Robotic Assisted Design Workflows: A study of key human factors influencing team fluency in human-robot collaborative design processes.

ABSTRACT

This paper presents the initial results and rationale towards the development of human-robot collaborative design workflows. An introduction to the basis of collaborative workflows and its impact for robots in architectural design is presented. Key elements, such as trust, reliance and robustness for the successful cooperation between humans and robots are identified and analysed. Human-robot collaboration is a multidimensional construct context dependent, this makes essential to understand how trust and team fluency develop when non-expert designers interact with industrial robots. A design process is then described based on sensor feedback, and phase-changing material formations that encourages human-robot collaboration during the genesis of the design. Two stages of development are presented. In stage one, an exploratory study was conducted to collect designers' opinions quantitatively and qualitatively. The results were analysed and led to the identification of the primary parameters that affect human-robot collaboration in the design process. In the second stage, machine learning is used to enhance the collaborative characteristics of the robotic partner in relation to the formation process of the material. The results reveal insights on human perceptions of robotic collaboration, and also explore neural-network-based feedback to enable expanded collaboration and communication between the robot and the designer.

1. INTRODUCTION

Technical devices, machine learning technologies and digital fabrication tools allow for innovative practices and are capable of opening new understandings of matter, new ways of organising and new complex and irregular relations that expand material processes to create novel non-linear workflows, and that can lead to a language particular to the robotic era in architecture.

Robots and more specifically robotic arms are increasingly being explored beyond fabrication machines as design tools capable of augmenting and extending the designer solution space to the fabrication and material manipulation stages. Recent approaches try to embed craft knowledge into the robot for its path planning decisions. These include the analysis of actions such as those from a carpenter for wood carving (Brugnaro 2017) or from a stonemason (Steinhagen et al. 2016). Common among these projects is the idea of establishing a direct link between physical material manipulation tools and machine intelligence by training the machine to replicate and eventually augment the actions of the human.

One of the fundamental problems designers encounter when working with tools like the robotic arm is that the needs of the designer are in total opposition to the needs of the robot. Whereas the design process is mainly a process of continuous speculation, iteration and the testing of ideas; robotic manipulators are for the most part tools for efficiency which need from very specific problems to solve in a single, repetitive way. The process of creative enquiry requires from flexibility to formulate questions and more importantly to find the right questions, whereas robotic processes thrive on finding the right solutions from very specific problem parameters.

The paradigm shift is in taking robots from tools designed to find the right answers to partners in finding the right questions. New design workflows have to be designed which enable robots to move beyond being only a more sophisticated fabrication tool, and into tools that can influence the ways of generating and thinking about design. In this scenario, the change that robots as physical manipulators, in combination with other tools such as machine learning, are bringing will be profound and similar to the emergence of new tools that during the Renaissance gave birth to

architecture as we currently know it. As Antoin Picon describes: "At the Renaissance, the adoption of new tools and procedures, coordinated projections in plan and elevation, an perspective representation, was inseparable from a broader phenomenon like the emergence of the modern architect and engineer and the new importance given to conception"(Picon 2010). The industrial revolution, with the introduction of the production line and its emphasis on the division of tasks further pushed the role of the architect towards that of the concept maker.

2. ARCHITECTURE AND TECHNOLOGY

The relationship between architecture and technology, and more specifically digital technology has always been a special one. In the 1960 cyberneticians Nicolas Negroponte at the MIT, John Frazer at the AA , and Cedric Price attempted to rethink architecture from a cybernetic frame (Steenson 2014). Christopher Alexander decompose the design problem as one based in patterns (Steenson et al. 2008). Lionel March responded in his influential essay 'Design Machine' by decomposing design as the combination of four parts: receptor, effector, the language of design and a theory which made a design machine. He emphasized the equal importance of each component and their close relationships with them, this in a frame based in equations (Stiny & March 1981). Digital equipment and software during the 1990s crystallized the idea; taking architecture into the virtual realm for a decade, and hence changing the relationship between the virtual generation of architecture and its materiality (Loukissas 2012). Two divergent avenues of the visible form vs invisible computation evolved changing the relations between information, digital technology, architecture and machines.

Robotic design gives architects the opportunity to explore the physicality of their designs from early stages. In a world where the genesis of architectural design is digital, robots could offer a viable opportunity to experiment and transfer design ideas to the physical world and get immediate, accurate feedback by using the strengths of the robot such as precise manipulation of the physical object. In this scenario, robots do not only redefine the design process but also the hierarchy of the building parts and their meaning.

3. HUMAN – ROBOT GENERATIVE DESIGN WORKFLOWS

Humans and robots can establish meaningful collaborations where they can benefit from the strengths of each other and work as partners towards a common human objective. The most successful human–robot collaborations today are in underwater or space operations where robots have sensors and autonomy for some tasks but are also remotely controlled by humans in real time in what is called "tele-operation". The most flexible component of a manufacturing system is the human operator. After a race for full automation, the manufacturing industry has come to realize that "ensuring a meaningful involvement of people in decision–making and operation of manufacturing robots is critical to their success" (ElMaraghy 2005). The manufacturing industry is turning its attention to a more harmonized human–machine systems. Against predictions from the early AI enthusiasts in the 1950s, today humans remain 'incredibly adaptable, dexterous as well as fast, skilled and cheap when compared to robots' (Gevarter 1985). We can then conclude that robots are more suitable for semi-autonomous or pre-programmed precise tasks while humans are more suitable for making judgement calls.

This raises the idea of working with the machine not merely as the medium but as an active collaborator in the process of exploration and discovery. The computer and hence the robot become then active agents during the search of the design space, and not just as the medium used to create the resultant artefacts.

The proposition in this paper is that the robot can become a collaborator to the human designer through the design process by using novel materials that enable formative design processes. Differently from subtractive or additive material processes that require to be calculated and defined in advance and are difficult if not impossible to revert once done; a formative material process offers opportunities for the material, the robot and the designer to interact and combine their agencies through the phase-changing step before a final result is achieved. The aim is to enable a design framework that is open towards the interaction of both human and machine agencies during the design of a form-found shell. The result is a design solution that would not have been possible with only one of the two parts alone. Machine learning is tested in stage 2 as a method to train the robot in understanding how the phase changing material can deform giving it the ability to anticipate the designer intentions.

4. HUMAN- ROBOT COLLABORATIVE DESIGN PROCESS (POP-UP METHODOLOGY)

4.1 Defining the Collaboration

In the context of human-computer collaboration (HCC), collaboration is defined as a "process in which two or more agents work together to achieve shared goals"(Terveen 1995). Collaboration in this way has enabled two different approaches: The first one, which tries to endow computers with human-like characteristics to enable them to act like humans and engage in collaborations similar to human-human ones. The second approach tries to get computers to collaborate with humans by exploiting their unique abilities in a way such that they complement humans. Licklider in 1960, defined this second approach as a man-machine symbiosis. Traditional symbiotic partnerships between man and machine, as set-out by Licklider in 1960 involve "men setting the goals, formulating the hypothesis, determining the criteria and performing the evaluations, while the machine does the routinizable work to prepare the way for insights and decisions"(Licklider J.C.R. 1960). He already anticipated that man through these symbiotic partnerships would be able to perform intellectual operations more efficiently than alone. In this research exercise a set of parameters such as trust, reliance, and robustness between the designer and the robot confederate were selected to be evaluated as they are considered fundamental for a successful man-robot collaboration in an architectural design tasks.

