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Improving Human-Robot Interaction: Gesture-Based Interfaces Featuring Unrestricted Force Feedback Alongside Gesture Elicitation Methodology Based on Levels of Frustration

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Abstract: **This paper presents a groundbreaking method for human-robot interaction (HRI) utilizing a gesture-based interface coupled with unrestricted electromagnetic force feedback. The interface integrates a markerless gesture tracking system, empowering operators to intuitively control robot manipulators without the need for markers. A key innovation lies in its unrestricted electromagnetic force feedback mechanism, addressing common issues like friction and hysteresis found in traditional actuation dynamics. This ensures operators experience immersive force feedback, thereby enhancing operation precision. To achieve accurate force feedback control, a broad learning system (BLS) is introduced. Furthermore, two interval Kalman filters (IKFs) enhance measurement precision by estimating the position and orientation of the operator's hand. Experimental findings underscore the interface's efficacy in executing high-precision tasks, enabling operators to concentrate on tasks and efficiently manipulate dual robot manipulators. This fosters a natural and effective human-robot interaction environment.**

IndexTerms **– Gesture elicitation, human–robot interaction, gesture vocabulary, intuitive gestures, psycholinguistics.**

I. INTRODUCTION

In recent years, artificial intelligence has enabled robots to handle various complex and sometimes hazardous tasks that were previously performed by humans. However, certain highly intricate tasks, such as surgical procedures, still require collaboration between humans and robots to leverage human decision-making and intelligence. Human-robot cooperation not only improves compliance in robotic manipulation but also necessitates effective multi-modal interfaces to enhance robots' decision-making capabilities. Visual-haptic guidance, exemplified by various contact human-robot interactive interfaces, has gained traction. While contact interfaces, including brain-computer interfaces, enable effective human-robot interaction through mechanical devices like computer mice and joysticks, they often lack force feedback, thereby limiting immersion and accuracy.

Recent studies have explored contact human-robot interfaces with restricted force feedback to enhance operator immersion. However, these interfaces encounter issues such as friction and hysteresis, which can affect interaction accuracy. Conversely, non-contact interfaces, while avoiding motion constraints, may face challenges with occlusion of markers used for tracking human motion. Markerless methods have been proposed to address occlusion issues but require improvements in accuracy and immersion, particularly in providing force feedback.

To tackle these challenges, this study introduces a novel human-robot interface integrating unrestricted force feedback and markerless gesture tracking. The interface enables operators to control robots naturally without the need for markers, thereby enhancing interaction immersion. Electromagnetic force feedback addresses limitations of restricted force feedback mechanisms by eliminating friction and hysteresis. The proposed interface utilizes a broad learning system for accurate regulation of force feedback and interval Kalman filters for precise gesture tracking. Experimental findings confirm the effectiveness of the interface in high-precision tasks.The future ubiquity of robotics relies on improved human-robot interfaces. While gestures offer an intuitive communication medium, existing research often lacks clarity in gesture elicitation methodology. This study aims to fill this gap by proposing a reproducible methodology based on psycholinguistic concepts to elicit intuitive gesture vocabularies for human-robot interaction. The methodology introduces an Intuitiveness Level metric to rank gestures based on their intuitiveness, thereby facilitating the development of robust gesture vocabularies. Overall, this study contributes to enhancing human-robot interaction by providing natural, intuitive interfaces and methodologies for gesture elicitation.

