works offers an overview of features that could be used to express certain emotions, but they not give precise feature values to implement the emotions.

Other approaches have been adopted to get a better understanding of the contribution of diverse features to express emotions through movement. For example, Suk and collaborators payed a particular attention to speed, smoothness, granularity of movement path and volume of a non-bioinspired object [7]. Their results suggest that arousal increases as speed increases and that there is not any clear tendency for smoothness. On the other hand, granularity is positively correlated with pleasure and arousal, while volume is negatively correlated with pleasure and positively correlated with arousal. Alike, Tan and collaborators [17] have studied the contribution of velocity, fluidity, direction and orientation of a small box. Their results suggest that direction is directly correlated with dominance, but that fluidity does not influence the perception. While flat orientation is related to positive valence, leaning positions are related with negative valence. Finally, velocity is correlated with valence, arousal and dominance.

Due to the popularity that quadrocopters have received in the last years, Sharma and collaborators [18] used a quadrotor to study how different Laban's effort [19] parameters could impact on the perception of affection. A professional Laban certified actor was asked to generate 16 different paths, for each one changing one of the four Laban's parameters (space, weight, time, and flow). Each generated path was recorded using the Vicon motion-tracking system ad then replicated on the quadrocopter. Cauchard and collaborators [20] studied how flight paths could project personal traits and emotional attributes. All these works present a very nice starting point to identify features and values that could be used to project emotions in robotics, which could help in coordinating humans and robots [21]. However, these works do not give a clear guideline to elicit precise emotions. This could lead to implementations that express an undesired emotion [22]. For example, people could confuse an implementation of *Happiness* with *Anger*.

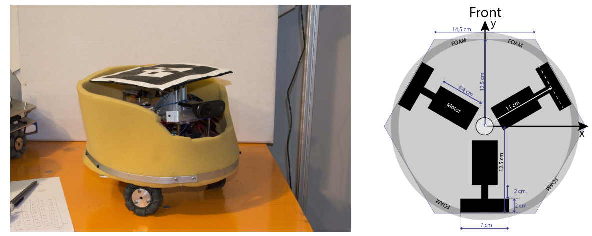

Fig. 1. Platform used in the case study (left), and holonomics's blue prints (right). The arrows represent robot's frame of reference.

III. System

A non-anthropomorphic robotic platform was created to limit the influence of shape on the participants' perception. The robotic platform is holonomic and it included Odroid U3 and Arduino Due as processors, 3 metal gear motors with 64 CPR encoders, and omniwheels. Arduino Due is in charge to interface motors, and Odroid U3 hosts the Emotion Enrichment System described here below. The platform is shown in Figure 1.

An Emotional Enrichment System was designed and implemented to automatize the process of emotion expression [23]. It is intended to provide an emotional expression to an action decided a priori, e.g., by the planner. It modifies actions' parameters and adds actions to create the illusion of emotion expression in a robot. To achieve this, the system receives two messages. One message describes actions and the order in which they should be executed. These actions could be executed in parallel, sequentially or as a combination of both. This kind of representation enables the possibility to communicate several actions in one message. The other message tells the system the emotion to be expressed and its intensity. These two messages could arrive asynchronously and without any particular order. Every time a message is received, the system updates the robot movements to convey the desired emotion in the specific action.

IV. Case Study

The case study presented in this paper was held at an exhibition with two main objectives: (i) Cross-validate the findings obtained from a previous experiment [24], which was done to study the attribution of different linear and angular velocities, oscillation angle, direction, and orientation of the platform to express: *Anger*, *Happiness*, *Sadness* and *Fear*. A total of 196 value combinations were designed, 20 of which, randomly selected, were presented to each participant. Subjects had to select for each presentation the most representative term describing it among the four emotions and two mental states (i.e., *Excitement* and *Tenderness*), added as confounding terms. (ii) Verify whether participants would prefer scenes where the robot moves expressing emotions, or rather moves on the same trajectory without any emotion expression. To control scene variability two cameras and eight AR tags were used together with a Kalman filter to improve robot localization on the stage. AR tags were detected using the ROS package ar_track_alvar [25]. The distribution of the cameras and the tags is reported in Figure 2.