Teamwork is defined by the dictionary as 'work done by several associates with each doing a part but all subordinating personal prominence to the efficiency of the whole' (Merriam-Webster 1828) Designer-robot collaboration during architectural design tasks is still a relatively unexplored field of study. In the design studio, the integration of both digital and physical model is critical for the conceptualization and development of the design process (Oxman 2010). Michael Speaks describes the design studio morphing from a place where data and feedback were continuously exchanged between students as they build up their models, to one where students are looking at the machine waiting for something to pop out of it, similar to a baker's oven (Speaks 2011). Robotic manipulators can become a collaborator and team member with the designer, by feeding him data and information while performing accurate actions upon it; robot and designer can have different roles and agency throughout the design process to provide complementary means of conceptualising design.

Moving the robot from being a final fabrication tool to a partner and facilitator of an environment that integrates the different material, human and digital agencies in which design develops, encourages novel ways of thinking and non-hierarchical design modes. It brings techniques and technological knowledge into a deeper relationship to the narratives of the discipline of architecture by augmenting the relationship between the digital model, the designer and the physical object.

Through iterative feedback mechanisms and observations of the relations created by the robot and an augmented designer, this research speculates how a deeper collaboration that acknowledges the 'potential otherness' (Picon 2004) of these tools, in a learning-by-design method, can lead to new choreographies for architectural design and fabrication. The emphasis throughout the experiment is on the connections and relationships facilitated by digital software and hardware between design intent, computation logic and physical material.

5. THEORETICAL FRAMEWORK

The approach taken by this research is based on a 'post-human' view of the design activity. This allows it to turn its focus to how things and people perform together, create relationships, influence each other and organise in certain ways. **Actor Network Theory** (ANT) will be used as a theoretical framework to orientate this investigation.

ANT is a theory pioneered by Michael Callon and Bruno Latour concerned with investigating the social and technical taken together as an actor- network of human and nonhuman elements (Latour 1999) . It gives the social and the technological equal value by treating them as inseparable, in fact, it argues that 'people and artefacts should be analysed with the same conceptual apparatus' (Walsham 1997). ANT enables thinking about hybrids of people and technology and hence offers a way to investigate the issues and dilemmas for robotic augmented designers. In this context, the question is how actors become interconnected and perform as a product of their associations rather than of their individual characteristics (Dolwick 2009). ANT focuses on the relationships between agents or 'actants' rather than giving primacy to perception. The design process can be understood as a human abstraction, related to the human, or as a subjective component, an element within a wider assemblage of humans and machines. This later understanding of design as an assemblage doesn't separate the human actor from other actors in the network, but they are all understood symmetrically.

6. TRUST IN ROBOTS

To enable robots to become collaborators in the design process it is important to understand how designers relate to them and work with them as a team. The development of trust is essential for the successful operation of any team(Charalambous 2014). Furthermore, without trust in the capabilities and intentions of the team partner, it is safe to assume there won't be team dynamics (Kruijff & Janıcek 2011). The specific capabilities in which the human feels that can trust the robot will become the basis of the collaborative task. The human will delegate and cooperate with the robot based on the robot capabilities that he or she perceives. 'Guiding behaviour within a team then comes down to controlling in what capabilities trust can be developed, and the effects of such placements on levels of trust on levels of autonomy' (Kruijff & Janıcek 2011). The meshing of the characteristics of the human, the robot and the operational environment (design task), from a human-centred perspective, influence the development of trust (Hancock et al. 2011; Hoffman et al. 2015). Trust in automation is a well-studied concept in the literature, human factors that contribute to increase or decrease trust in the system have been identified and used to explain why automation sometime leads to overall lower team performance. This is comparable to the performance of human teams that do not trust each other. However, trust in robots is a more recent concept loaded by the high expectations that humans have of robots.

Furthermore, the comprehensive body of research regarding trust in robots is focused in assistance, autonomous and military robots, little research has been directed to address trust in human - industrial robots' interactions (Charambolous 2015; Park, Jenkins and Jiang 2008). This is perhaps

due to traditional settings in which industrial robots are confined behind a cage with no expectations of human contact nor collaboration. Research in the relation between designers and industrial robots is even more scarce. As robots become more ubiquitous assessing the factors and parameters that influence designers' relationships with them becomes crucial to enable the design of physical machines and digital workflows which support them to become partners in the design process.

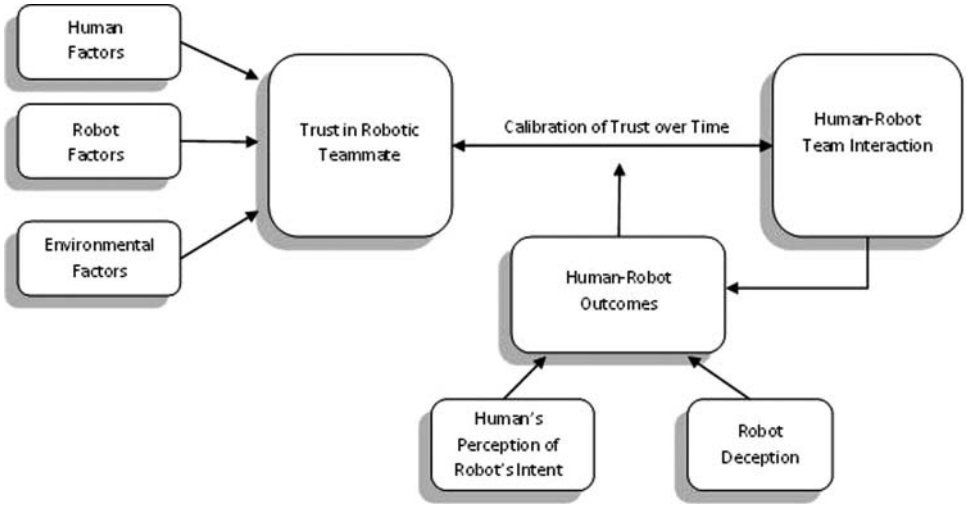


Figure 1. Diagram of human-robot trust factors and evolution of human trust (Hancock et al. 2011)

7. EXPLORATORY STUDY

Due to the little understanding and research regarding how designers relate to, or place trust in, robots and how they influence designers who are not expert robot users an exploratory study was carried out to collect designers' opinions and impressions qualitatively and quantitatively. The study was designed for a robot to work on the design of a form-found concrete shell structure with untrained participants. There are no current measure guidelines and parameters for successful human - industrial robot collaboration (HIRC) in design tasks and the literature on collaborative HRC when the robot is an industrial arm is nascent. The fields of HRC, industrial HRC, collaborative design and collective agency in natural and artificial systems have been reviewed to define the different element that influence trust and team work in human-robot interactions. This led to the development of a team work fluency and trust related themes relevant to the design context. Following this, a pool of items was developed describing the identified human – industrial robot collaboration (HIRC) related design themes. Figure 1 shows the themes and sub-themes evaluated on the exploratory study under the overarching umbrella of 'Team Fluency'.

