Neuro-Robotic Technologies and Social Interactions

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ABSTRACT
The current bandwidth for understanding cognitive and emotional context of a person is much more limited between robots and humans than among humans. Advances in human sensing technologies over the past two decades hold promise for providing online and unique information sources that can lead to deeper insights into human cognitive and emotional state than are currently attainable. However, blind application of the human sensing technologies alone is not a solution. Here, we focus on the integration of neuroscience with robotic technologies for improving social interactions. We discuss the issue of uncertainty in human state detection and the need to develop approaches to estimate and integrate knowledge of that uncertainty. We illustrate this by discussing two application areas and the potential neuro-robotic technologies that could be developed within them.

Keywords
Neuroscience, robotics, human-robot interaction, artificial intelligence, confidence, design, reliability, human factors

1. THE CHALLENGE
A fundamental challenge for the field of robotics, and more specifically, human-robot interaction (HRI), is to effectively integrate robotic technologies into natural human social interactions. Here, we define effective integration as 1) humans considering the robotic technologies as a member of the social interaction and 2) the perceived quality of the interaction rising above mere execution of a prescribed set of tasks.

A significant barrier to effectively addressing the challenge posed by human-robot social integration is that robotic technologies are limited in capability to understand the cognitive and emotional context of humans. The primary issue underlying this barrier is that individuals' behavior within social settings cannot be reliably and robustly predicted online with any level of precision, even with substantial information regarding task and environmental context. Significant variability in humans has been demonstrated in many ways, from the nervous system through behavior, and this variability undermines precise prediction of individual instances of human decisions and action choices. For instance, it is well known that: different individuals vary widely in their capabilities, limitations, biases, and proclivities within a given situation; individual's decision processes and outcomes are variable across time and context; and individual's behavior can be significantly impacted by variations in physiological and psychological states. While models have been developed to predict behavior in specific scenarios and under particular constraints; they generally represent the average human behavior and only occasionally represent the variability found across the population. More to the point, the developmental background and cognitive-behavioral repertoire of an individual human, which make-up the cognitive and emotional context, are not sufficiently accounted for in any models. Consequently, the behavior of the specific individual in a given context cannot be reliably predicted. Thus if specific knowledge of an individuals' behavior within context is needed, but not reliably predictable, it becomes exceedingly difficult to integrate robotic technologies with humans in a social context.

2. HUMAN STATE DETECTION
Humans often face a similar issue in interactions with other humans. Individuals generally do not have a complete understanding of the background, knowledge, skills, and capabilities (i.e. the repertoire) of other individuals with whom they are interacting. To address this issue, humans integrate a wide variety of cues such as facial expressions, body posture and actions, vocal tone and inflections, with prior information to estimate cognitive and emotional context. While far from perfect, the human's wider information bandwidth and superior processing for such bodily and behavioral cues provide a clear contrast with robotic technologies in social situations.

The integration of neuroscience with robotic technologies provides an opportunity to both increase the human-robot information bandwidth and to provide robotic technologies with unique information sources that may ultimately provide advantages over human-human interactions. One opportunity is availed through the explosion in human sensing, and specifically real-world neuroimaging technologies, over the past two decades (e.g. see [1], [2]). These modern biotechnologies provide multi-aspect online information sources that enable inference of human cognitive and emotional state. However, sensing advancements offer only a partial solution in that they must be combined with computational and data mining approaches that leverage research advances towards understanding interactions between psychological, physiological, and behavioral variables that represent human state. For example, using such approaches in controlled laboratory settings, researchers have demonstrated advances in automation that adapt the human-robot relationship based on the workload of the operator [3]. Concomitantly, technology also increasingly progresses toward providing detailed on- and off-line inference while humans performs complex tasks in progressively less constrained environments than are typically seen in laboratories [4], [5].

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While the recent progress has been impressive, modern sensing and state estimation technologies remain unable to provide strong real-world demonstrations applicable to HRI in natural human social interactions. One of the limitations in current technology is its robustness and reliability. Quite simply, technologies have focused on providing estimates of behavior and state but rarely provide any indication of the uncertainty in those estimates. However, this limitation can be overcome; as illustrated by recent advances in brain-computer interaction (BCI) technologies, which have leveraged uncertainty estimates for cognitive variables and integrated that information to improve system design [6], [7].

The use of state sensing techniques in autonomous driving technologies offers an exemplar domain within which increased human-robot information bandwidth can play an important role. Real-time sensing and advanced state inference can enable adaptation of human-autonomy system responses to account for a wide variety of human states. For example, the content and timing of warnings, cautions, and alerts can be manipulated online based on estimated capabilities of the operator. Even implementation of operator state estimation alone can enable inference of changes in emotion, stress, fatigue, and inattention (among others) that then may serve as valuable information for integration into vehicle control decisions, e.g., collision avoidance systems that adapt when drivers are fatigued or inattentive. From a broader social interaction perspective, these technologies create an opportunity for communication across vehicles, both human-driven and autonomy-driven, as well as non-vehicle agents in a broader traffic management infrastructure. Street-legal vehicles are already required to have indirect indicators; such as brake and hazard lights, and observation of their use can betray the state of the operator inside to a small degree (e.g. rapid brake light cycling may indicate an uncertain, fatigued, or otherwise compromised driver). These types of indicators serve as a form of vehicle-to-human communication that can warn drivers of other vehicles to beware when approaching. It is reasonable to consider that, with adequate operator state sensing, generalized warning indicators (e.g. automatic triggering of the hazard lights) could be created to enable external alerts when the operator is compromised. Such information could be propagated through local vehicle networks to, for instance, warn of an increased risk in the vicinity without necessarily betraying the identity of the specific vehicle or vehicles of concern. These scenarios portray a potentially unique social integration wherein the neurotechnologies for sensing the human are highly integrated with the robotic technologies, creating human-robotic vehicles that form a basic unit of the social interaction.

3. SHARED SEMANTIC LEXICON

The application of advancements in BCI technologies to human-robot communications offers additional opportunities for disambiguating communicative signals sent by a human to a robot. One example of this is use of a BCI to improve human-robot communication by improving the mutual understanding of concepts between a robot and a human. For instance, the same language can lead to different intent depending on the communicator's context. Two advancements show promise in addressing this challenge. First, the increasing use of exemplar-based learning systems for machine vision and robotics suggest that the incorporation of image-based communications may increase efficiency in human-robot communications. Second, some BCI technologies have been developed to extremely rapidly label images based on high-level semantic content and context, and then extrapolate class membership and then propagate those labels to a larger set of examples in a database [6]. By combining these advancements, it may be possible to rapidly label a set of images that a human user associates with a high-level semantic concept using a BCI, and then use those images as a database to train a computer vision system to recognize images that represent that user's understanding of this high-level semantic concept. This trained model would then represent an "image-based shared understanding" of the specific semantic concepts desired.

By placing a dictionary of these image-based semantic models on a robot, a shared, context-specific understanding may be created, which could be used to disambiguate and interpret operator intent, thereby improving communication between the human and the robot. These semantic concepts could be trained for different human cognitive and emotional contexts, as well as environmental or task-specific contexts. In the longer term, these technologies, when coupled with the concepts of pervasive intelligence, could provide capabilities for broader social interaction. When humans communicate in non-face-to-face modalities, they lose access to nonverbal communication, thus increasing the possibility of misunderstandings caused by communicative ambiguity. By providing individual 'communication agents' with shared semantic understandings coupled to environmental, task, affective, and cognitive state, these technologies could create a mechanism for identifying ambiguities that cause misunderstandings in non-face-to-face human-human interaction.

4. REFERENCES

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