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Assessing the sense of control during affective physical Human Robot Interaction

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ABSTRACT

Body posture and movements play a key role in the expression and recognition of emotions during social interactions. Such signals have been used for the prediction of emotions, both when considering discrete affective labels and affective dimensions. In this work we explore how posture and movements information of the human arm can be obtained from the robot onboard sensing in order to discriminate the affective states of the human in physical Human-Robot-Interaction scenarios. Specifically we focus on the Potency dimension of the affective state, that provides information about the sense of control in situated interaction contexts. Our envisaged application scenario is assistive robotics for eldercare.

CCS CONCEPTS

• **General and reference** → **Evaluation; Measurement; Experimentation.**

KEYWORDS

Emotions, Physical Human Robot Interaction, Potency, Dominance, Eldercare

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1 INTRODUCTION

The world population of is increasing in age both in absolute term and as a share of the total [22], raising the need for more reliable and long-term healthcare solutions. On the one hand, there is an

increased interest in "ageing in place" (at home) [33], while on the other hand there is a growing shortage of caregivers that could potentially provide for such needs [21]. These factors highlight the need for new technologies that could tackle such challenges, targeting not only the physical but also the cognitive well being of people through the development of Cognitive Assistants and Personal Robot Assistants [19]. Such setups should adapt to the user to provide comfortable and personalized care. Initially, Assistive Robots have been designed either for rehabilitation applications, such as smart wheelchairs, artificial limbs and exoskeletons, or as social companions that can enhance the psychological well being of the user, but more recently there is increased interest on more general purpose robots that are able to provide both types of assistance [32] [34] [2].

Although very promising reports show that such robots and other technologies were positively received [4], assistive robots might not be readily accepted [35]. Early studies have highlighted how designers of such systems must be careful in balancing the need for both independence and engagement during activities of daily life. Additionally, they must account for social, emotional and environmental factors, which play key roles in the acceptance of such technologies [14]. Importantly, among these various aspects affecting such acceptance, the sense of being in control over the technology is crucial [3] [35]. Thus, such sense of independence and control by the elderly (and other users) might conflict with a fully autonomous system and would require a system that can be adapted by the user to her preferences and needs. At the same time, in the context of unstructured environments, the robot must face the challenging task of adapting autonomously to its surroundings but also allowing the user to adapt its behavior in order to retain a sense of control [13]. These preliminary findings suggest that any general purpose architecture should ideally be able to perceive how much and if the user feels in control. This is precisely the question we address in this paper. We present a model about how this information could be inferred by perceiving the way the person interacts with the robot, particularly regarding the level of control with respect to one of the main dimensions of affective state. We address this issue by taking an Affective Computing approach, which is novel in the context of physical Human-Robot-Interaction.

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2 RELATED WORK

Emotions have been traditionally studied by focusing on facial expression [8] but more recently there has been a surging interest for the role of other modalities, such as physiological signals, speech and posture [15]. In the Affective Computing field two main theories of emotions are considered, the discrete and the dimensional [1]. Although discrete emotion categories can inform us about a few prototypical affective states (happiness, sadness etc.), the specific emotion encountered in the real world is usually more nuanced, more ambiguous and less pronounced [17]. An alternative approach is to consider affective states as points in a multidimensional space which is more appropriate when considering scenarios where a single label might be not informative and difficult to assess [29]. Among the various multidimensional formulations used to describe affective states, one of the most popular is a three dimensional Pleasure-Arousal-Dominance model [20]. Pleasure, sometimes referred as Valence, provides information about positive or negative quality. Arousal indicates the level of intensity of an emotion and Dominance (also called Potency) is used to indicate how much a user believes to be in control of a situation [20] [29][11].

Posture and kinematic features of the full body have been used to recognize both discrete emotion categories and emotion dimensions [16]. Different works on the other hand have focused on specific body parts and their capacity to convey some aspects of the expressed emotion. The role of kinematic features in the recognition of emotion arousal dimension has been investigated using point-light animations of arm movement in emotion perception in the seminal work by Pollick et al. [23]. The focus of the authors in this work was on perceived features during acted drinking and knocking scenarios. The main result highlighted a linear relationship between Arousal and velocity and acceleration of the arm. On the same line of research, [6] focused on dynamic arm gestures during acted speech interactions. They obtained similar results as for the Arousal dimension but additionally they also found a strong correlation between Potency and the perceived gestural dynamics, in particular with the spatial extent of the arm movement and the perceived physical effort put into the arm during the emotion expression. Interestingly they did not find pronounced differences between emotion with different Valence levels. In [24] a user subjective study was carried together with a quantitative extraction of features using state of the art pose estimation techniques from a stream of images. Among their main findings they reported that postural rather than kinematic features discriminated between emotional categories, both for computational and subjective ratings. Some postural features such as symmetry, limb angles and shoulder ratio played a significant role in the emotion category classification. Furthermore they observed that the wrists were the most relevant body parts in the prediction of discrete emotion labels. Together, these all the findings reported above highlighted and reinforced the already established idea in the literature that specific body features of the arm and hand movement play a significant role in the emotion expression [27] [6] [23] [7] [25] [26].