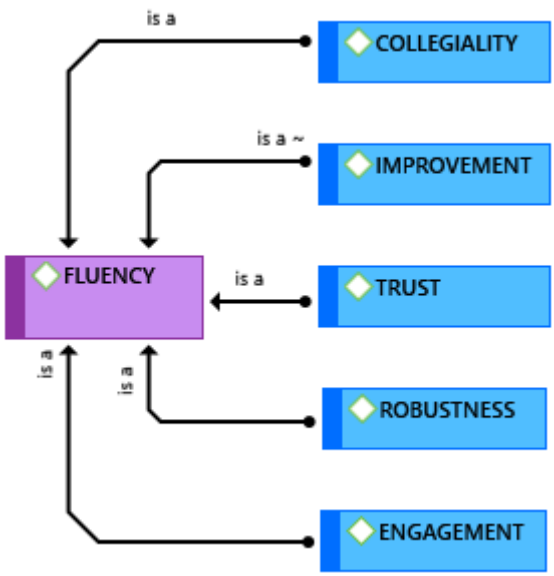
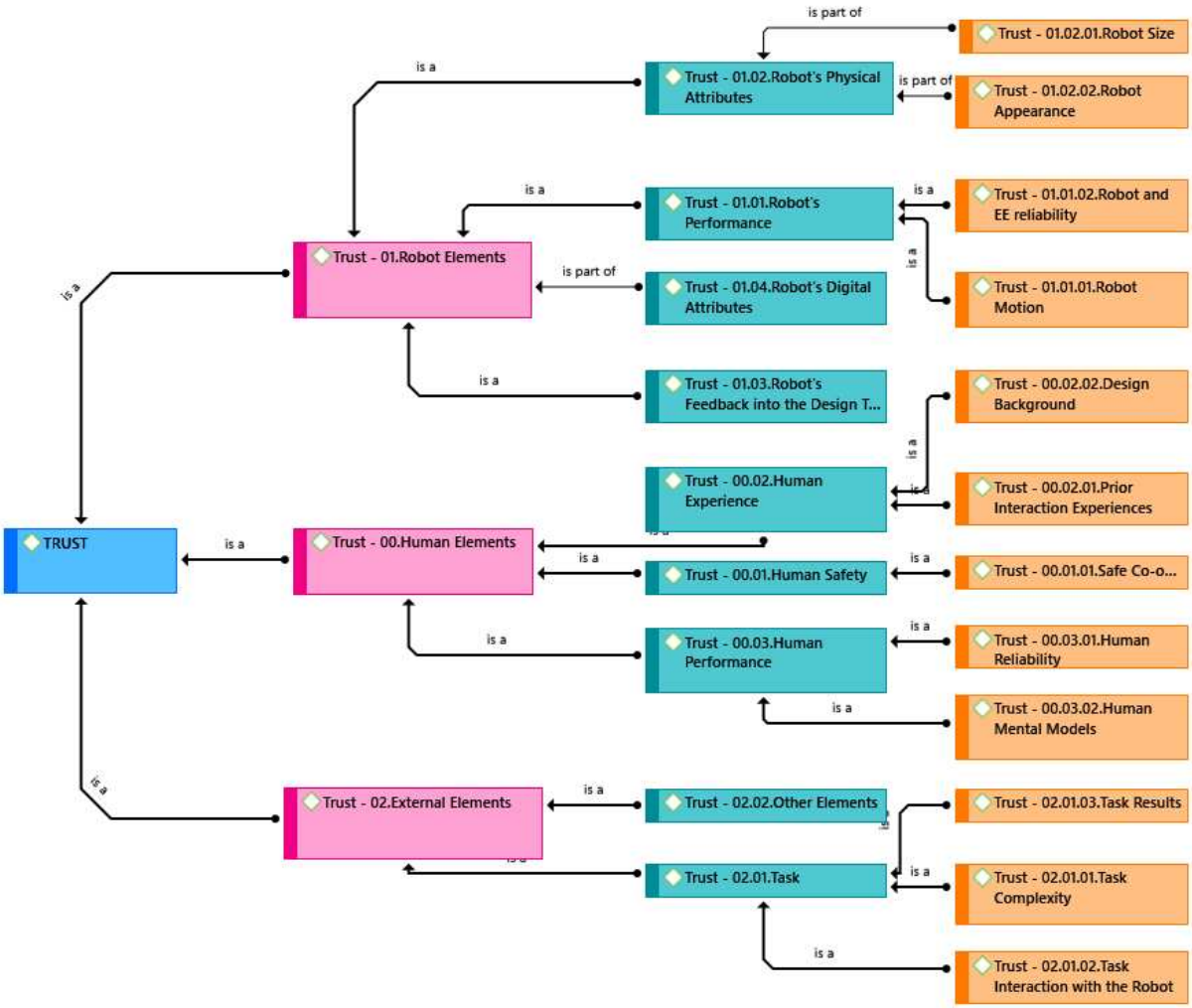
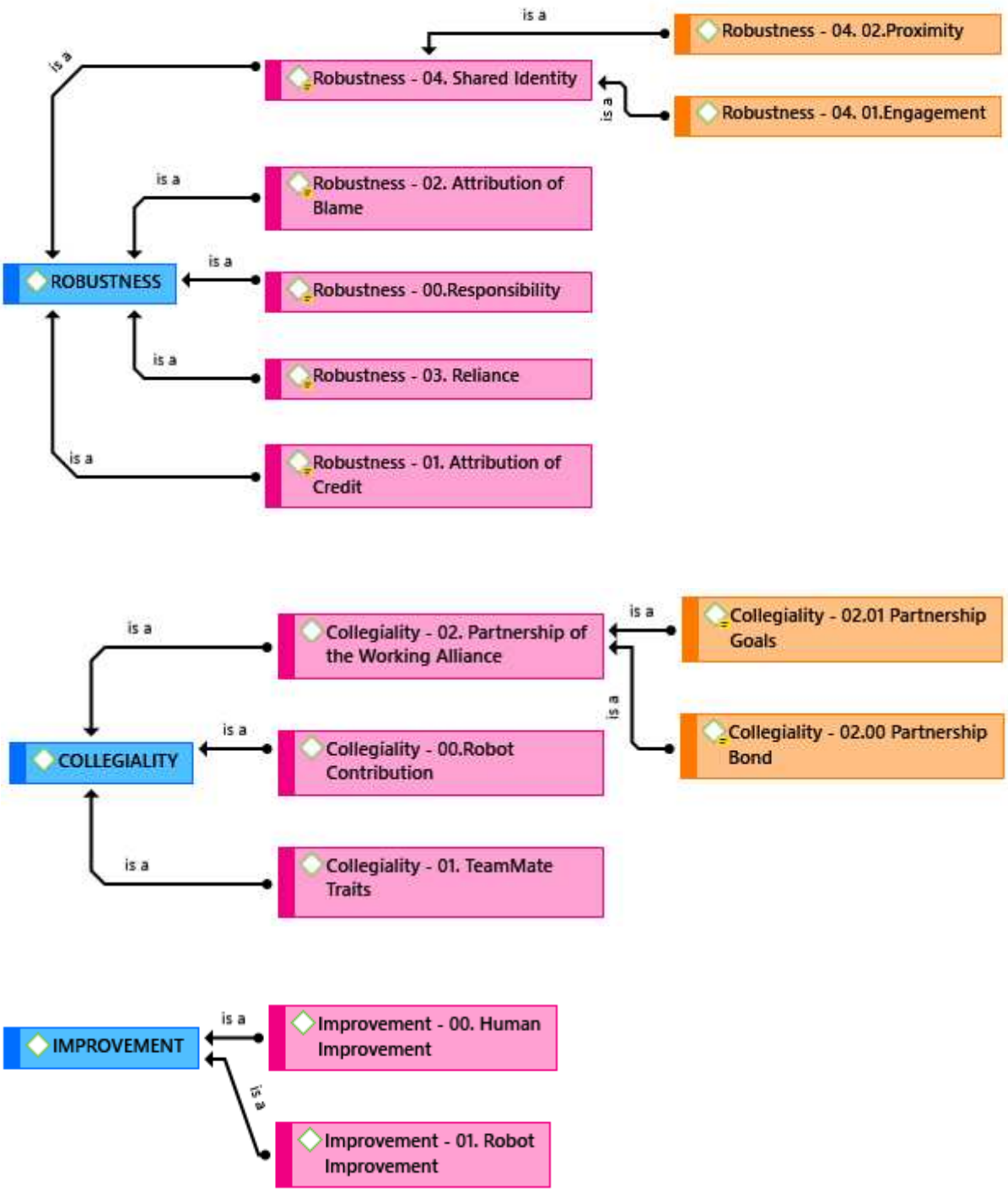


Figure 2: Main team fluency constructs evaluated from the literature in HCI and HCC as relevant to the design process.





