Task Analysis of Discrete and Continuous Skills: a Dual Methodology Approach to Human Skills Capture for Automation

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Abstract

There is a growing requirement within the field of intelligent automation for a formal methodology to capture and classify explicit and tacit skills deployed by operators during complex task performance. This paper describes the development of a dual methodology approach which recognises the inherent differences between *continuous* tasks and *discrete* tasks and which proposes separate methodologies for each. Both methodologies emphasise capturing operators' physical, perceptual, and cognitive skills, however they fundamentally differ in their approach. The Continuous Task Analysis recognises the non-arbitrary nature of operation ordering and that identifying suitable cues for sub task is a vital component of the skill. Discrete Task Analysis is a more traditional, chronologically ordered methodology and is intended to increase the resolution of skill classification and be practical for assessing complex tasks involving multiple unique sub tasks through the use of taxonomy of generic actions for physical, perceptual and cognitive actions.

Keywords: automation; human-centred automation; task decomposition; hierarchical task analysis; human factors methods

Research problem

The technological capability of automation to replace or supplement human activity in manufacturing is increasing. As automation technology becomes more intelligent so does the capacity of automation to supplement not only the physical, but also the perceptual and cognitive aspects of a task. Whilst tasks that were previously the exclusive domain of skilled human operators can now be supplemented or replaced by intelligent automation, there exists no formal methodology to determine what tasks are suitable for intelligent automation, and to what extent they can or should be automated.

Within the human factors literature a number of papers have been published discussing the process of automation implementation, function allocation and suitability for

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automation with an emphasis on both operator well-being and system reliability (Endsley and Kaber, 1999; Kaber and Endsley, 2004; Lin, Yen and Yang, 2010; Parasuraman et al., 2000). The more recent papers can be summarised as advocating the 'levels of automation' approach (LoA) which assigns an automation level to specific components of the task such as 'option generation' or 'decision making', or to a task as a whole. Levels are defined from 1 (full manual control) to 10 (fully autonomous). Yet, whilst some guidance towards optimal automation is offered (Parasuraman et al., 2000), it is difficult to generalise how the level of automation affects overall human-automation performance (Endsley and Kaber, 1999), thus the burden of determining the suitability of automation is still largely left to the discretion of the system designer.

Notably the initial capture of the task is not discussed by these studies, perhaps under the assumption that traditional methods such as Hierarchical Task Analysis (HTA) and Cognitive Work Analysis are suitable skills capture for automation (Marsden and Kirby, 2004; Tan, et al., 2008). Although powerful, both of these tools are designed to be flexible and used in a range of applications beyond automation implementation, as such in specific cases these tools rely heavily upon the skill and experience of the analyst to know *what* information about the task is needed and *how* to structure and represent the information in a manageable way. Shepherd (2001) notes that as an analyst's experience with HTA grows so does their ability to try out new ways of task structuring and determine how to best visually represent information and thus the effectiveness of a HTA is tied to the skills of the analyst.

However it cannot be assumed that all automation projects will have access to this level of expertise for reasons relating to cost, being a small scale project or general access issues. Yet effective automation strategy depends upon accurate and sufficiently detailed decomposition of tasks, thus one of the challenges of effective intelligent automation in

manufacturing is being able to accurately capture both the implicit and tacit skills deployed by human operators during task completion, physical, perceptual and cognitive.

From a mechatronic perspective, experts in that field are better suited to determine the feasibility of automation based upon technical possibility and/or cost effectiveness, however human factors is ideally placed to inform and advise these decisions by offering a formal automation specific tool to accurately account of the processes that facilitate skilled behaviour. This detailed account of the human faculties would assist system designers to identify analogies between human processes and potential automated solutions which mimic human performance, but also devise ways in which automation may circumvent the required faculty.

In summary, automation engineers currently lack a formal methodology to fully evaluate the suitability of high skill manual tasks for automation. To address this problem, this paper describes the development of an accessible and comprehensive interpretation of task analysis to capture human skills specifically for the assessment of intelligent automation implementation suitability. The development of the TA is grounded in industry case studies capturing highly skilled manual manufacturing tasks; Tungsten Inert Gas (TIG) welding, aircraft assembly and steel polishing.