II. LITERATURE SURVEY

A. PSYCHOLINGUISTICS FOR GESTURES Thought and language are linked to body actions, and, even though communication is performed in verbal and nonverbal ways, every human is first (as a baby or infant) in a pre-linguistic period, which is characterized by motions and gestures such as smiling, arm waving, hand gestures, and head motions, known as paralinguistic behaviours. This paralinguistic development shows different levels of complexity [11], [12]. The evolution of gesture types has a communicative function, and, therefore, several studies have demonstrated the relationship between gestures and cognitive processing, i.e., the interconnection between language, thought, and gesture [13]. Specifically, psycholinguistic studies found a correlation between linguistic abilities and hand gestures, as gestures are related to language development. Furthermore, hand gestures are important elements in organizing cognitive processes, being able to express a variety of thoughts [14]. Psycholinguistics supports the grouping of gestures into four types: iconic, metaphorical, rhythmic, and deictic, with different complexities and functions [2], [15]. In this paper, a mixture of these for types will be analyzed

B. INTUITIVENESS OF GESTURES According to Davidson [17], the word intuition originates from Latin, intuitionem, and has the following etymology: seeing through the eye, visual perception. Thus, intuition may be defined as an immediate perception of an external object as soon as it is seen, without the need for any previous reasoning to analyze it. According to Wachs [10], gestures intuitiveness can be defined as ‘‘the cognitive naturalness of associating a gesture with a command or intent’’. This means that an intuitive gesture can be understood as a gesture that can be perceived and interpreted immediately, without the need of any inference of reasoning. According to Wexelblat [1], to be intuitive, a gesture must be performed as naturally as possible. McNeill [2] explains that natural/spontaneous gestures have a core of meaning larger than gestures performed with restrictions, such as in the case of sign language, for example. In this way, a vocabulary of intuitive gestures cannot be restrictive, and should be conceived in a manner that maximizes their immediate execution by the users.

C. APPROACHES TO GESTURE ELICITATION The dynamic interplay between humans and robots stands as a pivotal inquiry in the realm of robotics. In this section, we explore several studies that delve into this inquiry by utilizing gestures as a means of communication interface.Human-Robot Interaction (HRI) falls within the purview of Human Machine Interaction (HMI) and Human Computer Interaction (HCI), wherein methodologies for eliciting gestures or other symbolic vocabularies for machine interaction have been proposed. For instance, a formal metric assessing the guessability and agreement of symbol vocabularies was introduced in a previous study. While these metrics contribute significantly to the elicitation of symbol vocabularies (where gestures can be construed as symbols for actions or commands), they solely rely on symbol frequencies. Notably, these studies overlook the elicitation process itself, which plays a pivotal role in determining the resulting vocabulary's quality. The involvement of end-users, as advocated in some studies, can enhance vocabulary quality, yet its impact on intuitiveness remains unaddressed. Nonetheless, numerous studies have employed guessability and agreement metrics for eliciting gestures or other symbolic interactions with machines.According to research, methods aimed at increasing the variety of elicited symbols may prove more advantageous for Gesture Elicitation Systems (GES), countering the legacy bias often observed in technical individuals.

The Production Principle is one such method, advocating for users to propose multiple interactions for each task, thereby fostering innovative techniques that surpass conventional approaches. However, this approach necessitates specific and non-standard instructions for each elicitation, potentially influencing the intuitiveness of gestures obtained. Open challenges in this domain include determining the minimum number of symbols participants should perform and how this affects their creativity, both of which directly impact the intuitiveness of the elicited vocabulary.Given the propensity of a Production Principle-based approach to gather numerous candidate gestures for each task, there arises a need for metrics based on scores and votes to differentiate these gestures, thereby facilitating their ranking for task representation.Nielsen et al. proposed a selection procedure based on learning rate, ergonomics, and intuition for gesture selection in HCI. While the authors underscored the significance of considering intuitiveness, the absence of psycholinguistics theory in their approach raises questions regarding the chosen vocabulary's intuitiveness.