Figures 3 a, b, c and d. Hierarchy of sub-themes evaluated under each of the 'team fluency' constructs which compound to make team fluency. This were evaluated through quantitative Likert-scale questionnaires and qualitative semi-structured interviews and field notes during the case study.

3A sub-themes under trust; 3B sub-themes under robustness; 3C sub-themes under collegiality;3D sub-themes under improvement

7.1 Method

7.1.1 Participants

25 participants were recruited from the Welsh school of architecture at Cardiff University. 12 female, 13 males. The age range between 18 and 29 years with a mean age of 20 (M= 20.84) and Standard Deviation of 2 (SD= 2.26) .17 participants were on their second year of study, 7 participants on third year and 1 postgraduate student. 8 participants reported having no prior experience with any kind of digital fabrication and computer numerically controlled machines while 17 reported having some experience with different digital fabrication machines from which the laser cutter was the most popular. 22 participants reported not having any experience with robots while 3 reported having some experience with them.

Participants were coded for their age, gender, year of study, previous digital experience, previous digital fabrication machines experience and whereas they did their design or not, before starting the analysis. The number of participants is in-line with other research studies in the areas of HRI and HCI which recommend between 15-30 participants before the law of diminishing returns begins to apply and more participants stops equating further insights (research methods in HCI, chapter 1, the politics and aesthetics of participatory HCI). As the coding and analysis was completed of the last participants it was clear that no new concepts were being introduced and the central categories were well developed. It was then concluded that saturation was achieved and the results were sufficient for this research procedure.

7.1.2 Design

Participants had to perform a design task which was designed to capitalize on the unique capabilities of the robot (i.e. translate a 3D shape from the digital environment to the physical, precise path cutting on a hard material, force and strength to deform a concrete shape), although still making sense for the human partner and requiring from an intentionally collaborative input. The task was designed or unexperienced robot users.

Some ambiguity was built into the task to increase uncertainty and cause the participant to make explicit decisions about whether or not to rely on the robot for more than just the labour-intensive aspects of the task (e.g. cutting the material). Three opportunities where built in which the robot had better information than the designer. After each scan designers could select whereas to trust and consult the robot for information about the digital and physical models or follow their intuition which wouldn't be accurate. These opportunities for errors also provided a basis on which the participant could assign responsibility and blame.

The design task was made of three sessions, an initial introductory session to the digital design workflow with a software tutorial; a second session to introduce them to the robot motion, teach pendant and jogging and the third session to realise the design exercise. The two training sessions and the development of the design task were treated as a single unit, considered to be "the task". Each session had a duration of approximate 2 hours. Participants couldn't take part in only one of the sessions, the three of them had to be sequentially completed.

7.1.3 Materials

A single arm industrial robot with a 60kg payload was used. The robot was placed inside a cage to ensure safe separation between the robot and the user when running in automatic mode. For manual mode tasks, participants were in proximity to the roboy. For the completion of the design task, three end-effectors were used: 1) a circular rotary blade; 2) a Kinect scanner ; 3) a wooden sphere mounted at the end of the Kinect.

Concrete impregnated fabric was used as the design material. The material was selected for its dual properties of soft and flexible when dry and hard and rigid after hydrating. The phase-changing properties open a 3- hour window where iterative manipulation and collaboration between the human and robot team can happen.

The design task starts with participants designing a pattern of curves which will then become 'cut' and 'joint' areas. The pattern is then exported to a form-finding software where physics solvers are used to simulate the concrete pop-up process and approximate the shape digitally. Patterns are established as boundary conditions and relaxed to find the different resultant pop-up geometries within the pattern. This step allows the designer to change the pattern until a satisfactory set of results is achieved. Concrete pop-up forming is a formative fabrication process; it allows flexibility and interaction between the human and the robot throughout the formation. However, the cutting step cannot be modified in the physical prototype hence making the simulation of the pattern important. Four main factors influence the final shape that the concrete would take: 1) pattern of cuts and joints; 2) plunging position; 3) plunging depth; 4) concrete hydration.

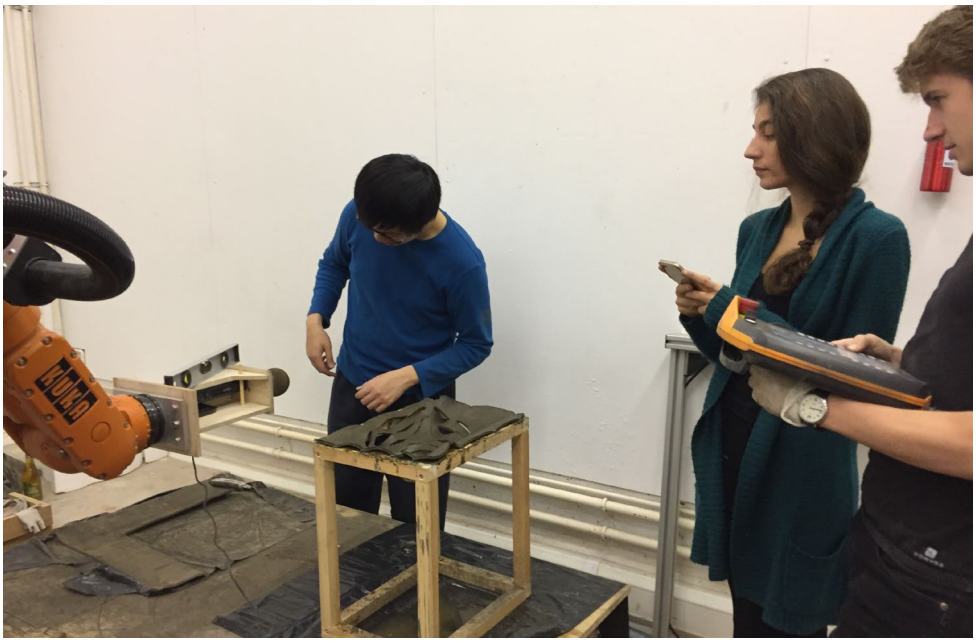


Figure 4: Participants scanning and deciding on plunging sequences for their geometries

7.1.4 Task

Identical task conditions were provided to all participants. The aim was to design and then iteratively with the robot form-find a concrete shell. Matching the physical to the digital was seeing as a soft objective, it wasn't required from participants to achieve a match but to achieve a design that they felt comfortable with. The fabric cloth was initially located in the table for the robot to cut. After cutting, participants had to manually hydrate and attach the cut concrete fabric to the wooden frame for the deformation process to start. The plunging process would then start. The robot would do the deformation by plunging and massaging the cloth. After each sequence of deformation, the robot takes a scan and shows to the participant the deformation achieved in respect to the digital model and in respect to the previous status of the fabric. Participants would decide their next step based on this information. Next steps could be additional plunging and massaging by the participant jogging the robot which means the participant standing in close proximity to the robot jogging it. Participants could also do the plunging and massaging by running the program generated by the robot in which case participants have to walk outside the cage and run the program. The last option

was for participants to leave the concrete to settle without further deformations. Once the participant was satisfied with the deformation of the concrete cloth, the completed item was hydrated and moved to a safe location where it was left to cure. Participant would then move outside the cage and the task finished.