Hierarchical Task Analysis

Hierarchical Task Analysis (HTA) (Annett, 2003; Annett and Duncan, 1967, Shepherd, 2001) remains at present the most widely used task analysis methodology within human factors (Salmon et al., 2008). The HTA process identifies the primary goal of the task and then identifies the sub goals that must be achieved in order to complete the primary goal. Each subtask is in turn subjected to a similar analysis until a nested hierarchy of goals and subordinate goals has been created. Plans are added to the hierarchy representing the

unobservable decisions of an operator and which determine the sequence in which the operations are performed. Tasks can be analysed down to very precise movements and the level of detail provided is limited only by the extent of analysis by the researcher.

In its basic form HTA emphasises the identification of task goals; the recording of operations is achieved through the identification of their sub goals and plans (Shepherd, 2000; Stanton, 2006). Whilst the identification of task goals is an imperative step of mapping a task for automation to capture the tacit operations associated with high skill tasks as such to effectively account for the human faculties which are utilised, an emphasis must also lie in capturing the *process* as well as the goals. Although it could be argued that sufficiently deep analysis by a skilled analyst would be sufficient (even for highly skilled tasks), but merely describing goals, sub-goals and plans an analysis doesn't emphasise identifying the mechanisms which facilitate such action. For example, for an individual finger movement the goal may be stated as 'press a button', the plan may state how operator moves their hand and their fingers. However this would not account for *action-facilitating factors* such as visual judgement and haptic feedback to ensure the correct button has been selected and regulate the amount of force used to press the button etc. Whilst these factors may be superfluous for simpler, repetitive tasks associated with automation currently, when considering the implementation of intelligent automation for high level, tacit skills these mechanisms must be accounted for in order to achieve a comprehensive account of the task and how optimal performance is achieved. Shepherd (2001) notes that HTA is not a cognitive task analysis method but serves as a useful structural basis upon which cognitive tasks can be identified and appraised, and provide context for deeper analysis of cognitive elements. Therefore it is proposed that an effective and accessible human skills capture methodology is built upon traditional task analysis structure to provide context but also formalise the process of identifying the action-facilitating factors.

Human skills capture

Recently two key papers have been published which explore the capture of human skills for automation, the first; Bullock, Ma and Dollar (2013) proposed taxonomy of human and robot hand manipulations to enable the transfer of fine motor skill tasks to automation by describing the anatomical movements of the hand and its relation with the object. Manipulations are coded by their combination of sub classifications which in turn are rigidly defined terms such as 'contact' and 'prehensile' (i.e. whether contact is made and whether that contact is prehensile, respectively). The taxonomy is supported by examples of simple tasks that were successfully transferred to automation by mimicking human performance (e.g. picking up a coin). It could be inferred that the use of taxonomy to describe actions and facilitating factors in generic terms presents a reliable method to 'capture' the human skill and facilitate the development of automated solutions.

However its current form may be unsuitable for automation feasibility assessment; firstly it was designed for skill transfer of simple, fine motor tasks to automation and as such its scope is limited to hand and wrist actions only. Whilst it's resolution to distinguish between fine motor actions is comprehensive, this scope is too narrow to be applied to larger, more complex tasks employing larger body movements, sensory, and cognitive functions. Furthermore the depth and detail of the analysis required demands significant time and resources to capture even minute actions. Whilst this level of detail of physical movements may be necessary for skill transfer to automation, if the goal is to merely assess the feasibility of automation then it may be surplus to requirement and thus impractical. If the goal is use taxonomy for rapidly and effectively assessing feasibility of intelligent automation of larger, more complex manufacturing tasks then a simpler, broader scoped taxonomy of generic skill classifications is required.