3 RESEARCH QUESTION

In this work we focus on physical Human Robot Interaction (pHRI) and inquire on relevant signals that can be used by the robot to

assess the affective state of the user. Such signals can play a significant role in physical interaction scenarios in assistive robotics. For example if the user behaves hesitant and fearful or determined and in control by assessing the motion of her arm, as she interacts physically with the robot. The recognition of the user intent is also a core component of such applications [18]. Emotions have been directly linked to action selection and intent [12]. Thus these signals can be extremely useful in designing appropriate strategies for the control of the robot during the interaction.

Building on the studies reported above we specifically focus our analysis on the postural and kinematic features of the arm but with an additional emphasis on an often neglected property of the emotions, the Dominance dimension, sometimes referred to as Potency [20]. In a high (low) Potency state "*the person believes that he/she can (cannot) influence the situation to maintain or improve it (if desired)*" [30]. As reported above, the perceived Potency was linked to forcefulness and movement expansiveness in [6] in speech-based interaction. We postulate that a robot could exploit force torque sensing or estimation techniques in order to differentiate physical interactions designed to span different Potency values. Specifically, we hypothesize that the Potency dimension of the human affect during physical Human-Robot-Interaction can be **positively** correlated with the force applied by the human interacting with the robot, and the amplitude of motion. We summarize the hypothesis in Table 1.

In particular, we use state-of-the-art pose landmark detection techniques¹ to extract relevant wrist features and assess their relationship with the different dominance levels. We exploit information coming only from a depth camera and the on-board force-torque sensing available in most commercial cobots. To summarize, we investigate the following **research question**: *what features of physical interaction can be used by a robot to measure the Potency of the affective state of the human, computed by using a minimal set of sensors comprised of a depth camera and a force-torque sensor of the arm of the robot?*

4 MODEL

In this section we propose a simple linear classifier model that takes into account arm movement characteristics and robot sensed forces to differentiate between different levels of Potency. In particular, we postulate that the external (human) force sensed by the robot and the amplitude of the gesture during the physical interaction are the two relevant features that affect the classification. While most of the recognition techniques have focused on instantaneous features, it has been recently shown that considering time information is very relevant [24]. Therefore, we compute the features in a time window, defined as $T_{emo} \in \mathbb{R}$. Additionally, we consider $\mathbf{f}_{ext}(t) \in \mathbb{R}^3$ to be the vector of linear components of the six dimensional external wrench vector applied at the robot end-effector at time t (either sensed by a Force sensor or eventually estimated using the robot model [9]) and $A \in \mathbb{R}$ the amplitude of the motion during the emotion expression window T_{emo} . We compute the maximum of the Euclidean norm of the force at time t as $\mathbf{f}_{max}(t) = \max(\|\mathbf{f}_{ext}(t)\|_2), \forall t \in [t - T_{emo}, \dots, t]$. Similarly the maximum amplitude of motion at time t can be defined as

¹<https://nuitrack.com/>

Table 1: Expected features

Expressed emotion dimension	Computed gestural dynamics	Level of force exerted on the robot
High (low) Potency	High (low) expansive motion	High (low) force

$A_{\max}(t) = \max(|A_{\text{ext}}(t)|), \forall t \in [t - T_{\text{emo}}, \dots, t]$. Then, the Potency $p(t)$ at time t can be described by the following function:

$$p(t) = \begin{cases} 1, & \text{if } (f_{\max}(t) \geq f_{\text{ext}}^n \wedge A_{\max}(t) \geq A_n) \\ -1, & \text{if } (f_{\max}(t) < f_{\text{ext}}^n \wedge A_{\max}(t) < A_n) \end{cases} \quad (1)$$

This model discriminates between two levels of Potency, **high Potency** when $p(t) = 1$ and **low Potency** when $p(t) = -1$. In equation (1), f_{ext}^n and A_n are a constant force and a constant amplitude values.