Figure 5: Plunging sequence, robot plunging and massaging the concrete at each position.

The design exercise included 3 steps: 1) familiarisation with the design process as described above and the robotic manipulator; 2) design of a pop-up concrete shape; 3) Start the physical deformation process of the material in order to achieve the digital target. Throughout the deformation process the robot was continuously scanning the deformed material and comparing it with the digital simulation that the designer initially made. This information was available to the designer but he could choose to consult it or not. After each plunging iteration the robot would perform a scanning step, compare the resultant point cloud to the initial simulation and propose a new plunging iteration to achieve the desired shape. At this stage the designer could go with the proposed path or generate his own plunging paths.

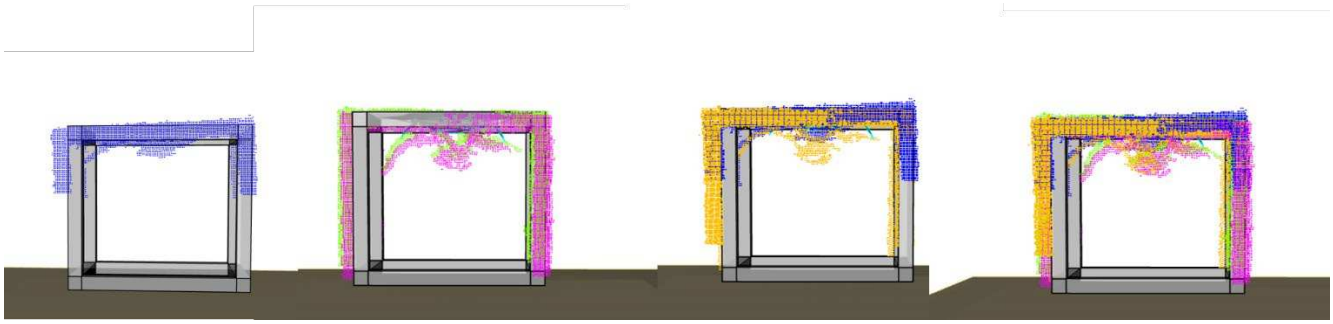


Figure 6: Comparison between the different plunging iterations, the desired and simulated digital shape is 85% match at the end of the process. The 'horn' areas overhung due to the cuts. The participant was satisfied with the result. Participant CS2-001.

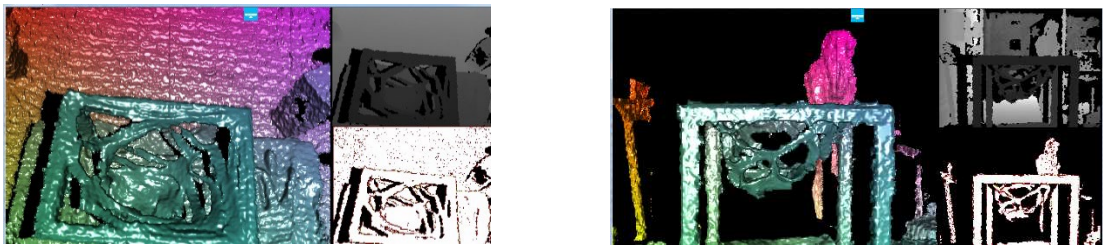


Figure 7: Participants scan the shape from different perspectives and view points as they go through the exercise. Participant CS2-009.

7.1.5 Data Collection

Data was collected via a 36-question Likert-scale questionnaire developed based on literature analysis and HCI and HRI parameters relevant to the design scenario, semi-structured interviews, field notes and videos of the design task. Participants started with the questionnaire which was divided in two parts and applied immediately after finishing the design exercise. The first part of the questionnaire evaluated aspects of trust in the robot, in the human and in the human-robot confederate. The dependent variable of the study consisted of 20 phrases describing the physical attributes of the robot, the robot performance, the human elements of the task and the complexity of the task. For each question there was a 5-point scale ranging from Strongly Agree to Strongly Disagree. The second part of the questionnaire was focused on evaluating the robustness of the team and the reliance on the robot: 1) Robustness defined as the opposite of dysfunction. Robustness in teams is related to the task and to the division of labour for members on the task. 2) Reliance described as the extent to which people relied on and ceded responsibility to a robot co-worker. 3) Improvement of the team, the robot and the human. The dependent variables for the study consisted of 15 phrases describing the task as responsibility of the participant or of the robot and distributing the success or blame of the task accordingly. For each question, there was a 7-point scale ranging from 1 (not agree at all) to 7 (fully agree)

Additionally, semi-structured interviews, video recordings of the participants during the design exercise and field notes were qualitatively coded and evaluated. Previous research in HRI has suggested that performance-related and attribute-based factors are highly influential in human's relation to non-industrial robots' which led to choose semi-structured interviews as tools to compliment the quantitative questionnaires (Charalambous 2014). Reliance and trust between the human and the robot agents are variables which measure was affected by the coding of the video recordings and the non-verbal indicators of both, such as the proximity of the participant to the robot, participant motions and collective or individual language when talking about the robot and about the design exercise. A video camera was mounted at the back of the robot room to record the sessions. Additionally, the researcher was always present taking field notes and providing technical support to the participants.

7.1.6 Procedure

A standardised procedure was developed identical for all participants. Participants were individually recruited from the school of architecture. Participants were informed about their right to withdraw, the anonymity of the research procedure and gave they written consent. Participant sessions were scheduled around their work and school commitments and they could attend them individually or as a group if preferred. During the first session participants were taken to a quiet room to familiarise themselves with the task. Following this, during session two, participants were taken to the robot cell to interact with the robot. The researcher instructed the participants regarding the task and the interaction with the robot. The third session, was done in the robot cell with participants moving inside

or outside the cage as required by their task decisions. The researcher was observing and helping the participants with technical difficulties that arise during the task. Upon completion participants completed the 36-item questionnaire, administered on paper. Upon completing the questionnaire, participants took part on an 8 -question semi-structured interview led by the researcher and which was recorded. After the interview participants were debriefed and reminded regarding their right to withdraw.

7.1.7 Data Analysis

All the interviews were fully transcribed and analysed using the Template Analysis in accordance to the guidelines provided by (King 1998). The template analysis process is based on the development of a coding template which represents the major themes in a hierarchical form. In this way, the coding process develops in a form where top codes represent the broad themes while lower level codes represent sub-themes. Themes outside the main ones and which were identified in a small number of transcripts were assigned their own codes. The template is iteratively revised to ensure that it reflects all the data reflected by the participants in the most suitable manner. Data was classified according to elements that correspond to the human, the robot physical, the robot digital (coding, scripts), externals (environment), design task (simulation, 2D to 3D design)

7.2 Results

Five main themes emerged from the qualitative analysis of the data as the main drivers for the human integration and comfort in the robot team-mate.