The second paper by Caird-Daley, Fletcher and Baker (2013) explored the utility of task decomposition (TD) built upon HTA to capture the observable and unobservable, activities in manual tasks. The HTA and TD were constructed from observations, walkthroughs, talk-throughs, and interviews with experienced and novice manual Tungsten Inert Gas (TIG) welders laying a routine butt weld. As the methodology was specifically devised to 'capture' tasks to assess their suitability for automation it considers both physical and cognitive functions and analyses tasks at a resolution which is practical for complex tasks. However the resultant TD was susceptible to vague outputs where the human operator did not possess the specific required sense: for example, a tactile cue was described as "feeling how tacky the weld pool is when the filler rod is dipped in" (p353). The human operator cannot directly feel the tackiness (viscosity) of the weld pool as the operator isn't in direct contact; there must be some medium by which information from another source is translated to monitor the tackiness of the weld pool. A better resolution of skill classification would reduce this 'sensory leap' between non-directly observable parameters in the environment and perception by formalising the process of determining how physical stimuli are perceived.

Proper analysis of perceptual elements and reduction of the sensory gap is of particular importance for human skills capture for automation. This is to inform system designers of potential analogous automated solutions when feedback from the task environment is required and to assist the selection of suitable sensory systems. For example, if the analysis posits that a human operator visually tracks an object in three dimensions, this would suggest that some form of 3D tracking apparatus may be required for an automated solution. However it cannot be assumed that an optimal automated solution would necessarily mimic human operations, thus it is important to separate the actual parameter and the human perceptual mechanism within the analysis. At this point it should be reiterated that skills

capture alone cannot evaluate automation feasibility; rather the description of action-facilitating factors and identification of potential analogous automated solutions can only be used to *inform* decisions regarding automation implementation in concert with the expertise of mechatronic experts.

The study also found a predominance of 'skill' or 'rule' based performance (Rasmussen, 1983) which indicates that operators' actions are largely governed by pre-determined procedures. Although this represents only one scenario it could be speculated that most manufacturing tasks follow suit as they are by their nature predictable, occur in stable work environments, and are oft practiced and repeated. Therefore, it is argued that a manufacturing specific skill capture methodology should assume a procedural *modus operandi* and emphasise capturing the tacit procedural rules used by operators in task performance (Everitt and Fletcher, 2015). However, some tasks may not be rigidly procedural; instead they may be reactionary to environmental stimuli. This difference is the difference between *discrete* and *continuous* tasks which is discussed in the next section.

Discrete vs Continuous tasks

Within Caird-Daley et al's (2013) TD, the subtasks observed can be separated into two distinct groups: *discrete* and *continuous*. Discrete tasks are defined by a fixed beginning and end, usually with a change of states, for example, throwing a ball or pressing a button. In contrast, continuous tasks have no clearly defined beginning and end, and usually the objective of the task is to maintain a status quo in opposition to confounding influences, for example, steering a car or maintaining a reactor core temperature. Both types of task require operator skill but of different kinds: in the former actions occur in a fixed procedure whilst in the latter actions are reactionary to the context.

A key difference between discrete and continuous tasks is the nature in which subtasks are cued. Due to the clear definition of start and end states, discrete tasks are often cued by the completion of a previous subtask which gives rise to an arbitrary chronological ordering of the sub tasks. In contrast, within continuous tasks subtasks are cued when required by factors outside of the operators control and not in any particular order, thus the non-chronological nature of continuous tasks should be reflected within a task analysis. Furthermore it could be argued that part of the skill of continuous tasks is recognising within context *when* an appropriate subtask should be initiated. This means that one cannot represent the more fluid nature of subtask ordering within continuous tasks effectively using traditional, chronological based task decomposition methods.

This fundamental distinction makes it difficult to design a methodology which can effectively accommodate both fluid continuous tasks and rigid discrete tasks. It is acknowledged that traditional HTA through the use of plans can be used to accommodate and analyse fluid continuous tasks (Shepherd, 2001) however tradition methods become increasingly difficult to comprehend as complexity rises as traditional methods are grounded in actions and sub goals rather that the parameters which provoke them. Thus the analysis structure is stretched further and further to cope with ever increasing levels of interaction between factors. From an automation designer's and systems perspective this is unsuitable for assessing automation feasibility as one cannot easily trace the flow of information between the stimulus and the operator/potential automated solution. Furthermore by grounding the analysis in actions and sub goals the analysis encourages automation designs to simply mimic human operations, whereas a dedicated methodology grounded in the root parameters better facilitates designers to consider more novel automated solutions which match the parameters and not necessarily just mimic human actions. It is therefore proposed that discrete and

continuous tasks are analysed separately by differing paradigms designed to accommodate their individual requirements.