D. VOCABULARY SELECTION After meticulously assessing the Intuitiveness Level (IL) of each gesture using our devised methodology, we compiled a set of gestures for each task. These gestures were organized in descending order of IL, as detailed in Table 3. Fig. 2 provides a visual representation of the resulting vocabulary, highlighting gestures with higher ILs selected for each task. In our study, we opted to include gestures with ILs surpassing 0.90 in the final vocabulary selection process. For example, the task "Ok" is depicted by two gestures, as showcased in Fig. 2, accompanied by their respective IDs from Table 3. It's important to note that if the gestures portrayed in Fig. 2 are executed using only one arm, they are considered equivalent regardless of the chosen arm.The Frustration-Based Approach (FBA) not only tackles the challenge of capturing multiple gestures from each volunteer without imposing a predetermined quantity but also embraces a user-centered methodology, which previous research has identified as most conducive to eliciting intuitive gestures. Additionally, by employing the Wizard of Oz (WoZ) approach, similar to numerous studies focused on command elicitation for interactions with computational devices and software interfaces, volunteers are prompted to perform gestures that best represent each task. These methodological aspects significantly contribute to the practical implementation of our approach and enhance the overall intuitiveness of the elicited gesture vocabulary. In experiment , there are four different shapes of workpieces including circle, star, square, and triangle. The radius of the circle object is 40 mm; the circumradius of the star object is 70 mm; the side length of the square object is 80 mm; the circumradius of the triangle object is 50 mm. Furthermore, steel plate housing included four holes corresponding to the above shapes of workpieces. The clearance between each hole and its corresponding object was less than 1 mm. Through the proposed interface or the four other compared interfaces [23]–[26], the operator guided the robots to manipulate the four workpieces and placed them into the holes. A 3-DOF force sensor was fixed on the EE of the robot. When the collision force between each workpiece and its corresponding hole exceeded a preset threshold value (2N), the robot would stop working, denoting that the placing workpieces task was failed. If the collision force was less than the threshold value, the force would be set as the feedback force to assist human operation.

III METHEDOLOGY:

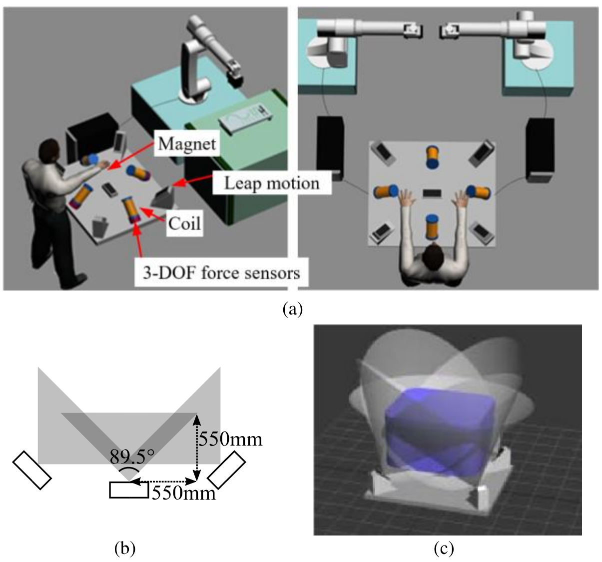

FIG. 1. SYSTEM STRUCTURE OF THE HUMAN–ROBOT INTERFACE. (A) DETAILS OF THE SYSTEM. (B) SECTIONAL VIEW OF THE CONE DETECTION SPACE FOR EACH LM. (C) THREEDIMENSIONAL WORKSPACE FROM FIVE LMS AND THE REGULAR WORKSPACE.

The methodologies aim to improve human-robot interaction (HRI) by focusing on intuitive gesture recognition and force feedback. The first methodology centers on selecting gestures and building a gesture vocabulary, while the second addresses hand position and orientation estimation using an Iterative Kalman Filter (IKF) and force feedback generation through a novel Biologically Inspired Learning System (BLS).In the first methodology, tasks relevant to gesture representation are chosen based on their importance to HRI. Gestural data is collected using a subconscious approach inspired by psycholinguistics, allowing volunteers to express intuitive gestures without conscious thought.