The robot performance was one of the most discussed themes. This includes the reliability of the robot, the robot end effectors and the feedback provided by it to the design task. This is in line with previous and more recent literature (van den Brule et al. 2014; Lee et al. 2004). Hancock et al (2011) in their meta-analysis of human-robot factors classify reliability of the robot performance factors as having the highest impact on trust. This has been reconfirmed by the work of Charalambous and van de Brule (Hancock et al. 2011; van den Brule et al. 2014; Charalambous et al. 2016) which highlight how the robot performance on the task influences human trust. An unreliable robot will eventually decrease the human trust and acceptance in the robot. What is important to consider, and that hasn't appeared on previous literature to the best or our knowledge is that the robot system includes the reliability of the end effector as part of it. Designers don't make a specific differentiation between both. This is of particular relevance to design HIRC. Robot arms have been perfected in their design through the year as well an industrial end effector such as grippers, welding and painting guns etc. However, designers are constantly making new, untested end effectors and when their reliability decreases so will the human trust in the robotic partner.

Physical attributes received little attention from the participants with most of them describing having a big robot as encouraging and empowering. Making the robot make what they want makes them feel empowered and gives them a sense of control over the design results. This is opposite to what the researcher expected and to previous literature in which smaller size robots increase the trust of the human. The robot appearance did not seem to be a factor or contribute to how designers felt about the robot. The literature on this provides contradicting results with some research suggesting that robot should not be too much human in appearance, while others suggest that a more human – like appearance is more engaging to people (Bartneck, Kanda, et al. 2009; Broadbent et al. 2009; Rau et al. 2010). Somethings that has come across in both cases, anthropomorphic and tecnomorphic robots, is that the robot appearance should match the robot abilities so that no unrealistic expectations are generated on the human user which will harm the

relationship later when they are not met (Bartneck, Kulic, et al. 2009). A possible explanation for this measure is that designers perceive the industrial robot as a tool designed to complete a task, hence its appearance is not important.

Robot feedback was embraced by the participants and constantly described as one of the best things from interacting with the robot. Participant from third year and higher engaged further with the scanning process, doing it from different angles, and continuously comparing the physical and digital models, even if manually jogging the robot they will consult the comparison having the screen with the scan and the digital model up for reference. Younger participants, 2nd year, were more inclined to follow their intuition and disregard the information given by the machine or consider it only as a curiosity. A level of maturity seems to be needed in order to understand the feedback and give some agency to others (humans or non - humans), and to accept external comments over their design process which might be different from their own intuition

"The feedback from the robot allows me to have a clearer understanding of what is going on and how the material is being affected. Because I am so immersed in the process of creation, I lose sight of the overall picture, I was thinking the horns were deforming a lot but after analysing the scan it became clear they are maintaining a more regular position that the rest of the shape. I feel that I see the deformation in a more subjective way mixing what I believe that is happening with what is actually happening, I don't get an overall perspective. The robot helps me put some distance between me and my design and have a more objective, clearer view of what is happening"

Participant CS2-001

The improvement of the robot team, although the task was performed over three 2-hour sessions was positive across participants. Although the robot was not improving neither learning through the design exercise participants rated the team improvement as high with comments *like "using the robot made me feel highly empowered when it was doing what I asked him*". Participants also credit the robot for allowing them to adapt and then empowering them to do more as the task progressed over time. *"First it was a little scary for me, and then it became really exciting and rewarding"* (CS2-003), *" it increased my reach, possibilities and vision, and my enthusiasm"* (CS2-019).One went so far as to claim that *"by the end of the session, we were good friends, the robot was understanding me, now I feel that I love him",* another participant commented *"He is adorable. Oh, I love talking to him"*.

The robot motion was a positive factor on the participants perception of it. The motions are very controlled but emotionally were described as *"the robot becoming alive"*. There is a valley between human rational and instinctive reactions to machines. Participants know the robot - specially in this case with an industrial robot- is nothing more than a programmed automaton. However, describing it as a live creature or how it goes from dead to live when it starts to move and becomes part of their lives is something recurrent. It is important to note that participants are describing as alive an industrial robot arm which is huge parts of metal, not describing a humanoid or a softer robot. A possible factor influencing humans attributes of liveliness to the robot is the human "like-me" perception of the robot (Hoffman & Breazeal, 2010) and tendency to antropomorphize even simple interactions by assigning them intention. This becomes specially relevant when objects, including robots, are in motion (Saerbeck & Bartneck 2010)

Figure 8: Catalogue of concrete shells resultant from all 25 participants. The boundary condition was the same for all. The pop-up pattern was designed and decided by each participant as well as the deformation during the process. Participants could go outside of the simulated shape

7.3 Discussion

The evaluated metrics of trust, reliance, robustness and improvement and their associated sub-metrics showed significant differences between the questionnaire answers and the answers during the interviews and field notes. In open questions, participants would attribute more human qualities to the robot such as gender, intelligence, emotional preferences as well as credit for success than in questionnaire answers. Interestingly, there is also a tendency towards self-deprecation from the participant in regards to his or her performance during the task. A high-number of participants comment on how the robot did his part of the contract correctly but it was them who messed it up. This poses an interesting challenge going forward, when considering robots that can learn and adapt which might have detrimental effects to human self-confidence and trust. The adverse effects of robot performance to the human intellect have not been sufficiently addressed by the literature.

The qualitative answers of the participants for the four main notions that compound fluency are more favourable than the quantitative scores given to the robots' performance. Positive comments go from participants been *'highly surprised and impressed with the robot performance'*, participant being surprised that the robot *'knows'* where to push the fabric to achieve the desired shape and even more surprised that he can actually do it. Participants claim that they connected with the robot *"The first I jogged the robot we had that first connection, and now if I had to do something and jog it*

manually, it was something like powerful, I couldn't believe that I could really tell it what to do" (CS2-019).To participants going as far as saying *"Is like that he is like a third hand"* (CS2-003). The emotional response to the robot was positive with participants using terms as *'amazing', 'cool'*, *'empowering to use'* with five calls each and two going as far as saying *'fascinating how it comes alive'*

Several negative comments were also found throughout the participants interviews, in particular with regards to communicating their design intents to the robot comfortably. These included *"I find that you need to master it and it takes time to be comfortable and it's not so much about what's the problem of the robot is about the problem of the gap between the user and the robot… I feel like it's interesting but then it takes such a learning curve. Is not like grasshopper"(*CS2-012), and *"after interacting with the robot all my concepts and ideas had a change, how to confront and to begin a design have to pass through a new concept"* (CS2-001).

There is also a reflection on the overall sense of robot performance with respect to the designer intentions, - differently from robot performance in general which received very good comments-.Comments included *"Sometimes the robot does whatever do you want whereas in others you start feeling that the robot has his own personality"* (CS2-022), "*Well, that's a problem with computers, that they do what you tell them to do not what you want to do"* (CS2-014) and *"Either you change your design or the robot will, so it must be adapted"* (CS2-025).Interestingly participants also saw the constraints of the robot as an opportunity to incorporate its agency into their designs *"We always try to dictate the rules -like in life - but we are not always on control, If we know how to be flexible to the constraints we can achieve more interesting results"* (CS2-001) and *"I think is good because. Because we got our hands, we don't have limitations in the way we've learnt to model traditionally. So, you know playing with something that does call for safety and limitations on the way, it's useful because if pushes the way you think"* (CS2-012) or *"It gives you a kind of freedom to create, even with its limitations"* (CS2-015).