Dual Methodology Approach

In response to the differences highlighted between discrete and continuous tasks this paper proposes a dual methodology approach in which continuous and discrete tasks are analysed separately by Continuous Task Analysis (ConTA) and Discrete Task Analysis (DTA) respectively. ConTA is fundamentally structured to emphasise the stimulus cued nature of continuous tasks and also work to capture the 'skill' of deciding the most appropriate action in response to the prevailing context. Discrete Task Analysis presumes the procedural nature of tasks and facilitates the categorisation of tasks, similarly to Bullock et al (2013), but with a more practical and broadly scoped taxonomy. Both methodologies also place an emphasis upon the separation of parameter and perception to reduce or eliminate the sensory gap for reasons described earlier.

In the following sections ConTA and DTA will be individually described and then discussed in the context of an industrial case study (large aircraft assembly tasks and TIG welding respectively). The implementation of both methodologies in tandem will then be outlined and similarly discussed in the context of a case study which employs both discrete and continuous elements (steel polishing).

Continuous Task Analysis

Continuous task analysis requirements

To summarise the issues highlighted, an effective skill capture methodology for continuous tasks should:

- Recognise non-chronological nature of subtask ordering

- Recognise that identifying when to perform an action is part of the skill

- Reduce the sensory gap

Proposed paradigm for capture of continuous skills

The proposed methodology for the skill capture of continuous tasks presented here is a rapid departure from previous methods discussed. Instead of breaking the task up into chronologically defined stages ConTA emphasises identifying the relevant stimuli in the work environment and capturing the flow of information between the stimuli and the operator, as well as how this translates into behaviour. Four categories are proposed to achieve this:

- **Parameter** – describes the physical parameters within the stimuli which are monitored by the operator.

- **Perception** – describes *how* the operator perceives information regarding the Parameter.

- **Decision** – describes what decisions are made based on perceived information.

- **Action** – describes how decisions are translated into physical actions.

In theory each parameter will form the base of a 'procedural tree' which branches out depending upon the number of ways it is monitored (perception), the number of different conclusions to be made about the state of the parameter (decision), and the number of possible actions which can be taken (action). The branch tips then represent all the possible actions taken during the task, this bottom up approach ensures that the skills identified remain grounded to tangible parameters in the environment. The distinction between *parameter* and *perception* is designed to reduce the sensory gap described earlier, this is of particular importance for assessing intelligent automation feasibility in order to highlight potential analogous automated solutions. Inversely, by formalising the process of identifying the real-

world parameters separately it facilitates system designers to consider completely novel automated solutions as well as analogous.

In order to evaluate the practicality and effectiveness of the proposed task analysis format a case study was conducted to investigate the continuous skills employed by operators during a simple TIG weld. TIG welding was chosen as direct continuation of Caird-Daley et al's (2013) task decomposition study and the analysis was focused purely upon the actual welding stage, negating the preparatory and post weld tasks.

Case study 1: TIG welding

Ten welders (9 male, 1 female) were interviewed immediately after performing four short TIG welds: 2x butt joints (constant and varying gap), 1x lap joint, and 1x T-joint. The interviews were unstructured but questioning was directed to establish their perspectives on the four categories: parameters to be monitored, how to monitor said parameters, what possible decisions are made based on the state of a parameter, and how these decisions translated into actions. After the first transcript was analysed the sensory cues and procedural rules alluded to by participants were organised into the ConTA tabulations (table 1). After each subsequent transcript analysis the ConTA was refined to incorporate the new information until all transcripts were analysed and thus achieving redundancy. All data collection and analysis was conducted by one researcher.

