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Computational ethology-based human behaviour modelling: First investigation for Human-Robot Collaboration

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Abstract

Human-Robot Collaboration (HRC) has been proposed to add flexibility to traditional production systems. Digital Twin (DT) has been integrated with HRC for safety collaboration. The human behaviour model is an essential part of the DT. This paper aims to identify a research gap and possible solutions for human behaviour modelling in HRC. Therefore, this paper reviews human behaviour studies in HRC and ethology. The results show that the current HRC focuses on recognizing and monitoring human behaviour, but a deep analysis of human behaviour is still lacking. Computational Ethology (CE) has the potential to be applied to HRC to model human behaviour in a structured manner. Future work could focus on transferring knowledge from CE and designing robot control strategies for HRC safety.

Keywords: Human behaviour modelling; Human-Robot Collaboration; Computational Ethology; Digital Twin

1. Introduction

There has been increasing demand for personalized and individualized products. This requires production systems to produce small batches and various products [1]. However, the traditional production systems are designed for large batches and standardized products, thus it is rigid and has difficulties fulfilling the requirements [2]. Therefore, the production systems should be adapted to be flexible and reconfigurable.

The human-robot collaboration has been introduced to make the production system flexible. In traditional production systems, robots can work continuously but focus on repetitive activities. Hence, robots are efficient but less flexible [3]. In contrast, humans have dexterity and creativity and thus can solve problems or finish complex tasks in dynamic production environments [4]. However, humans are prone to fatigue from repetitive activities and might be less efficient than robots. Therefore, the HRC has been proposed to combine the flexibility of humans and the efficiency of robots.

The primary concern of HRC is human safety [3]. Humans and robots might have unexpected, potential and harmful collisions during collaboration [5]. Collisions can injure humans thus interrupting the production process, and reducing human's trust in robots [6]. The digital twin has been applied in HRC to address the safety concern [7, 8]. The DT can map physical objects into the virtual space as exactly as possible. In the virtual space, the properties, behaviours and rules of the physical objects can be accessed by corresponding digital objects [9]. Therefore, the HRC system, which includes physical objects, such as robot systems, human operators, sensors etc., can be monitored, predicted and optimized based on DT [8].

Humans are more complex and less predictable compared to other physical objects. Therefore, the human behaviour modelling has been a hot research trend in HRC [10-12]. Specifically, the human behaviour includes anthropometry [13], motion [14], gesture [15] and human cognition [12]. This work aims to identify the research gap of human behaviour modelling in HRC environments and proposes a potential approach to bridge the identified gap. The roadmap of this present paper is arranged as follows: firstly, human behaviour studies in HRC and ethology are reviewed and analyzed. Secondly, the research gap of human behaviour in HRC is identified and CE-based approach is recommended for bridging the gap. Thirdly, first attempts is explained. Finally, the next steps are presented.

2. Literature review

Levitis et al. [16] defined behaviour as: "The internally coordinated responses (actions or inactions) of whole living organisms (individuals or groups) to internal and/or external stimuli." This behaviour definition was also referred to the human information-processing model [17] shown in Fig. 1. The model includes input, processing and output of the behaviour. The information collected form these three parts is the foundation for behaviour analysis. Therefore, the following literature review will refer to different information sources in Fig. 1.

Furthermore, the behaviour studies are classified in HRC and other domain to identify the research gap and possible methods for filling the gap.

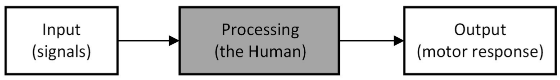

Fig. 1. The simplified human-information processing model (adapted from Schmidt et al. [17])

2.1. Human behaviour studies in HRC

- Physical human model

The physical human model refers to the "Output (motor response)" such as motion. The motion refers to the position changes of different body parts over time. This area has been studied intensively in HRC. For example, Melchiorre et al. [18] monitored the human position by point cloud and then calculated the minimum distance between human and robot, to control the robot to avoid colliding with the human. Moreover, the motion of different body parts was used to extract the posture and gesture for ergonomic assessment or non-verbal communication [19, 20]. Furthermore, researchers have done massive studies on human motion prediction, posture prediction and action prediction by integrating machine learning and artificial intelligence [21-23]. However, these studies focused on human behaviour monitoring, recognition and further application, the study of the behaviour itself was still limited.