5 APPARATUS

To assess the Potency levels during affective pHRI we have tested the model in the interaction with a Franka robot arm. This platform has been widely used for collaborative robotics applications and has been designed for safe interactions. Additionally we record the posture of the user using a depth camera (IntelSense 440²) and the off the shelf human skeleton detector NuiTrack³. We defined scripted scenarios where we interacted with two clearly defined behaviors, hesitant and determined, for a duration of one minute each. The hesitant behavior was acted as a state of hesitance or worry (for example caused by the closeness to the robot) while the determined state was acted as a state of determined, cold anger toward the robot. To ground our analysis in the literature, we used as a reference the same descriptions reported in the GEMP, a corpus of acted emotion portrayals [5]. The hesitant/worried behavior is considered to be a low Potency emotion while the determined/(cold) anger behavior is a high Potency state [6]. Additionally we chose these emotion categories because they both fall in the group of low Arousal affective states, allowing to control for interaction effects that might results with high and low emotion intensity levels [6]. The scenarios have been selected for their relevance both in the context of physical and physiological care of the elderly. We focused specifically on activities that require both physical interaction and body movements. The first scenario (S1) is a physical exercise with the arm where the user is required to move back and forth the robot arm. This exercise falls mainly under the category of tasks designed for physical rehabilitation [4]. The second scenario (S2) is a Pong game on screen where the user moves a striker by pushing and pulling the robot arm. Such interaction has been inspired by the games designed in [10] for elderly people and have high relevance in the context of social interaction. Indeed trough the guidance from experts of game design, rehabilitation, and physical and occupational therapy and a thorough human study, it has been shown how a social-physical exercise with a robot is more pleasant, enjoyable, engaging, cognitively challenging, and energetic than similar interactions that lack physical touch [10]. Affective signal detection in real-time could then further improve the user

experience by informing a more human-aware architecture that personalizes the robot behavior to the human state. We thus compute features using only non-invasive sensors, namely the output of the force-torque sensor providing the external wrench exerted on the robot end-effector and the depth images coming from the camera, see Figure 1 for a picture of the setup during S2. The latter are then processed by a skeleton detector algorithm, that represents the human body as 33 landmarks. We focus in this work only on the landmarks describing the dominant arm of the user. Specifically the human pose feature refer to the motion of the wrist.



Figure 1: A user playing the Pong game by physically interacting with the robot while a depth camera is used to detect his skeleton (S2).

6 RESULTS

We computed the maximum norm of the exerted force on the robot end-effector and the maximum absolute value of the amplitude of the wrist motion during the interaction, for each user, for each condition and for both the scenarios. Then we averaged the features among the users. The results are reported in Table 2 and we can observe that the the exerted force follows the prediction of Table 1 confirming its role in assessing the Potency level. Furthermore we observe also that the amplitude of the motion during the affective interaction is positively correlated with the high Potency condition, in line with other results in affect recognition from postures [16].

7 CONCLUSION

We focused in this work on affective physical Human Robot Interaction scenarios. We showed how different levels of the Potency dimension of the affective state can be distinguished using onboard cheap sensing by a robot during different acted interaction contexts. Specifically by exploiting state-of-the-art pose landmark detection

²<https://www.intelrealsense.com>

³<https://nuitrack.com/>

Table 2: Experimental results, showing the mean values for the three users (N stands for Newtons, to measure the force, and mm stands for millimeters, to measure the amplitude)

Scenarios	Hesitant condition	Determined condition
S1	$f_{\max} = 30[N]$, $A_{\max} = 111[mm]$	$f_{\max} = 56[N]$, $A_{\max} = 163[mm]$,
S2	$f_{\max} = 19[N]$, $A_{\max} = 53[mm]$	$f_{\max} = 55[N]$, $A_{\max} = 272[mm]$

algorithms and force sensing on the robot end-effector it is possible to obtain a minimal description of the affective state of the user. The linear classifier that we present in Section 4 serves the purpose of highlighting some key aspects of emotion expression in the form of constants in the model. Their value must be adapted to the particular scenario and eventually also to the user, for example by gathering a larger dataset to train the model. These preliminary findings suggest how even with very limited sensing it might be possible to discern two levels of Potency and use it in real-time robot control architectures to modulate personalized behaviors. Examples of such applications are the emerging assistive technologies that target eldercare and require non-invasive procedures where user comfort and safety is of primary concern. Overall, we showed in this preliminary work how the sense of control during Human-Robot-Interactions, an important factor in eldercare technologies, could be assessed by taking an Affective Computing approach. Additionally we showed how this perspective could benefit from the use of touch sensors in the context of physical interactions between humans and robots.

However, the current work presents several **limitations** that should be tackled in **future works**. First, real-world emotion expression might be more ambiguous, the features described in this work might manifest with less intensity, and might not be sufficient to design accurate affect recognition algorithms [17]. Experiments (acted and non-acted) with a significant number of users should be carried out, and to improve performance, multiple body parts and other expressive channels (e.g. facial expressions) could be considered together. Second, affective states are context-dependent and features relevant in one scenario might be attenuated in others [17]. It is then necessary to design more diverse experiments that could cover a broader range of applications. Third, the relevant features used to differentiate levels of a particular affective dimension have been shown to have interaction effects in the recognition of other dimensions. For example, it has been found that the effects of arousal are independent of Potency but that the effects of Potency are dependent on the level of arousal [6]. Furthermore, the Potency dimension was shown to be correlated with valence [28] [31]. Experiments should then be designed by keeping these factors in mind. Additionally, to be able to use the model in real world application scenarios we need to conduct a user study, with a significant number of users with a variety of profiles.

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