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Industrial Human-Robot Collaboration

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Abstract

In the future, robots are envisioned to work side by side with humans in dynamic environments both in manufacturing and in societal contexts like health care, education, and commerce. Before this vision can be realized, robots must be socially accepted. Acceptance will have to be build through improvements in robot adaptability and through a gradual introduction, where robots learn on the job. It is our conviction that this can be achieved through a combination of human-robot interaction, multimodal signal processing and AI techniques. We seek to prove this in real world applications. We discuss how we intend to utilize end-users in the continuous training and refinement of AIs and we highlight some of the challenges involved in building collaborative production cells.

1 Introduction

The premise for Human-Robot Collaboration (HRC) in the workplace and in contexts like health or elder care, education, commerce, is that robots are envisioned to work side by side with humans in highly dynamic environments. The next step for industrial robotics is going to be robots and humans operating side-by-side in close collaborative relationship [Hayes and Scassellati, 2013]. Collaborative production offers a "dream combination" of machine efficiency and human flexibility [Tan *et al.*, 2009]. A lot of the processes that are still handled by human hands cannot realistically be fully automated, at least not in the near term. However, in many cases the physically straining and repetitive tasks could be handled by a robot, leaving the more intricate tasks to human workers. For other processes, full automation seems to be within reach, but most intelligent system will not always perform reliably. Improving performance and covering edge cases during development is inherently expensive. Our own experience has proven how difficult it can be to achieve the wanted performance for autonomous systems that must deal with significant biological variation. To speed up development we want to rely on the existing workforce for supervising and assisting in the training and refinement of future intelligent systems.

2 Collaboration Between Humans and Robots

Our initial focus is on one-to-one collaboration where one human worker interacts with a single robot. In reality, we envision that we will see all the following combinations of interactions:

- One-to-one: The robot is unable to perform all aspects of a task or has not learned to reliably perform a task. The human coworker performs the tasks the robot is unable to do and/or provide guidance for robot learning.
- One-to-many: The robots are able to perform the task autonomously. The human takes on a supervisor role, only interacting with the robots in case a problem arise.
- Many-to-one/many: Training of human coworkers in human-robot collaboration. Tasks that require multiple people and robots.

2.1 Challenges in Human-Robot Collaboration

Achieving close and effective human-robot collaboration is no easy task and many challenges have yet to be overcome [Chandrasekaran and Conrad, 2015; Hayes and Scassellati, 2013; Bauer *et al.*, 2008]. A particular challenge from an Human-Robot Interaction (HRI) perspective is the complex multimodal interplay of different interaction partners with asymmetric communication capabilities and preferences. This creates the need of a multilevel coordination between interaction partners for realizing successful interactions: (i) Coordination on a communicative level: e.g. turn taking, non-verbal alignment [Admoni *et al.*, 2016; St. Clair and Mataric, 2015; Jung *et al.*, 2013]; (ii) Coordination on a physical level: e.g. movements, trajectories, tools [Maeda *et al.*, 2017; Iqbal and Riek, 2016; Karami *et al.*, 2010]; Coordination on a social level: e.g. group dynamics, emotions [Medina *et al.*, 2017; Keebler *et al.*, 2012; Scheutz *et al.*, 2006]; Coordination on a task level: e.g. task interpretation, task efficiency, task reasoning [Li *et al.*, 2017; Nikolaidis *et al.*, 2017; Fiore *et al.*, 2016; Bagosi *et al.*, 2016].

All of these coordination tasks require a high degree of contextual and situational adaptability and thus a tight coupling of multimodal signals and AI techniques for signal interpretation, behavior generation, and learning. Solving these coordination tasks will advance HRC to a level, where actual collaboration is possible between user and robot and will naturally lead to pro-active instead of reactive robots.

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3 A Need for AI

Successfully building robots that can perform tasks with significant variation and complexity, while collaborating with humans will require the use of state-of-the-art methods from HRI, robotics, and machine learning. With the increased availability of sensing technology and advances in machine learning, more data and new methods are now available for renewed automation efforts. High complexity and a need for continued refinement makes conventional programming of control and decision software impractical. We think it is necessary to extensively employ machine learning methods for continuing the expansion of the uses for robots. We have a long way to go and from experience knows that systems relying on machine learning techniques can be significantly challenged when faced with reality. The training of AIs should not end the day it is deployed. The AI systems must be able to continuously adapt and improve while in use. This is necessary because the environment changes, the product changes and the coworkers changes.

3.1 Machine Learning and Feedback

The training of AI agents requires feedback. The amount and type of feedback that is available depends on the task. Feedback can be categorized as either; evaluation, e.g. good/bad and numerical rewards, or as correction, which typically comes in the form of annotations, correct answers and demonstrations [Cuayáhuitl *et al.*, 2013]. Furthermore, feedback can either be directed towards the past, which is what is most widely use, or towards the future, where it can be seen as guidance [Thomaz *et al.*, 2006]. The often sparse and weak signal from evaluation type feedback is used with reinforcement learning methods, while the more direct correction type feedback can be used with supervised learning methods.