- Cognitive human model

Demirel et al. [11] stated that the cognitive human model includes workload, stress and situation awareness. Hopko et al. [12] presented a systematic review of considered human factors in HRC. The top five human factors were trust, cognitive workload, anxiety, safety perception and fatigue. These factors refer to the human's psychological states, which can affect human behaviour. Therefore, the cognitive human model refers to the "Processing (the human)". There have been models such as Adaptive Control of Thought-Rational, mReasoner and MAC/FAC to model the cognitive human. However, these models fall short in long-term scenarios and wide task scope [10]. In contrast, subjective or objective measurement was applied to model the cognitive aspect of humans.

Subjective measurement utilizes interviews, surveys, and self-report and focuses on the offline analysis of gathered qualitative data, which is unsuitable for real-time HRC [12]. The objective measurement utilizes bio-instrumentations such as Electroencephalogram, Electrocardiogram and Electromyogram, which is suitable for online situations [12]. However, current studies based on the bio-instrumentations are limited to constrained tasks and complex set-ups. Thus, they are still at research level and have not been adopted in industrialenvironments [24].

- Context model

The context refers to the information that can characterize the situation of an entity [25]. The context model includes information such as location, movement, velocity, sound or temperature. The context can influence human behaviour, so it can refer to the "Input (signals)". The context was also included in HRC research. On the one hand, the context was used as extra information for human behaviour recognition. For example, researchers added context information for human motion or action prediction [26, 14]. The prediction accuracy was improved compared to just using information from human. However, the association between behaviour and context was not studied. On the other hand, the context was considered as influencing factor on human cognition. Hald et al. [27] illustrated that human trust could be affected by the velocity of the robot. This study illustrated that the context can affect human cognition, but the causal effect was quantified or specified to a specific person. Therefore, the context-associated behaviour of an individual has not been explored so far.

2.2. Human behaviour studies in Ethology

- Ethology

Ethology means "the description and characterization of behaviour, typically of intact freely moving animals in their natural environment." [28]. Hence, the ethology can also refer to the "Output (motor response)". Brown & de Bivort [29] identified several principles of behaviour by relating ethology to traditional physics. Firstly, the behaviour has low postural dimensionality due to the coordination of the movements, which can provide basis for behavioural analysis. Secondly, behaviour is discrete and stereotyped, so it is shown in distinct patterns and behaviour within a distinct pattern cluster can be surprisingly similar. This is the basis for behaviour segmentation. Thirdly, behaviour is organized hierarchically, which is a guiding principle for analysing behaviour. This can analyse behaviour at different scales, produce the action sequence and transfer probability.

Ethology has been introduced in robotic studies. For example, the hierarchical organization was adapted to form complex adaptive behaviours for robots [29]. Moreover, ethology was also utilized for evaluating human-robot interaction [30, 31]. Specifically, ethology methods substituted the self-report or interview for evaluating interaction. However, these studies focused on social robots instead of industrial robots.

- Computational ethology

The ethology has evolved to CE by combining computer vision, machine learning and artificial intelligence [28]. CE has advantages of automatic behaviour tracking, segmentation and analysis. Hence, the dimensionality and throughput of behaviour analysis can be increased. Furthermore, Mobbs et al. [32] presented a study of human computational ethology. Fig. 2 presents the analysis steps including detection, tracking, action detection, behaviour analysis and further steps link to cognition. Hence, CE can be linked to both "Processing (the human)" and "Output (motor response)". The CE has been applied to study the effect of genotypes, drug treatments and disease conditions on behaviours [33]. Mobbs et al. [32] stated that the CE can be applied to discover novel behaviour to form new behaviour theory. Moreover, Pereira et al. [34] presented an approach to link brain activity and behaviour via CE. Therefore, CE is capable to model individual behaviour and link behaviour to cognition.