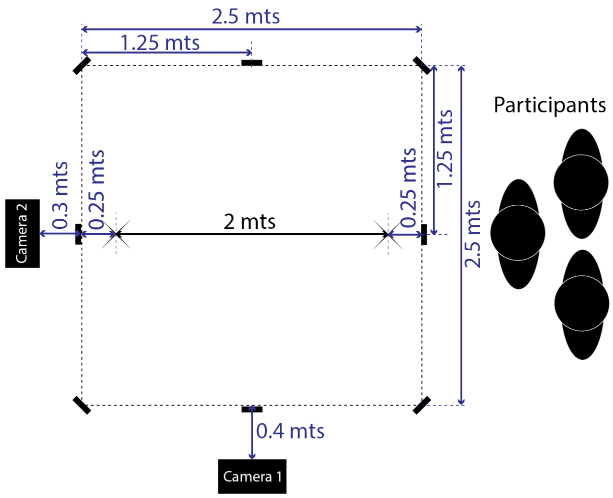

Fig. 2. Environment setup for the case study. The crosses represent the starting points.

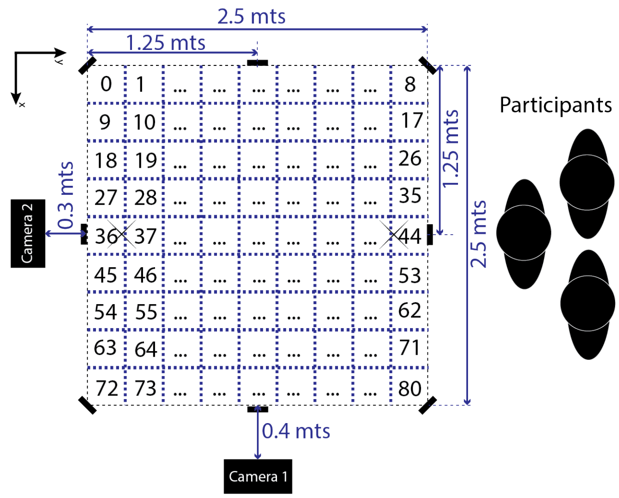

Fig. 3. Stage discretization used for the scene. The dark squares correspond to the each zone, while the numbers correspond to the ID given to each zone.

TABLE I

PARAMETER VALUES SELECTED FROM THE PREVIOUS EXPERIMENT.

Emotion	Direction (rad)	Orientation (rad)	Linear Velocity (mm/s)	Angular Velocity (rad/s)	Angle (rad)
Happiness-1	0	0	500	3	0.349
Happiness-2	0	0	900	3	0.174
Anger-1	π	0	500	3	0.087
Anger-2	0	0	900	1	0.087
Fear-1	π	π	900	2	0.174
Fear-2	π	π	500	2	0.087
Sadness-1	π	0	200	1	0.349
Sadness-2	0	π	200	1	0.349

A. Emotion Description

The parameters selected to implement *Anger*, *Happiness*, *Sadness* and *Fear* are shown in Table I. As it could be observed, two configurations for each emotion were selected among the ones evaluated in the previous experiment to be cross-checked. These configurations had to satisfy two conditions: (i) the linear velocity should be greater than 0, so the robot should show some displacement, and (ii) it should be in the top 10 list of the configurations tested in the previous experiment.

B. Scene

Stage discretization was used to give zones of movement instead of absolute positions. This idea was brought from human theatrical actors, who arrange their movements based on zones on the stage [26]. This allows them to adapt their position based on other actors and stage dimensions. The stage was discretized in 9x9 matrix as shown in Figure 3. Robot's movements are given in terms of matrix positions to the Emotional Enrichment System. The robot's final position is calculated by the Emotional Enrichment System during execution. In this setting, the scene was designed on a 3 x 3 meters stage, but in the presentation at the exhibition the stage was 2.5 x 2.5 meters.

The scene can be described as follows. The robot starts in the middle of the stage to move to the upstage right (see [27]), close to the right wing. Then, the robot moves to upstage right center and rotates to $\pi/2$ left (see [28]). Next the robot moves to the right center. Then it goes to the center. When it arrives there, it turns full back and move backwards to downstage center with a full front orientation. There, it turns full back to move to center. Finally the robot turns to profile right and it does a step back; then it goes to the upstage center and then upstage right. The sequence of movements of the robot are depicted in Figure 4.

Movements have been enriched by emotional expression as follows: movements one to five do not express any emotion, movements six to ten show fear. Movement eleven depicts happiness, and the remaining movements depict sadness. The actions describing this scene are executed by the Emotional Enrichment System and the emotion selection is designed via a graphical interface.