[table 1 near here]

The methodology was able to identify how parameters are perceived and monitored by differing senses (visual, tactile, etc.) allowing the operator to 'triangulate' a more accurate perception of a parameter's current state. This is shown if the example discussed earlier (viscosity of the weld pool) is re-examined through the lens of the ConTA: whilst Caird-Daley *et al* (2013) reported weld pool viscosity as a factor, the ConTA (table 1) was able to

also determine that the viscosity (or rather the heat) in the weld pool is perceived indirectly by a combination of visually monitoring the *size* of the weld pool but also tactilely by the level of resistance felt when adding filler material to the weld pool. Furthermore visually observing 'Size/width of the weld pool' is also used to help gauge 'heat in the work piece', this suggests that observing the size of the weld pool is a primary visual perception in monitoring the state of the weld. This was supported by qualitative interview analysis of the transcripts in which participants, from a subjective standpoint, alluded to consciously concentrating on this parameter.

In terms of automation design these findings suggest that an analogous intelligent welding robot able to achieve the same performance as a human welder would need to be able to monitor the viscosity of the weld pool. Furthermore based on human performance this may be achieved by a form of visual sensor capable of detecting the size of the weld pool. Whilst this concurs with Caird-Daley et al's (2013) traditional analysis, crucially the ConTA also found tactile feedback from the filler wire to play a crucial part in controlling the weld suggesting some form of force/torque sensory system may also be required to achieve human performance levels. The advantage of the ConTA is that subsequent analysis of each perceptual avenue is kept separate which facilitates potential sub routines of any automated system to approximately modelled based on its potential sensory system. This in turn allows system designers to rapidly appraise the hardware requirements and the complexity of potential sub routines as independent separate systems, but by keeping the analysis grounded in the root real world parameter the potential need for triangulation of sensory inputs remains salient.

Discrete Task Analysis

This section will outline DTA, a task analysis designed specifically for capturing discrete,

procedural tasks in manufacturing; as such it is based upon the classification of subtasks into taxonomy of physical, perceptual and cognitive activities.

Discrete task analysis requirements

With respect to the points outlined, the following requirements are proposed:

- Categorisation of tasks into generic 'skill classifications' like Bullock, Ma and Dollar. (2013) but simpler, more practical and more comprehensive.

- Assume a rigid procedural nature of tasks.

- Reduce sensory gap

Proposed paradigm for capture of discrete tasks

DTA directly builds upon the Caird-Daley, Fletcher and Baker's (2013) task analysis, and as such is based more upon traditional HTA than ConTA. However, the categories represent different human faculties, and each category is supported by taxonomy of different skills within that faculty allowing each action to be categorised by what faculties are used and how they are being used. There are broadly three types of category: physical, perceptual and cognitive.

In terms of physical movements the classification paradigm is aimed to be a simpler, more practical version of Bullock, Ma and Dollar's (2013) methodology and two categories are suggested: fine motor skill and gross motor skills. The difference is defined as whether a physical action is performed within the hand (fine motor skill) or using muscles outside of the hand (gross motor skill). This allows the researcher to describe and discriminate both larger, more powerful actions predominantly performed with the shoulders and arms, and precise, delicate actions predominantly performed with the hands and fingers. Furthermore both action types can be performed simultaneously and independently of one another, thus it is

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prudent to record them as independent actions rather than assign a task as either fine or gross motor skill based. The implication for automated solutions from this part of the analysis is a straight forward description of the physical movements being undertaken.

Perceptual categories are derived from the traditional five senses: vision, hearing, touch, taste and smell. Olfactory and gustatory perception were omitted as they were deemed unlikely to be critical within manufacturing (they can of course be included if a future application demands it). Thus three categories are proposed: visual, tactile, and auditory perception. Accordingly with regards to implications for automated solutions the visual taxonomy is intended to reveal the potential requirement for 2D or 3D vision systems, the tactile taxonomy would suggest the potential requirement for force/torque sensors or laser scanning among others, and the acoustic taxonomy indicates the potential requirement for noise monitoring capabilities.