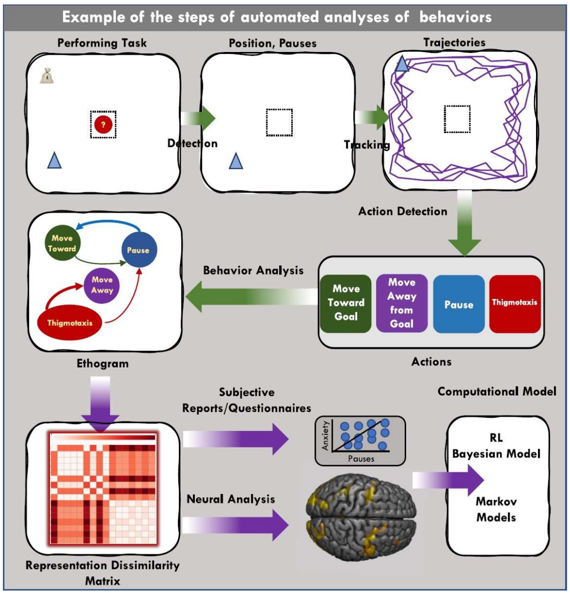

Fig. 2. Steps in automated analysis and modelling of natural behaviour (adapted from Mobbs et al. [32])

The physical human model in HRC has similar process in terms of detection, tracking, and action detection. However, the behaviour analysis to model action sequence, transform probability and structure is still lacking. This additional information might be helpful for individual behaviour modelling at different time scales. Therefore, the robot has potential to understand the personal profile such as human preference, ability and skill by applying CE, so that the robot can be controlled adaptively.

- Virtual ecology

Mobbs et al. [32] defined virtual ecology as "Self-contained virtual environments where subjects can move freely throughout the environment". The virtual ecology was introduced because the naturalistic environment lacks control of stimuli and information. Therefore, virtual ecology links to the "Input (signals)". However, current virtual ecology cannot represent the real environment well.

The virtual ecology is similar to DT because they both contain virtual environments and entities. The virtual ecology has difficulty to model complex naturalistic stimuli and parametrise environmental factors. In contrast, the DT of HRC can model the relevant context. Therefore, the modelling of context-associated human behaviour could be feasible.

3. Result and discussion

3.1. HRC and Ethology Mapping

Human behaviour in HRC can be mapped with the simplified human-information processing model (as shown in Fig. 3). Current HRC research focuses on the external context and physical human model, because these are essential elements of DT. These studies created a sound base for human behaviour monitoring and recognition. However, the behaviour has not been analysed in depth to reveal personal preference, ability and skill [24, 35, 36]. In contrast, researchers claimed the internal cognitive human model needs to be considered for safety, smooth collaboration and human wellbeing [11, 12]. The efforts have been put into applied psychology and neuroscience methodology for cognitive human modelling. The purpose was to understand the causal effect of cognition on human behaviour. Nevertheless, these research outcomes are limited to being implemented in industrial environment due to instrumental constraints.

Therefore, the research gap of human behaviour modelling is that current researches focus on recognition and monitoring of human behaviour, but the deep analysis of human behaviour is still lacking.

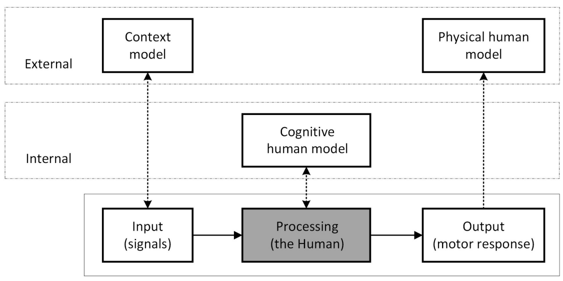

Fig. 3 Human behaviour studies in HRC mapped with simplified human-information processing model

Likewise, human behaviour in ethology can alsobe mapped with the human-information processing model (as shown in Fig. 4). Traditional ethology focused on observation and analysis of the naturalistic behaviour of animals [28]. Computation ethology is the extension of ethology which can link the observed behaviour with neural activities [32]. Virtual ecology has been proposed to model naturalistic stimuli of the behaviour, but still has difficulty representing the complex natural environment. Furthermore, the ethology studies focus on how the behaviour adapted to the environment [30]. The study of controlling the environment to fit the behaviour is out of the scope of ethology.