C. Study

This case study was done at an exhibition during a period of two days. People coming to the stand were asked to volunteer to participate in this study, which was divided in to parts. In the first one, each subject was exposed to two emotion expressions. The two emotions were generated to guarantee a random uniform presentation. In the second part, participants were explained that a small scene was going to be presented twice, and they had to select the one they like more. The order of the scenes (e.g., with or without emotion) was generated beforehand. The total number of volunteers was 256: 128 males, 126 females, and 2 that chose not to specify their gender. The average age was 27.29 years, with standard deviation of 16.58, minimum age was 4 and maximum 76. We accepted this variability as representative of a general population.

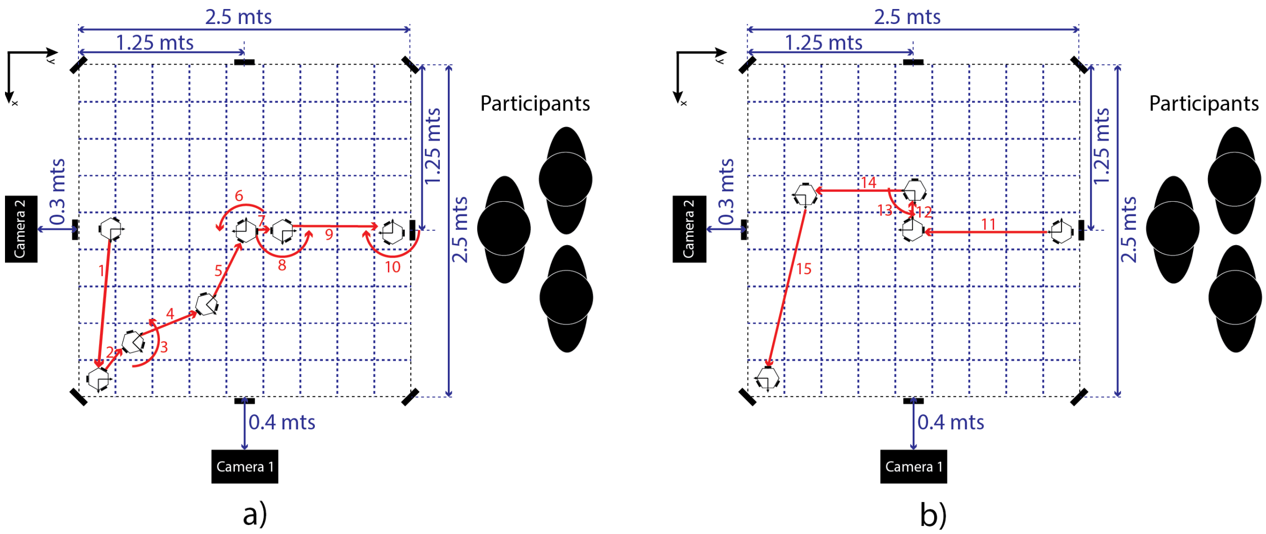

Fig. 4. Sequence of robot's movements. The red arrows show the trajectory, while the numbers show the order among the movements. a) The first ten movements b) The last five movements

TABLE II
SUMMARY OF THE ANSWERS OBTAINED IN THE PRESENTATION OF EMOTIONAL MOVEMENTS.

Presented/Reported	**Happiness**	**Anger**	**Fear**	**Sadness**	**Excitement**	**Tenderness**	**Other**	**Total**
Happiness-1	8	16	7	4	16	4	7	62
Happiness-2	11	11	6	2	19	3	1	53
Anger-1	7	5	6	2	21	7	1	49
Anger-2	14	29	13	2	13	3	2	76
Fear-1	6	2	28	1	9	6	0	52
Fear-2	7	3	37	2	20	4	1	74
Sadness-1	3	5	17	14	5	16	5	65
Sadness-2	5	5	15	28	6	15	7	81

V. RESULTS

This section reports the results obtained during two days for the two parts of the case study.

A. Part I: Emotion Recognition

The results obtained from the presentation of emotional movements are summarized in Table II.