3.2 Transfer of Knowledge and Skills to Robots

The way AIs are trained to solve complex tasks is through either self-exploration or expert feedback or a combination. Training AIs to solve most real world tasks using only self-exploration and sparse feedback does not seem to be a possibility. A solution may be to incorporate expert demonstrations and thus circumvent much of the need for exploration encountered with standard RL. By using both demonstrations and typical RL exploration, the need for carefully engineered rewards can be reduced. The combination of the two also allows the agent to keep improving on the demonstrations that where presented to it [Večerík *et al.*, 2017]. Combining Hindsight Experience Replay [Andrychowicz *et al.*, 2017] and demonstrations has been shown to produce impressive results in a block stacking task where rewards are relatively sparse [Nair *et al.*, 2017]. Expert behaviour can be modelled using generative adversarial networks, where a generator network is trained to produce behaviour that is indistinguishable from the expert [Ho and Ermon, 2016]. Even sparse human feedback providing only a weak yes/no signal, has been shown to provide sufficient signal for a RL algorithm to learn complex behaviour [Christiano *et al.*, 2017].

Robots should be able to learn on the job from people without expertise in ML. The training of AIs should move around the exploration-guidance spectrum to leverage human knowledge when available as well as do exploration and learning on its own. Furthermore, the training interaction can either be lead by the machine, as is the case with active learning where the machine learning algorithm queries the teacher, or it could be a human lead interaction ruled by how and what the human trainer wants to teach [Thomaz *et al.*, 2006].

4 Human Robot Collaboration in the Slaughterhouse

We will use the remainder of the paper to present some examples from our work in relation to human robot collaboration in a very distinct kind of industrial production, which has some unique challenges. The slaughtering of animals differs from most other manufacturing in being a disassembly process where products with natural variation in size and composition must be deconstructed into the products that customers demand. Automation in slaughterhouses is characterized by specialized machines that rely on simple measurements. The low hanging fruits have long since been harvested. What remains are tasks where automation has failed to compete with the flexibility and dexterity of human workers. For an overview of the major developments in meat industry since the 1950s look to [Kristensen *et al.*, 2014].

4.1 Cell Production

Current meat production follows a classical production line paradigm and focus has largely been on increasing throughput. However, as the limits of the people and machines along the lines are reached this path to improving competitiveness becomes less attractive. Running a production line at very high speeds increases the risk and impact of breakdowns as well as the workers' risk of developing musculoskeletal disorders. In our opinion, the way forward is to transition to a cell based production paradigm where the focus is on flexibility and quality. Cell production where the efficiency of machines is combined with the flexibility of human workers is the potential solution to rapidly changing marked requirements and the demand for small made-to-order series [Tan *et al.*, 2009]. The idea of cell production in slaughterhouses is currently gaining traction through research projects such as the Norwegian "Meat 2.0" project [Animalia, 2018] and the Danish "Augmented Cellular Meat Production" project [Danish Technological Institute, 2018].

4.2 Demonstration Processes

We are focusing on transforming three slaughterhouses processes into collaborative production cells. Each process will require extensive collaboration between human and robot coworkers.

Process 1: Picking unwanted elements

We want to assist human quality control workers by augmenting their vision with information from an x-ray machine. This will help identify and remove unwanted elements such as pieces of bone that may exist on or below the surface of the product. Simultaneously, we want to relieve workers by introducing a coworker robot for performing the pick-and-place task along side and supervised by the workers.

Process 2: Processing pork bellies

The processing of pork bellies includes heavy lifting, fine motor skill and requires extensive experience to perform well. Pork bellies must be cut and trimmed to a customer given specification. The most challenging task involves determining how deep to trim the layer of fat, which must be left with a specified thickness. Again we want to augment the senses the human worker. Information from a computed tomography scan of the product will be used to produce a visualization showing the butcher where and how much to trim. A robot will take over the straining task of manipulating the meat such that the butcher can work on every surface of the product. To improve efficiency and ergonomics the robot must take into account the butcher's preferences for the presentation of the product.

Process 3: Multi-functional robot cell

A range of processes can be automated to a large degree. However, because of natural variation or because of the occasional mistakes made in prior processes, the automation is bound to encounter cases that are outside of its capabilities. For these types of processes we envision collaborative production cells where robots execute a pool of tasks such as; tenderloin extraction, cutting of toes and ears, and removal of the head. In problematic cases the robots must allow a human supervisor to guide the robot to a solution or manually perform the operation. Perception has proven to be the main challenge for many of these tasks. In these cases the human supervisor can provide real time annotations.

5 Virtual + Physical Robot Cell

We are building a physical robot cell and a virtual twin to facilitate the development and evaluation learning methods. The virtual twin will allow for the collection of feedback and demonstrations, by means of e.g. kinesthetic teaching, through virtual reality. Figure 1 shows an overview of the system.

Figure 1: (Left) Virtual cell, (Right) Physical cell.

For experimentation in HRC we are building a realistic slaughterhouse simulation where participants can interact with virtual meat, robots and tools. See Figure 2.

Figure 2: Human-robot collaboration simulator.

6 Conclusion

In this position paper we have discussed the value of using end-users in the training of robots. We have highlighted some focus areas from our research on Human-Robot Collaboration. Specifically, the requirement for dynamic and flexible coordination between human and robot on several interaction layers (communicative, physical, social, task). We have given some examples of our work in an industry context, where we will rely on AIs for controlling robots in collaborative cells.

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