Digital Human Modelling in Action

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Digital Human Modelling (DHM) is an active research field with the goal of creating detailed models of the human body (Scataglini & Paul, 2019). The field has its roots in anthropometrics and biomechanics and careful measurements of the human body in terms of e.g., bone, muscle, and fat. Such digital models of human bodies are commonly used as, verification and visualization software, primarily to assess ergonomic aspects of e.g. driver environments and workstations in industry. With the shift towards Industry 4.0 and an increased use of simulation and visualization software in all design phases, DHM has become an important component allowing engineers to evaluate ergonomics of new products and workplaces early in the design phase, long before the first physical prototype is built.

In addition to models focusing on anthropometrics alone, there is also an array of models covering biomechanical and physiological properties (Bubb, 2019). However, modelling of cognitive functions has a vastly different tradition. Cognitive modelling has its roots in psychological descriptions of mental function, including studies of both human and animal cognition (Smith & Kosslyn, 2013). The first computational cognitive models appears in the 40's and 50's with the cognitive revolution. Here, we find seminal works by Hebb (1949) and Kleene (1956) that inspired the formation of artificial neural networks underpinning most of today's AI technologies and Deep Learning. The *Magical number seven, plus or minus two* by G. A. Miller (1956) was a very influential formalization of the limits of human working memory that still shapes our understanding of memory up until today. Another example is the *Human associative memory* (Anderson & Bower, 1973) that later developed into the cognitive architecture ACT-R, which is probably still one of the most well-known models of cognitive function around.

Notably, the dominant theories and models in both DHM and cognitive modeling are influenced by René Descartes' Mind–body dualism. The cognitive models mentioned above are in a very concrete sense "without a body" – the body is essentially described as a container with input and output modalities. Similarly, the tradition of digital human modelling describes the human body's mechanics without cognition. While DHM does involve simulations of actions and work tasks, modeled behaviors are highly specified by the designer with a focus on biomechanical constraints.

Over the last three decades, embodied and situated approaches to cognition have emphasized the role of the human body and its environment for cognition. We have to a large degree shifted from symbolic descriptions of reasoning to dynamic descriptions of behavior. As a result, cognitive models are increasingly formulated as complex systems of dynamic interdependent biomechanical and cognitive elements (Pfeifer, Bongard, & Grand, 2007). Still, very few of these models get close to the anthropometric detail found in DHM literature. Recently, there are also initiatives from the opposite direction, incorporating cognitive aspects into DHM models. One such example is RAMSIS Cognitive[1] allowing modelling of human visual perception, comprising analysis of direct view, minimum visual range, and optical attributes of displays. However, these examples are still sparse and are primarily used to evaluate a limited set of e.g. perceptual properties (Scataglini & Paul, 2019).

Within the project Virtual Ergonomics[2], gathering researchers from both DHM and cognitive sciences, we see a potential to bridge these domains in a way that is fruitful for both disciplines. Specifically, we aim to develop models that can assess and predict human action, considering anthropometrics, bio-mechanical and cognitive

[1] RAMSIS Cognitive is a plugin for the RAMSIS Software by Human Solutions, www.human-solutions.com

[2] Virtual Ergonomics is a synergy project lead by the University of Skövde, funded by the Swedish Knowledge Foundation (KK).

aspects of action selection and execution. While action selection can imply a wide range of scenarios from selecting a piece of candy from a candy bin to selecting a company's business plan for the upcoming fiscal year, we will focus specifically on the analysis of repetitive work tasks, e.g. as part of manual assembly in industry or lifting tasks in health care.

Modelling action

In DHM research, action selection is not part of the model itself, but specified at design time. The exact motions are typically put in terms of optimization over some performance index (Björkenstam et al., 2017). The performance index is derived from the biomechanical constraints of the human body, considering flexibility of joints, anthropometrics, and the human's environment including e.g. obstacles. Action goals are specified in an absolute frame of reference, without consideration of how humans' select and produce these actions.

DHM models provide biomechanically valid simulations of *preselected* actions and action plans but typically do not simulate the cognitive constraints that lead to the selection of actions and action plans. Given the abundance of motor degrees of freedom in the human body, additional constraints introduced by a cognitive system can have a significant impact in how the task is completed (Latash, Levin, Scholz, & Schöner, 2010). For example, in the context of object reaching and grasping, anticipation of end-state comfort can constrain both how and where an individual grasps a task relevant object (Rosenbaum, Van Heugten, & Caldwell, 1996). This phenomenon has also recently been modelled in a DHM setting (Yang & Howard, 2020). While motor variability in human behavior is often treated as noise to be reduced, recent attempts to quantify and model motor variability have demonstrated that some dimensions of variability can drive task learning and success more than others and that motor variability can be used as a measure of both expertise and adaptability (Latash et al., 2010; Scholz & Schöner, 1999).

In the present work, we will leverage on the modelling tool IPS *IMMA – Intelligently Moving Manikins*[3]. IPS IMMA comprise a detailed biomechanical model allowing designers to simulate many types of tasks involving complex working positions (Hanson et al., 2019), allowing ergonomic evaluations directly in the simulated environment. From a cognitive science perspective, tools like IMMA provides a powerful environment where many embodiment effects can be modelled and tested with a physical realism rarely available in cognitive models. The work is still in preparation phase, with focus on two specific directions:

Can we predict when people are reaching or walking? In previous research (Lamb et al., 2017), we studied hysteresis effect in human behavior. Specifically, action selection is not only based on an optimal strategy, but also primed by previous behavior. We plan to further investigate, and model, this phenomenon in a reach-grasp-carry task where participants have the option to either stretch over a table to reach for an object, or walk around the table to achieve a more comfortable reach. The setting bares many similarities to repetitive assembly tasks in industry, commonly modelled with DHM tools like IPS IMMA. Individual's selection of behavior (reach or walk) certainly depends on many factors, where anthropometrics is one. Using the detailed anthropometrical model fitted to each participant, we will investigate to what degree calculation of comfort in combination with hysteresis is a predictor for participants' behavior selection.

Is proactive eye-gaze present also in repetitive tasks? It is well known that people display a specific eye-hand coordination pattern during object manipulation, where the eye-gaze is proactive in relation to the hand. Since first demonstrated by Johansson et al. (2001), this phenomenon has been intensively studied in experimental settings, primarily during action observation (e.g., Flanagan & Johansson, 2003). Proactive-eye gaze could constitute a very useful clue for human-robot interaction (Billing, Sciutti, & Sandini, 2019; Sciutti et al., 2012). However, to what degree this proactive eye-hand coordination is present also in everyday, repetitive, conditions is to large degrees unknown. We plan to implement proactive eye-gaze as part of IPS IMMA and in this way model complex working situations. The model behavior can later be compared to observed worker behavior in industry, allowing underlying theories related to proactive eye-gaze to be validated in real working environments.

[3] IPS IMMA by Industrial Path Solutions, https://industrialpathsolutions.se/ips-imma/

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