An interesting thing to note, that hasn't been explored in the literature to the best of our knowledge, is the engagement with the software, coding and robot path planning aspects of the task. Research in the literature of human-robot and human -industrial robot interaction doesn't account for direct programming of the robot by the user. The digital programming of the task as a variable, in the literature, is considered as done by someone else and measured as the trust in the 'robot programmer' and participants are conscious that "they are not trusting the robot but the person who set it up" . Different from manufacturing tasks, designers are not using robots for programmed, repetitive tasks. The collaboration in a design scenario is not limited to the physical aspects of the task, designers have to relate their design thinking to the robot physical and digital capabilities in order to be successful in its specific realisation. Designers need to relate with the software and programming aspects of the robot and need to be able to communicate with it beyond physical intentions. The complexity or opaqueness of the robot software and interface can affect their overall perception of the robot as a partner. If they feel it is difficult to communicate their intellectual intentions to the robotic partner, they might see the robot as an obstacle rather than a collaborator in achieving the task, decreasing trust, even if the physical communication is clear.

8. STAGE 2

In the second stage of this exercise, based on the comments from stage 1, and aiming to give the robot more knowledge machine learning was introduced to enable the robot to learn and predict the material behaviour. The objective was to make possible for the robot to constantly suggest solutions from the defined design space and to evaluate the generated instances according to the

designer input, as well as to predict accurate results based on designer proposed new inputs. During stage 1 the robot was only offering the designer a scan from the material current state, a comparison with the desired state ('digital model') and the plunging positions to achieve it.

The experiment setup includes an ABB 6700 robotic arm fitted with a dual head end effector for cutting and plunging the concrete material. A realSense sr300 scanning device used to collect the deformation data, and the same concrete canvas material used. The 3D model was derived using a physics engine that simulates the behaviour of the concrete fabric material using the same form-finding process and cutting and joint pattern from before. The training method consist of two steps. The first step is focused on capturing, with the scanning device, a series of deformation sequences derived from the robot plunging and hydrating the concrete cloth. The second step, consists of cleaning, labelling the data and setting up the neural network architecture to match robot coordinates with material deformation.

8.1 Robotic Tooling

A robot tool with two heads, each at a 45-degree angle from the centre of the 6th joint was designed. On one head, the robot has a pivoting knife that allows it to cut the pattern of cuts and joints into the material, even when the material is hanging. On the other side of the head, it holds a pressurised water sprayer that ends on a sphere with multiple holes. At each plunging position, the sphere does a 360-degree rotation to 'massage' the concrete while spraying water around it. The hydration step is then controlled. Additionally, the amount of water that is covering each area during the plunge can be modified by reducing the length of the spraying. A point cloud is recorded during, and after the plunge, the effect of the water over the concrete becomes evident on the bounce back that the concrete presents on the resultant point cloud.

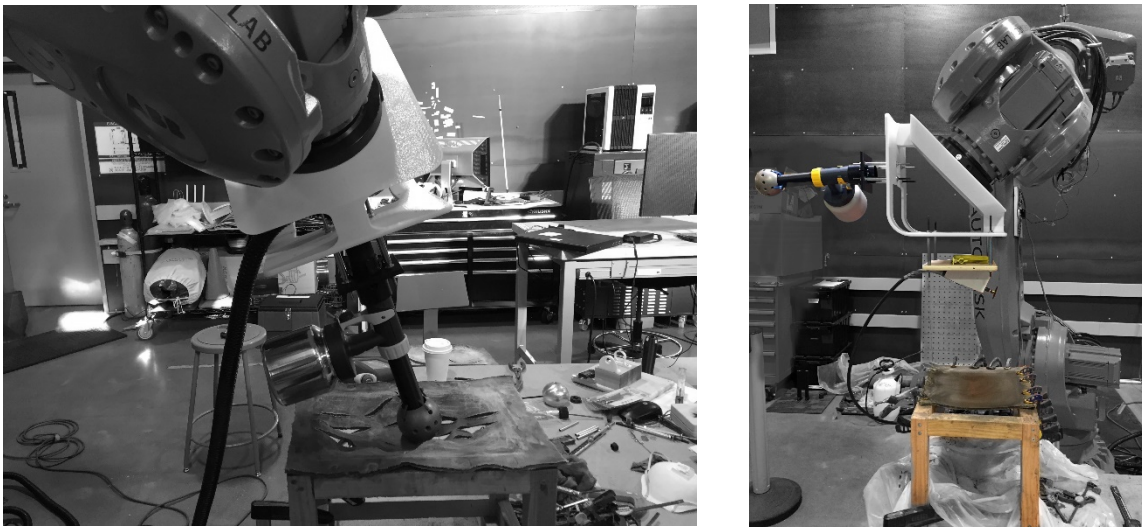


Figure 9: Robot Setup. Dual head for cutting, plunging and hydrating. Scanning Real Sense SR300 centred below the concrete shapes

8.2 Sphere calibration and Data Collection

A setup for data collection was designed so that all the point clouds on the data set are collected with the same origin position to reduce the amount of image processing to be done after collection. The setup consisted of a 500w x 600d x 400h mm wooden frame where the concrete cloth is stretched and hung for cutting and plunging. Situated at the bottom of the frame and centred to it an intel RealSense SR300 scanning device is positioned – inside its protective case.

A total of 3000 points clouds where collected across ten different concrete pieces - 1500 plunges and 1500 resultant conditions. The pattern of cuts and joints was kept constant in these ten pieces in an attempt to reduce the number of variables and test the strength of the system to predict the material outcome correctly.

Figure 10: Concrete pieces from the training data set. The initial pattern is the same for all, the plunging and hydrating coordinates are randomly generated for each of them.

8.3 Data Preparation and Neural Network Training

The captured point clouds of the concrete deformation where converted into depth images. Depth images contain the same amount of information needed for the neural network to understand the deformation at a lower computational cost. Initial 640 x 480 pixels images went through a dimensionality reduction process to generate a final training data set of 3000 images of 80 x 80 pixels each from concrete cloth deformations.

An additional set of images was generated containing only the coordinates of the sphere and a radius around it corresponding to the sphere dimensions. The images of the sphere positions where then overlapped to the images of the concrete deformation. Overlapping two images is a technique commonly used for machine learning studies of bridge structures: over-positioning the location of the acting loads to the collected images of bridge deformation (Gonzalez et al. 2017; Neves et al. 2018). The technique was used to ensure and accurate mapping of the plunging information to its resultant shape. A blur of 20 was applied to the set of overlapped images to reduce the noise.

A U-Net deep convolutional network architecture on Tensorflow was used as described by (Ronneberger et al. 2015). This method allows to effectively train a neural network using less annotated images by augmenting the data set relatively to traditional network training strategies. In this method, the contracting and the expansive path are more or less symmetric. Hence, a larger number of convolutional layers is preferred to keep a large number of feature samples. The dataset was trained using 40 feature layers on a 5 GPU core processor over 12 hours.