It could be observed that both implementations of *Happiness* were confused with *Anger* and *Excitement*. In a similar way, *Anger-1* was mostly confused with *Excitement*, which was voted twenty one times by forty nine subjects exposed to it. *Anger-2* shows an improvement of perception from 10% to 38% with respect to Anger-1. This implementation was perceived also as *Happiness*, *Fear* and *Excitement*. Both implementations of *Fear* had a high level of recognition, respectively 54% and 50%, although they have been mostly confused with *Excitement*, which was voted nine times for the first implementation and twenty times for the second implementation. Finally, the two implementation of *Sadness* were confused with *Fear* and *Tenderness*.

An analysis was done per groups, for each presented emotion. For each emotion, it was considered how many subjects presented with that emotion expression recognized it, how many identified a different emotion, how many identified the considered emotion when presented another one, and how many subjects recognized an emotion different from the considered one when presented a different emotion. This leads to a contingency table, for each presented emotion, like the one reported in table III for Happiness-1.

TABLE III
EXAMPLE OF TABLE COMPILED FOR EACH EMOTION ON THE SUBJECTS WHICH HAVE BEEN PRESENTED EACH EMOTION (HERE HAPPINESS-1).

Presented/Reported	Happiness	Other
Happiness-1	8	54
Other	42	355

For each of the contingency tables the classification accuracy and the no-information rate (NIR), i.e. the accuracy that had been obtained by random selection, are reported in Table IV. The results reveal that Sadness-2 is the only implementation that was correctly recognized among all implementations with some statistical significance ($p < 0.05$).

Additionally, the positive predictive value, accuracy and a Pearson's χ^2 were computed for each table. The hypotheses used in the test were:

- H_0 = there is a difference in recognition between the implementation with respect to the others.
- H_1 = there is not a difference in recognition between one implementation with respect to the others.

The results are shown in table V. They show that there is significant evidence to conclude that Anger-2, both of *Fear* and *Sadness* are considered as a different implementation

TABLE IV

CLASSIFICATION ACCURACY OF THE PRESENTED EMOTIONS BY THE SINGLE PANELS, COMPUTED AS MENTIONED IN THE TEXT, WITH CORRESPONDING 95% CONFIDENCE INTERVAL, NO-INFORMATION RATE, AND P-VALUE THAT ACCURACY IS GREATER THAN THE NIR.

Presented Emotion	**Classification Accuracy**	**95% CI**	**No-Information Rate**	**P-Value [Acc > NIR]**
Happiness-1	0.79	(0.75,0.82)	0.89	1.0
Happiness-2	0.81	(0.77,0.84)	0.88	1.0
Anger-1	0.8	(0.76,0.83)	0.88	1.0
Anger-2	0.89	(0.76,0.84)	0.83	0.95
Fear-1	0.79	(0.75,0.83)	0.88	1
Fear-2	0.78	(0.73,0.81)	0.83	0.99
Sadness-1	0.85	(0.81,0.88)	0.84	0.47
Sadness-2	0.85	(0.81,0.88)	0.81	0.035

TABLE V

ACCURACY, PRECISION AND RESULTS OF PEARSON'S χ^2 FOR EACH CONTINGENCY MATRIX WITH $\alpha = 0.05$ FOR THE CASE STUDY.

Presented Emotion	**Positive Predicted Value**	**Accuracy**	$\chi^2(1)$	**p-value**
Happiness-1	0.13	0.79	0.11	0.74
Happiness-2	0.21	0.81	3.7	0.054
Anger-1	0.1	0.8	$3.8e^{-29}$	1
Anger-2	0.38	0.81	34.4	< 0.001
Fear-1	0.54	0.8	36.2	< 0.001
Fear-2	0.5	0.78	35.8	< 0.001
Sadness-1	0.22	0.85	27.4	< 0.001
Sadness-2	0.35	0.85	72.9	< 0.001

when they are compared with other implementations. While both implementations of *Happiness* and Anger-1 are considered as similar to the other implementations.

To determine which implementations were perceived as different or similar, a Fisher's exact test was applied for ten different combinations of the implementations. Additionally, a Holm-Bonferroni correction was applied for multiple comparisons to get a better p-value estimation. The following are the hypothesis used in this test:

- $H_0 =$ there is a difference in the recognition of the two compared emotions.
- $H_1 =$ there is not a difference in the recognition of the two compared emotions.

The results are reported in Table VI. As it could be observed, both implementations of *Anger* were perceived as two different emotions ($p < 0.001$) and both implementations of *Happiness* were perceived as Anger-2 ($p = 0.69$ in both cases).

