Towards Social Robotics on Smartphones with Simple XYZV Sensor Feedback

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Abstract: Social Robotics normally assumes visual feedback between robotic trainees and human trainers. Given that robots rarely have adequate visual perception/recognition, such systems are noisy and prone to judgment errors. One way to resolve this problem is to simplify the communication channel between humans and robots. This paper uses simple gravity+motion XYZV sensors ubiquitous in modern personal devices – smartphones in particular – to power gait-based exo-systems (power leg assist, etc). This paper discusses current work in progress on this topic, specifically (1) gait modeling and recognition of kick-in moments for hardware, (2) use of the XYZV channel in both directions, allowing humans to send feedback in realtime, (3) social robotics constructs and methods that support maximum flexibility in applications of the otherwise traditionally narrow-purpose hardware systems.

Keywords: social robotics, accelerometer, G-sensor, smartphone sensors, reinforcement learning, smart robotics

1. On the Concept of Social Robotics

Proper terminology has to be established early in this paper to avoid missing the correct context for the term *social robotics*. In some contexts, this term refers to *social robots* which represent conventional robots but places in social context and therefore having to interact with humans in a *human*-like manner. For example, there is research on robots behaving like humans [3] and robots that attempt to interact with humans in socially acceptable way [4]. The boundaries of this kind of robotics are somewhat blurred but we are mostly talking about robots which are trying to pose themselves as humans in human-robot interactions. Another major distinction of this area is that social likeness in this case is completely artificial while the internals of the robots themselves remains conventional.

The term accepted by this paper is different in nature. The difference is properly explained in [5] which explains both kinds of *social robotics* without focusing on the either kind. An even better taxonomy can be found in [6]. The term accepted by this paper refers to a **new kind of learning** rather than to the *mode of interaction*. In fact, this paper will argue that non-social and non-traditional forms of Human-Robot Interaction (HRI) are better since they carry less noise. They key, however, is in the learning part, where *social robots* are expected to have:

- a bare minimum of fixed programming, sufficient to support dynamic learning via HRI;
- learn the various skills via HRI without any prior knowledge of the tasks they are supposed to accomplish.

The *intended* concept of social robotics is rare in recent literature but is a recognized research subject nevertheless. Inferring guidance from human feedback is studied in [10]. An interesting viewpoint of reducing the complexity of the decision space via HRI is studied in [11]. Finally, a wide range of topics from the conceptual designs to practical implementations of guidance mechanisms are considered in [12][13].

This research area remains incomplete. One of the major missing parts is the link between *social robotics* in its traditional hardware environment and *software automation*. An earlier study by this author discusses this very issue as part of software automation of *context management* [1]. Another recent study in [2] proposes a human-robot learning process in MultiDimensional Classification (MDC) which builds on top of the context management basics but also proposes the larger framework of a learning engine based largely on HRI. The method in *myt.metromaps.bayas* is the first known case of the concept of social robotics implemented in software automation settings.

Table 1 compares hardware and software forms of social robotics. The main differences are as follows. First, while Reinforcement Learning (RL) is common for hardware robots, software robots make more sense as Classifiers – the case of Multi-Dimensional Classifier (MDC) in [2] in most practical settings. This border, however, can grow thinner in the future as software automation becomes more commonplace – one particular area of

Table 1 Comparison of features between *social robotics* and *software automation*.

	Generic Use	Teaching, Guidance	Reasoning	Human Role
Hardware Robots	Wide range of behavior	Reinforcement Learning	YES. Vision, recognition	Guide only
Software Automation	Any kind of context	Bayesian Classification	NO Not needed	Guide and decision - maker

Potential for simplification

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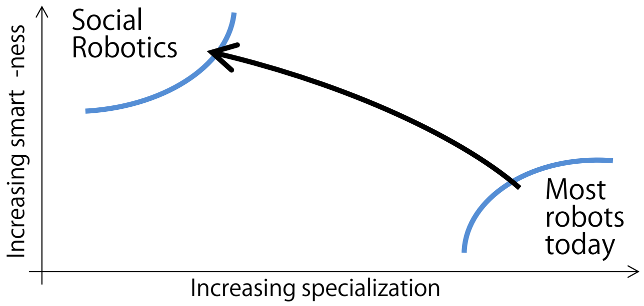

Fig. 1 The goal of the research on social robotics.