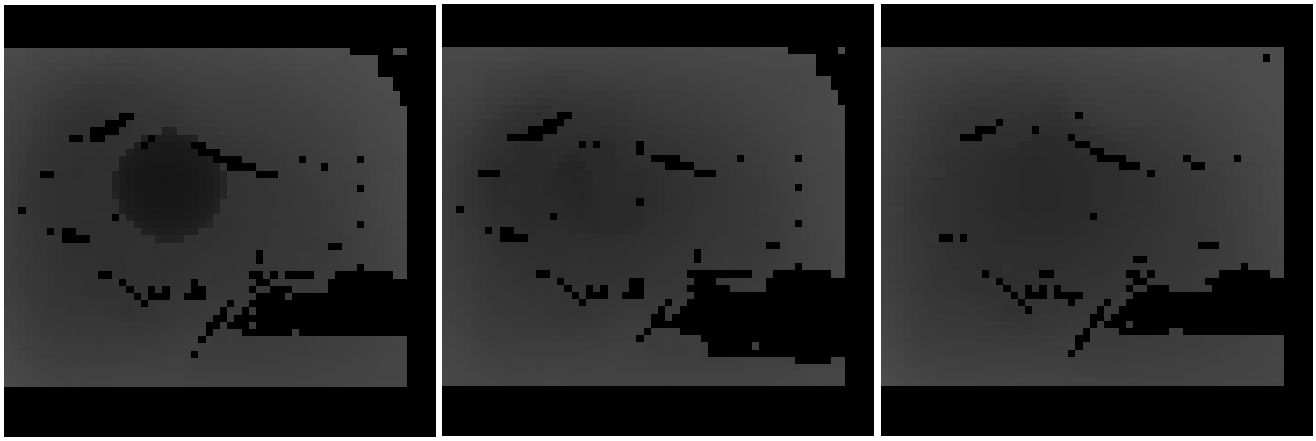


Figure 11: Example of input images from the training data set. Left: Input Image showing the initial condition with the sphere overlap; Middle: actual cloth condition after plunging; Right: Neural Network guess of the resultant shape after plunging

8.4 Data Validation

The evaluation of the training process was performed through a validation data set of 10 images - 5 pairs of plunging and resultant condition- which were reserved unseen to the network and used to test its prediction rate. From this dataset four predictions from the trained neural network where correct and corresponded to the results on the dataset.

Finally, two physical tests were performed with new pieces of concrete cloth. These pieces had the same pattern from the training data set cut by the robot. They were deformed using 120 randomly generated x,y,z positions and a scan was taken. This initial condition scan was then paired with a random x,y,z plunging position for the sphere. The results were scanned to be compared with the predictions of the trained neural network. In all cases, testing data set and new concrete forms, the trained network, successfully predicted the resultant concrete shape, including the deformation after plunging when the concrete springs back to place within a deviation of +- 2mm as measured from the point clouds between predicted and physical deformations.

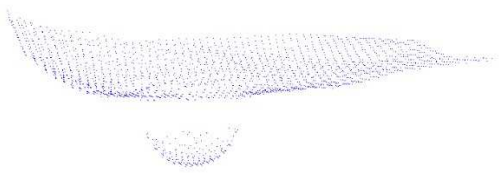


Figure 12: Physical test performed for data validation. Input image of a cloth existing condition with an overlap of the proposed plunging position.

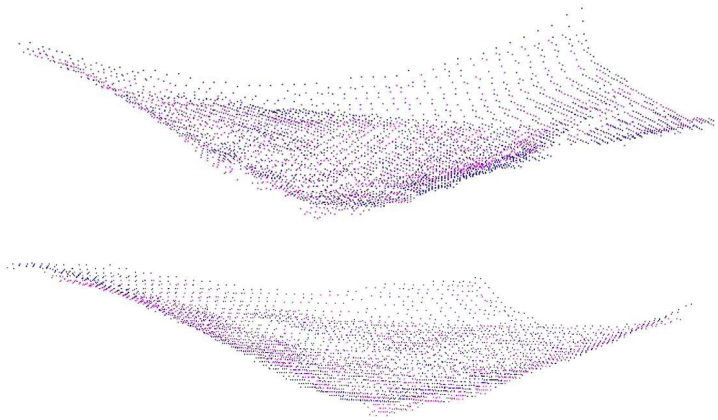


Fig. 13. Comparison between the neural network predicted result (blue) and the actual result after performing the plunge and scanning (red). Difference between points in less than 2mm.

9. CONCLUSIONS AND FUTURE SCOPE

The most interesting collaborative systems are those that produce emergent results, that are genuinely unexpected and rich and which could not have been predicted out from the constituent parts. The relationship between the input parameters and the output for these systems is generally complex and non-linear and there is a sensitive dependence from initial conditions. In many systems

the most interesting emergent behaviour occurs close to the boundary between regularity and chaos (MacKenzie 2013)

New robots are being developed every day utilising even better and more evolved technologies. The new frontier of research in robots is offering machines that can work together with humans as peers. These new robots can take the initiative and work in ways to accomplish high-level goals with its human partner. However, even for those cases the teaming between human and robot can be synergistic or counterproductive, depending on the level of human trust, robustness and reliance in the system. Understanding and starting to scope how designers relate to robots and what characteristics would make for a successful human-robot relation becomes crucial for understanding and designing robots and workflows that designers will engage with. This paper proposes the concept of team fluency based on notions of trust, robustness, reliance and improvement on a human-robot collaborative design task. It describes the design scenario and presents the metrics and their application to evaluate team fluency in human-robot design teams. Portions of this framework have been used in the past in the literature concerned with connecting and understanding the actions between humans and robots working on a common task. These metrics have to evolve, be refined and more added or removed as the intellectual relationship between designers and robots evolve. Initial results were presented of the design and evaluation framework on untrained designers. Evaluative HRC metrics (Hoffman 2019) have been generally validated in simple intellectual tasks such as robot and human collaboratively moving objects from one end of the table to the other. This paper presents the design and realisation of a intellectual evocative task, such as the design of a concrete shell, to evaluate HRC metrics during the design process. The task is representative of a common design exercise that architectural designers might have to do in a studio. Care was given to avoid a extremely difficult task that could cause work overload or overwhelm the designer.

There are aspects of team fluency that were not addressed and should be considered for future work. These include: how to take into account the correct and incorrect action of the robot and the human? (both were mentioned by the participants during the interviews), how can these measures be applied when there is more than one human and one robot working together? How will larger, human-robot mixed teams perceive each other when there are more agents to blame or credit? The proposed evaluative framework also leaves room for extension in design exercises that include different materials, and more human team members, while still providing opportunities for human-robot collaborative design. These scenarios might need from different objective metrics. There is substantial research required to fully understand human-robot collaboration in design tasks. However, we believe that a validated set of metrics and its initial findings evaluating team fluency in a human-robot collaborative design scenario is a great advance towards robots being accepted as partners and collaborators during the design task. The results also start to suggest how designers may respond to robot design partners and can provide input regarding collaborative design workflows and the roles that robots might play inside them and through the design process.

In the second stage deep learning is used as a successful tool to merge material deformation with robotic fabrication. It extends the role of machine learning towards design-oriented tasks and moves the robot role from that of final fabricator to becoming a central agent in the design process. This research also illustrates that machine learning can be an efficient tool to predict material deformations for non-linear materials where the physics are not known. The trained networks, also demonstrated the feasibility of capturing tacit material knowledge into a robotic system, i.e. the trained system successfully addresses changes in the material such as the bouncing back of the concrete after a plunge and hydrating sequence.

The next step for this research would be to combine the machine learning results from stage 2 with the designers and perform another set of questionnaires to evaluate their feelings of trust and reliance on a smarter team mate - robot confederate. The emphasis throughout the experiments has been on exploring the connections and relationships facilitated by digital software and hardware between design intent, computation logic and physical material. The focus of the framework implementation is on its use by designers who are not in a specialised digital or robotic fabrication course. Through the collected data, we are expecting to find how non-specialized users create relations between themselves, robots, the data and materials and how those influence their design thinking.The aim is to go beyond behavioural research to understand the key human factors for the design of novel visual and design communication technologies for human-robot collaboration during the design process that could be further developed in the future

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