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Detecting Emerging Challenges in Social Sidewalk Navigation

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Abstract
When mobile urban robots will share the sidewalk with people, the resulting interactions can cause unexpected undesirable outcomes to emerge – from people running away scared to people deliberately teasing and harassing such systems. How can we design such AI systems to aptly handle the unexpected? Directly anticipating and/or detecting these kinds of situations will inherently be unreliable; they are unexpected, after all. And yet, there exists a very clear signal for social slip-ups: the emotional response of people. We thus argue that such systems need to be imbued with a capacity to interpret the socio-emotional reactions to their own behavior.

Author Keywords
Urban Robotics; Social Navigation; Social Signal Processing; Emergent Behavior

CCS Concepts
•**Computing methodologies** → *Cognitive robotics;* •**Human-centered computing** → **Interaction design theory, concepts and paradigms;**

Introduction
Social Sidewalk Navigation will be fundamental to the success of the upcoming field of Urban Robotics. Companies and municipalities are more and more putting robots in ur-

ban environments, to fulfil functions ranging from last-mile delivery to garbage collection and from handing out flyers to guiding people. For the most, people seem quite willing to accept such robots and share the sidewalk with them: "once we put one of the robots out there onto the sidewalk, [...] the vast majority of the public didn't pay any attention whatsoever to the robots, even those seeing it for the first time" [7].

And yet, introducing such systems into the 'wild' also causes wildly unexpected reactions from people to emerge, which can have undesirable and unanticipated consequences (**emerging challenges**). Consider, for example, wheelchair users getting stuck on the street because robots occupy the curb[1]. Or what to think of the robot handing out flyers being harassed and assaulted by children [3] and other cases of robots being bullied in the wild [4]?

This raises the question: *How can we design the social AI for such urban robotics to ably handle such emerging challenges?*

We can't reliably avoid these challenges, because they are unknown upfront. While it will often be possible to patch them after they become apparent, such a patch will necessarily be applied only *after* the problem has arisen the first time. In addition, this may require an unfeasible amount of patches, given the complex and ever-changing dynamics of our social interaction; patches may not even be compatible with each other.

Even detecting when a system runs into such a challenge will be difficult, because of their unanticipated nature – how can we train a system to detect something unexpected?

[1] An account of one person, Twitter user Emily E. Ackerman, experiencing this, can be found on twitter.com/EmilyEAckerman/status/1186363305851576321

We argue that the only way to detect when such social problems emerge will thus be from the socio-emotional reactions of the people involved. It *is* impossible to reliably detect or predict when an urban robot will make mistakes, but it may be doable to detect when people are upset with you (**detecting emerging challenges**).

Patching in Socially Aware Navigation

There is an extensive body of work on Socially Aware Navigation, which has been successfully deployed in urban robotics and beyond; many approaches aim to navigate such that the system avoids getting closer to people than certain set distances (derived from notions of personal space, such as Hall's proxemics [11] and others [14]).

As with any set of rules, these approaches always run into exceptional situations not sufficiently covered by the rules. For example, in earlier work, a failure to properly predict human motion could result in erratic paths being executed [9] and the aforementioned case of a robot blocking someone in a wheelchair on the street. To further complicate this, people will often actively respond to the navigation behavior of such systems (e.g. [13, 10, 12]), which can make it even harder to anticipate what interactions will emerge.

To some extent, these exceptional situations can of course be 'patched' by updating the software after they arise and are picked up by the responsible engineers and designers. This is what happened to resolve most of the problems mentioned above: for example, the robot bullied by children was patched to seek the safety of their parents [3] and the robot with the erratic paths was patched to slow down when needed [9]. Of course there is a limit to how many such band-aids can be used; some patches will cause new problems, and some situations will have conflicting needs in terms of the patches that apply. In other words, a more fundamental solution is needed, ideally one that would allow for a solution to be found on the spot.

Detecting Socio-Emotional Reactions to Behavior

Human emotion is expressed through – and can thus be detected from – a wide range of social signals and cues [15], including facial expressions, verbal cues, body language [6], and gait/trajectories [5]. These latter two are most applicable to the context of social sidewalk navigation, because of their relative robustness against occlusions, effectiveness at a longer range, and because they require less privacy-sensitive information to function.

Recent work has attempted to take such socio-emotional reactions into account in social navigation, e.g. by assuming that negative emotions are caused by a robot violating peoples' comfort zones [2, 1], or that robots should give pedestrians more personal space when negative emotions are detected [8].

Though these approaches work well in their context, they still leave a lot of the expressivity of such socio-emotional reactions untapped. Other aspects of robot behavior, such as movement speed or obstructing a pedestrian's path, could also trigger negative emotions result in unexpected human responses. To tackle emerging challenges, a mobile robot should not only detect whether the negative emotion is caused by its own behavior [16] but also distinguish which aspect of its behavior is the cause, be it its speed, its distance to the pedestrian, its approaching angle, or another aspect.

Towards Responsive Social Sidewalk Navigation

Mobile robots navigating in urban environments will have to cope with emerging interactions and the unexpected challenges that can arise from them. This means that, as argued above, in order to respond appropriately, such systems will need to detect the socio-emotional reactions of pedestrians to their own behavior. We briefly discussed recent advances in social signal processing that suggest that such detections may soon be within reach.

Though these kinds of detections will thus be a necessary starting point, even with them it will still be a (design) challenge to handle emerging challenges appropriately. One approach would be to include a human operator in the loop, who can assume manual control when the system detects it is causing a negative reaction in nearby pedestrians. An alternative would be to have the system try to resolve the socio-emotional reaction autonomously, e.g. by using it as feedback for an online reinforcement learning system that tries to find/learn the appropriate behaviour.

Beyond urban robotics, these arguments may well also apply to the broader topic of urban AI. While the physicality of robotics gives a more direct urgency to responding to people's socio-emotional reactions, other systems may well benefit from a capacity to properly handle socio-emotional reactions.

And then, maybe, one day, if we are offended or otherwise inconvenienced by that robot in our city, it can detect that socio-emotional reaction and thus respond in a more understanding way.

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