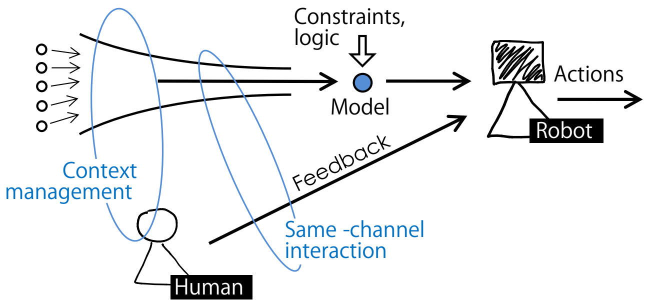

Fig. 2 The model of input channels for sensor data and human feedback. The ultimate simplification is when the same single channel is used both for sensor input and human feedback.

applicability here is BigData analysis. Secondly, reasoning is common only for hardware robots while software has a clearly defined objective. This is a problem for hardware robots because *visual recognition* is traditionally difficult to do reliably. This paper argues that simplifying HRI in such a way that vision would become unnecessary will help create a generation of highly reliable hardware robots in the future. Finally, *guidance itself* is different between the areas as humans in software automation need to both provide guidance and make decisions. Partially, decisions are absent from the harware case because of the reasoning. Here, the tradeoff between reasoning and decision-making is obvious – the less reasoning on the part of the robot requires more decision making on the part of human operators.

The *simplification* in Table 1, besides lowing the reliance on visual recognition and the related reasoning, can also benefit from minimizing the number of input channels. This paper argues that a single XYZV channel is sufficient for most human-based motion robotics. **XYZV** channel is defined as the mixture of gravity and acceleration sensor inputs available on most smartphones today.

The scope of this paper is limited to smartphone-based robotics and, to remain realistic, assumes only the presents of XYZV channel. To make social robotics work in these settings, the same XYZV channel has to be used for human feedback. This paper defines two models for natural HRI interaction of such type while the larger objective is for the smartphone-based robot to monitor and react to human gait. The specific reaction in this paper is to the *upward step* while walking up the stairs.

2. Towards Smart Robots

A good review of practical robots can be found in [7]. It includes many popular models like HAL but also discusses input channels and designs for many other kind and shapes of robots. HAL specifically – as a representative robot in Japan – is specifically interesting as it is a perfect illustration of both the current state of robotics and the objectives/expectations for social robotics.

Fig.1 is the visual representation of this statement. Most existing hardware robots – including HAL – are extremely specialized. HAL itself is cannot be used outside of the physical form it was created for because of its input channels. The core design feature in HAL is that it depends on two main input channels: (1) *bioelectricity* which measures impulses in muscle tissue just before the muscle contracts, and (2) the sensor on the bottom of the foot used to measure the so-called *floor reaction* – in plain words, when the person transfers the weight on its foot. These channels support very reliable decisions because HAL always knows which leg a person has the weight on and which mussle is about to contract. Together with several logical constraints at the level of *let us not move both legs at the same time*, the decisions are extremely reliable in practice. Note that the high reliabilty is achieved by an extremely specialized design that depends on irreplaceable/unchangeable sensor inputs, their relative positions (angle modeling), etc. For descriptions of decision function implemented in the original HAL and its recent back-support version see [9][9], respectively.

In this context, the research objective in this paper is to take robotics from the lower-right corner of Fig.1 to the upper-left corner by making possible a new generation of robots with (1) *flexible sensor inputs* and (2) *generic purpose*. In plain words, the objective is to facilitate evolution from *dumb specific* robots to *smart generic* ones.

A crucial element in making this evolution possible in practice is *context management*. This part is missing from existing research on social robotics. In fact, most robots discussed in current literature are somewhat narrow-purpose and thus violate the objective in Fig.1. This gap is due to the fact that generic approach to context management is not well understood today. The method in [1] uses metromaps for both visualization and representation of knowledge/context in any given system. While this author argues that metromaps can provide sufficient generic support for social robotics, this claim needs more support by future research results.

In the meantime, this paper makes several steps towards implementing the objective in Fig.1 in practice. While the robot further in this paper detects steps (human gait), the HRI part of the method is generic and can be applied to any kind of smartphone robotics, provided it can be implemented based on the XYZV sensor input.

3. On Input and Feedback Channels

Fig.2 shows the generic model of robots in the social robotics context. The novel feature is the presence of human feedback which provides guidance to robot at runtime. The features of this model are as follows.