Nevertheless, it is important to notice that the results were obtained using the lower part of the robot without any

TABLE VI

PAIRWISE COMPARISON AMONG ALL THE IMPLEMENTED EMOTIONS USING FISHER'S EXACT TEST FOR BOTH QUESTIONNAIRES WITH $\alpha = 0.05$ FOR THE CASE STUDY. THE * INDICATES THAT THE P-VALUE WAS ADJUSTED USING THE HOLM-BONFERRONI CORRECTION FOR MULTIPLE COMPARISONS.

Pair Compared	**p-value**	**p-value***
Happiness-1 vs Happiness-2	0.38	1.0
Anger-1 vs Anger-2	< 0.001	< 0.001
Anger-2 vs Happiness-1	0.137	0.69
Anger-2 vs Happiness-2	0.157	0.69
Fear-1 vs Fear-2	0.74	1.0
Sadness-1 vs Sadness-2	0.665	1.0
Fear-1 vs Sadness-1	< 0.001	< 0.001
Fear-1 vs Sadness-2	< 0.001	< 0.001
Fear-2 vs Sadness-1	< 0.001	< 0.001
Fear-2 vs Sadness-2	< 0.001	< 0.001

change in its shape. Another important factor to highlight is the impact that the words listed in the questionnaire have on the perception rate. As it was expected, mental states *Excitement* and *Tenderness* were confused with emotions with similar arousal level. In this precise case, the emotions *Anger*, *Happiness*, and *Fear* were confused with*Excitement*, and *Sadness* was confused with *Tenderness*. Despite the bias generated by the two mental states listed in the questionnaire, the recognition rate of five out of eight implementations was over 35%, being the two implementations of *Fear* the implementations with the higher recognition rates (54% for the first and 50% for the second).

B. Part II: Scene Preference

The results obtained from the scene trials are presented in Table VII. From this data, two questions had to be answered:

1) Do people prefer scenes with or without emotions?
2) Has gender an impact on the preference?

To answer these questions the following hypotheses were considered:

1) H_0 = there is a preference towards scenes with emotions. H_1 there is a preference towards scenes without emotions.
2) $H_0 =$ there is an association between gender and the preference. $H_1 =$ there is not an association between gender and the preference.

A χ^2 test with one degree of freedom and $\alpha = 0.05$ was done to verify them. The results of the tests show that there is enough statistical evidence to accept that people prefer scenes with emotions ($p < 0.001$). On the other hand, the test shows that there is no association between gender and preference ($p = 0.85$).

VI. CONCLUSIONS AND FURTHER WORK

The case study presented in this paper was done to cross validate the findings in a previous experiment [24], and to verify whether the subjects would prefer scenes when the robot expresses emotions rather than the same trajectories without any emotion expression. For each one of four

TABLE VII
ANSWERS OBTAINED FOR THE SCENE TRIALS.

Gender	With Emotion	Without Emotion	Total
Male	84	43	127
Female	81	45	126
Total	165	88	253

emotions (i.e., *Anger*, *Happiness*, *Sadness* and *Fear*) studied in the experiment two sets of parameters were selected to express them. The results show that both implementations of *Happiness* were confused with *Anger* and *Excitement*, while one implementation of *Anger* was confused with *Excitement*. Both implementations of *Sadness* were confused with *Tenderness* and *Fear*. This supports the hypothesis that the selected parameter values are related to arousal, since confusion appears among emotions with high arousal, and among those with low arousal. Both implementations of *Fear* had a recognition rate over 50%. This, together with the last statement may suggest that people have different models of *Fear* and that this single label is not enough to distinguish among them.

Additionally to the already mentioned results, it resulted that there are words that could bias participants' perception. For instance, *Happiness* and *Anger* were considered as *Excitement*. This misinterpretation is not surprising, given the fact that there is not a unique definition of emotion [29], [30], and each person would interpret a situation differently, so they will give a different label to the presented movement. Moreover, a misinterpretation of *Happiness* and *Anger* could suggest that additional features (e.g., trajectory or shape) should be added to increase differentiation between them. For example, Venture and collaborators [31] had reported that in human bodies the recognition rate of *Anger* and *Fear* are increased when torso and head are downwards. On the other hand, they found that *Happiness* perception is increased when the torso and head are moved upwards. These results could bring some insight to possible body changes that could occur in non-human like bodies, but it should still be tested in this kind of platforms.

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