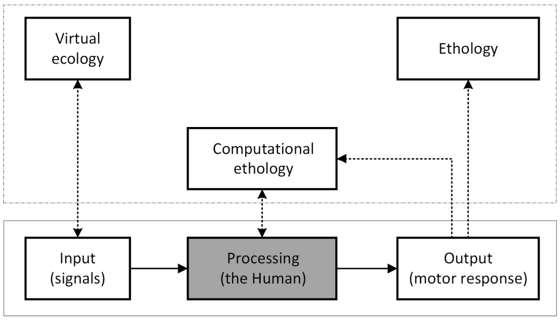

Fig. 4 Human behaviour studies in ethology mapped with simplified human-information processing model

3.2. Recommendation

The authors recommend the application of CE since it could add value to human behaviour modelling in HRC due to its sound base in the biology and neuroscience domain. Specifically, the current HRC studies considered human actions independently. The CE considered the action sequence, transform possibility and hierarchical structure, which is useful for human action prediction at different time-scale [33]. Secondly, the CE focus on behaviour observation from every individual. In contrast, the physical human model in HRC massively applied data-driven method, which lacks consideration for personal profile [24]. Thirdly, unsupervised learning has been stressed for discovering behaviour [37], while the human annotation of behaviour is still widely utilized in HRC. The manual labelled behaviour might be helpful for the human to understand and interpret, but it should be doubted whether this is also helpful for the robot to understand behaviours.

Nevertheless, CE has difficulty to model naturalistic environment, which could influence the behaviour. In contrast, DT of HRC can model the relevant context. Hence, the knowledge could be extended by modelling the context-associated behaviour. On the other hand, CE just focuses on observation and analysis but without any consideration to control the environment. Therefore, further studies are needed to apply CE for designing adaptive robot control strategies.

3.3. Preliminary implementation

This approach of applying CE for human behaviour modelling in HRC has the potential to support decision-making in terms of productivity, safety and ergonomics in manufacturing environments such as the HRC collaborative assembly lines [38]. The authors started the design and development of the proposed approach by using appropriate sensor systems (motion tracking system, indoor positioning system, Inertial Measurement Units, etc.).This is already prototyped during a completed research project, funded by EU-EIT Manufacturing, as shown in Fig. 5.

Fig. 5 Prototype of the motion capturing system used for human shape reconstruction (Source: BIBA)

These sensors are the basic instrumentations for building the physical human model and the human representation in the DT. Furthermore, existing Activity and Process Mining tools, as depicted in Fig. 6, will be used to support the CE-based human behaviour modelling. The focus will be given to human/process action sequence identification or extraction and prediction of potential future human operator activities.

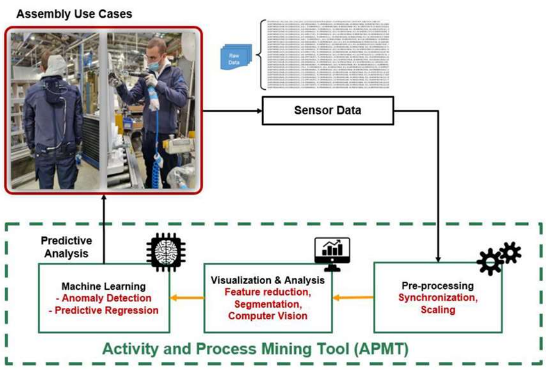

Fig. 6 Prototype of the motion capturing system used for human shape reconstruction (Source: WORKSUIT4.0 project)

4. Conclusion and future work

Current HRC applications are focusing on recognition and monitoring of human behaviour, but the deep analysis of human behaviour in HRC environments is still lacking. The cognitive model could explain human behaviour but fall short to be applied in industry scenarios. Computational ethology has the potential to be adopted in such safety-critical industrial applications to model human behaviour in a structured manner. Future work could focus on modelling action sequences, transform probability and structure to represent individual behaviour in different time scales. Furthermore, adaptive robot control strategies based on human behaviour model could be designed for addressing the safety issues, ergonomics and production efficiency in HRC workplaces.

5. License

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