Sensor Input is expected to be as generic as possible but allows for multiple sources. In fact, even the XYZV channel is complex and consists of four independent components – hence

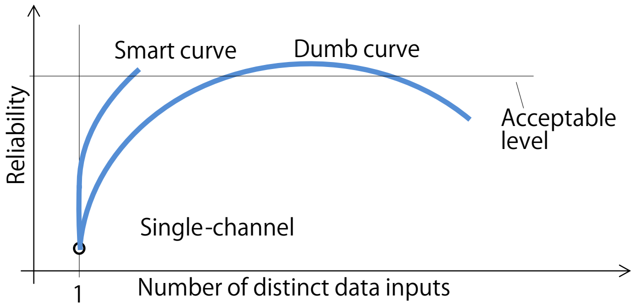

Fig. 3 A model representing reliability of robotic decisions represented in *dumb* versus *smart* (social) curves.

the name. In case of HAL, inputs are not only multi-component but also have multiple physical natures – bioelectricity, pressure sensor, etc. Regardless of the number of distinct inputs, the robot normally needs to make a simple decision. Again, in case of HAL the decision is when to start its leg assist system. This is a bit overly simplistic as HAL makes the binary decision once but then implements the *step cycle* which is implemented as a sequence of power levels fed to the hardware in such a way that the step is performed in a humanly compatible manner. Note here, that even HAL does not use a personal provide here but rather implements a generic step. However, even with these details, the most important part is the binary decision of when to start a given action.

Human Guidance is a communication channel between human and robot. The channel normally works in one direction as it is only necessary for humans to supply feedback to robots, and never the other way around. Physical channel can be anything. For example, in current literature, robots use vision (cameras in eyes) to monitor and detect gestures from human instructors. This paper discusses much more reliable gestures delivered over the XYZV channel.

Same Channel Interaction is an important objective for smartphone-based robotics. This idea demands that the same channel is used both for sensory input and human guidance. Note that this is already part of existing social robots which get feedback via the same cameras they use for motion control.

Context Management is the part which is given very little attention in existing literature. Given that decision space grows considerably for generic robots, context switching performed manually by humans can help reduce this complexity. This is the same problem tackled in software automation **?**. For now, humans are expected to change the context manually, while automatic switching can be considered in the future. A practical example of this problem can be in form of making out the contextual difference between *walking up* versus *down the stairs*. Existing robots are normally unable to make this distinction automatically.

Fig.3 is another representation of the research objective. The *dumb curve* represents traditional (non-social) robotics where reliability of robotic decisions are ensured via increasing the number of sensory inputs at the expense of increasing specificity. The dumb curve suffers from the *dimentiality curse*, where too much sensory data can have a negative effect on reliability.

In case of the *smart curve*, social robotics are expected to boost the reliability of decisions even for few – ideally only one – sensory inputs. Note that the simple one-channel robots such as those based on the smartphone may not achieve the industrial level of reliability, in which case it may take 2 or 3 channels before the curve goes over the threshold. However, even in this case, it is expected that both the combination and physical nature of the input are kept generic.

4. Experiments on the XYZV Channel in Smartphones

The concept of social robotics explained earlier in this paper has been tested on a commodity smartphone using the easily available sensor inputs, namely the *XYZ* input from the gravity sensor and *V* component from the acceleration sensor, making the *XYZV* input for short. Note that it is possible to connect various other sensors to a commodity smartphone to improve its sensory capability, but this paper only considers the simples hardware available to everyone by default.

Gait recognition using smartphones is a well-known research subject, with several reliable models found in existing literature. This paper implements one such method in order to detect *steps* in the *up-the-staircase* form, i.e. it is expected that the terminating point of an arc drawn by the foot is higher than the starting point. The results further in this paper show that detection was far from perfect which hints at a less than perfect implementation, but the main target of this paper is to establish a feasible HRI channel which the results for which were much better.

HRI was implemented as follows. The smartphone is attached to the foot where it monitors the gait continuously. Once the robot detects an *upward step*, it announces its decision by *vibrating*. Vibration is easily available to smartphone apps and is also natural to humans – many apps notify various events via vibration on modern smartphones. Note that vibration here replaces the need for an actual exoskeleton which was not available in these experiments. In future work, vibration will be replaced with physical actions performed by wearable hardware.

Human feedback is also expected to be as natural as possible to humans. Since it is restricted to the XYZV channel by design, the gestures can only delivered via physical interaction between humans and smartphones. The following two gestures were implemented:

Stroke Model is when human operator *hits the phone* as a penalty for a wrong robotic decision.

Jerk Model is when human operator shakes/jerks its foot in response to a wrong robotic decision. In the natural terms, this is the equivalent of a mis-behaving (too numb or cold) leg/foot, which one shakes in order to get it to work normally.

The obvious first technical problem with the above two models is that they are both *punishments* for wrong decisions. This is a major shortcoming of this method. But future work will attempt to improve in this area by introducing *encouraging* gestures. However, this might be a difficult task since it is natural to humans to apply greater force as punishment for bad behavior while encouragements are normally comparatively tender. Also note that positive feedback is not a requirement since the robot can learn from negative feedback only, theoretically.