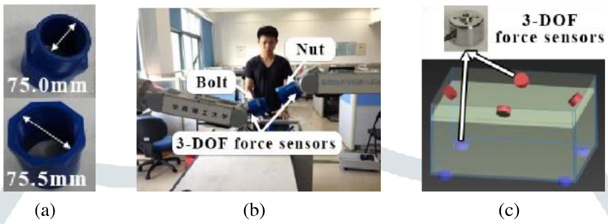

FIG. 2. EXPERIMENTAL ENVIRONMENT FOR SCREWING BOLT TASK(a) BOLT AND NUT. (b) SCREWING THE BOLT INTO NUT. (c) A BRIDGE GENERAL VIEW FOR THE PLATFORM WITH EIGHT 3-DOF FORCE SENSORS.

This approach, called the Frustration Based Approach (FBA), ensures spontaneity and intuitiveness in gesture selection. Recorded experiments are then analyzed to categorize gestures based on occurrence rates, using metrics like General Occurrence Rate (GOR), Volunteer Occurrence Rate (VOR), and Occurrence Rate by Time (ORT) to rank gestures. The Intuitiveness Level (IL) is subsequently calculated for each gesture, guiding the selection of the most intuitive ones for each task.In the second methodology, an IKF is utilized for precise position and orientation estimation of the operator's hand. The IKF incorporates data from LM sensors to estimate hand position and velocity in the world frame, reducing measurement errors. Orientation estimation is similarly achieved using another IKF, which integrates quaternion components and angular velocities for accurate hand orientation estimation. Force feedback is generated using a BLS, which learns from closed-loop control to estimate coil currents based on expected forces. The BLS utilizes a neural network structure and incremental learning to adapt to changing conditions and optimize force generation. Closed-loop force control ensures accurate force feedback by adjusting coil currents based on expected and measured forces.These methodologies offer holistic approaches to enhancing HRI through intuitive gesture recognition and force feedback. By leveraging advanced techniques in signal processing, estimation, and machine learning, these methodologies facilitate more natural and effective interaction between humans and robots. Moreover, the incorporation of innovative approaches like FBA and BLS demonstrates a commitment to progress and innovation in the realm of human-robot interaction.

IV. CONCLUSION

Recognizing the significance of interactive interfaces in making robotics more accessible and acknowledging the scarcity of studies prioritizing their intuitiveness, this paper presents a novel methodology grounded in psycholinguistics. The methodology is meticulously described to facilitate reproducibility and aims to yield an intuitive and resilient gesture vocabulary for human-robot interaction (HRI).Drawing on insights from psycholinguistics, which suggest that spontaneous gestures are inherently more intuitive, the proposed methodology entails conducting user-based subconscious experiments. It employs the Frustration Based Approach (FBA), introduced in this study, to elicit as many spontaneous gestures as possible from each volunteer. Additionally, the methodology introduces three occurrence rates that assess different facets of gesture intuitiveness, which are utilized to compute the Intuitiveness Level (IL) for each gesture. This IL serves as a scoring mechanism to rank gestures based on their intuitiveness, enabling the creation of a complex vocabulary where multiple gestures can be assigned to a single task, thereby enhancing robustness.The methodology allows for the acquisition of multiple gestures for each task, aligning with the 'Production Principle.' Furthermore, it provides an intuitiveness metric based on three sub-metrics, addressing an open problem in the field. Notably, the frustration-based approach eliminates the need to stipulate a specific number of gestures for the experiment, addressing another issue in the domain.

While the IL is calculated using an arithmetic average of the three metrics, future research could explore weighting these metrics differently to better reflect their relative importance. Additionally, conducting experiments in environments closer to real-world human-robot interaction scenarios could enhance contextualization and potentially stimulate volunteers to perform more gestures or eliminate those deemed less intuitive for such situations.In conclusion, the proposed methodology extends beyond HRI and can also be applied to Human-Machine Interaction (HMI). Further research and experimentation could refine and expand upon the methodology, contributing to the ongoing evolution of intuitive interaction interfaces.

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