Fig.4 shows example episodes for each of the two models.

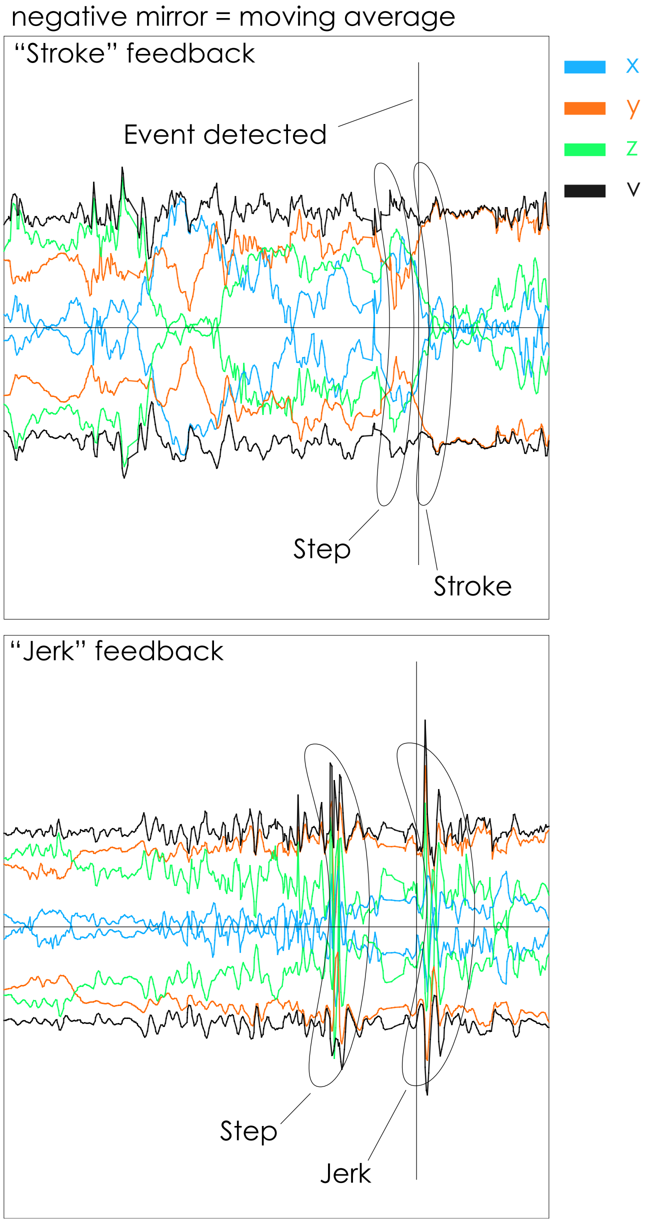

Fig. 4 Episodes of *step detection* followed by either *stroke* or *shake* feedback from the human operator.

Both are the cases when *(1)* the step was detected wrongly – that is, the robot detected an ascending step when the step was actually horizontal and *(2)* human operator reacted to the wrong decision via one of the two implemented gestures. The gesture in both episodes was successfully detected by the robot. Note that the announcement of the detection is delayed between 0.5 and 1s due to the delay in software that is required to call the system library for the vibration function. The same rule applies for all robots including HAL – the latter is at advantage only because it uses bioelectricity and can detect signals that happen before a physical actions is performed by muscle tissue.

The overall results for over 100 experiments was as follows. About 60% False Positives (FPs) and 30% False Negatives (FN) (TP is therefore 70%) were detected which means the part of software responsible for the detection of the step itself has major faults. However, for all FPs, the detection rate of the guidance gesture following within 0-3 seconds from the vibration was found at 90% which is a good result. The high detection rate owes to the fact that the search for the gesture is limited to the 0-3s interval from the vibration, which is a major positive effect on performance.

5. Conclusion

This paper makes the first attempt to implement the concept of social robotics on smartphone-based robots. Since the commodity smartphones only have access to the XYZV sensor input, the system was designed to use the same XYZV channel for both sensor input and human guidance. The guidance itself was implemented as actions that human operations can find natural – the operator would either hit/stroke the smartphone or shake/jerk it to convey the displeasement with the decision made by the robot. This represents although a simple but nevertheless a valid feedback that can be used to train the robot using the Reinforcement Learning (RL) technique.

This paper is the first step towards the objectives explained in this paper. The next study will propose an implement a flexible learning engine based on the simple RL technique (negative feedback) shown in this paper. The key to the full technology is its flexibility which can only be made possible with effective generation and management of context.

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