Cognitive activity is distinguished into two categories: decision making and communication. The identification of decision making processes is critical for the implementation of intelligent automation; the ability to capture the decisions made by an operator in relation to the state of current parameters is crucial to achieving the flexibility of human performance. Furthermore the capture of intra-task communication between two or more operators is of importance when one considers that novel automated solutions not only must integrate with the current system but also with the team of human operators. In order to effectively integrate from a human factors perspective any automated solution must be able to communicate the key parameters to remaining operators.

The categories and related taxonomy are outlined below:

- **Fine motor skill (FMS)** – this category is used to describe object manipulation with motor movement within the hand not including the wrist. It should also be noted if a

task requires both hands (bilateral) and each hand should be described individually. Subcategories:

- *Grasp* – prehensile contact that does not permit within hand movement.
- *Precision grasp* - prehensile contact that does permit within hand movement.
- *Precision screw* – rotating an object with a precision grasp.
- *Precision push/pull* – push/pulling an object with a precision grasp.
- *Non prehensile contact*
- *(T)* – added as a suffix to indicate the use of tool as opposed to manual handed actions

- **Gross motor skill (GMS)** – this category is used to describe object manipulation with motor movement beyond the hand (predominantly upper body). Subcategories:
  - *Place (remove)* – bring object/empty hand into contact with no/minimal force (opposite for remove).
  - *Screw* – rotate object (outside of fingers, e.g. with wrist).
  - *Position*
    - *Prehensile* – move an object to a certain location
    - *Non-prehensile* – move an object to a certain location without full freedom of movement (excluding gravity).
  - *Apply* – Place and smear object of surface.
  - *Push/pull* – Push/pull object outside of fingers.
  - *Strike* – Bring object/empty hand into contact with force.
  - *Hold* – Maintain position from last step.

- **Visual Judgement** – this category is used to describe information about stimuli being sensed visually. Elements of VJ which monitor directly controlled stimuli (such as FMS and GMS) are not included. Subcategories:

  o *Spatial judgement* – observation of position and motion of objects in 3 dimensions.

  o *Pattern recognition* – observation and recognition of patterns in 2 dimensions.

  o *Reading* – related to PR however is concerned with direct input of non-ambiguous information.

- **Tactile judgement** – this category is used to describe information about the environment being sensed by touch. During actions the regulation of force depending on resistance felt is assumed and so not noted in this category, unless a change of action is determined by tactile perception (E.g. switching from pushing to striking). Subcategories:

  o *Pressure* – detecting pressure applied to or against the operator

  o *Texture* – detecting differences in texture on a 2d plain.

  o *Temperature* – detecting level and changes in temperature.

  o *Vibration* – detecting level and changes in vibration on a surface.

- **Acoustic judgement** – this category is used to describe information about the environment sensed by sound. Subcategories:

  o *Presence* – detecting only the presence of a sound

  o *Pitch/volume* – detecting characteristics of a sound

  o *Acoustic source localisation* – determining the location of a sound source

- **Decision making** – this category is used to describe any decision making based on situational context. In the first iteration of the methodology it is open ended as decisions are often deeply grounded within the context and thus difficult to describe in generic terms.

- **Communication** – this category is used to describe communication between two or more operators that is essential to task completion. Note that this category is intended to capture intra-task communication rather than delegation of separate tasks.

From the output of this method an automation designer would be able to look up any individual subtask and quickly assess the physical, perceptual and cognitive capabilities required by any automated system to replace human input. The advantage of this approach within automation implementation is that it assists function allocation on two fronts: firstly, the output provides a template for further analysis and allows automation designers to gauge the level of difficulty for automating individual sub tasks in terms of technical difficulty or cost effectiveness. Secondly, this approach provides a view of the operations left for the human operator following automation which may be useful for evaluating possible impacts of automation and identifying training needs.

As with Continuous Task Analysis a case study was conducted to evaluate the practicality and effectiveness of the methodology. In contrast to the previous case study a different task was chosen in lieu of TIG welding; instead an aerospace manufacturing task was selected due to the task being seen as having a heavier emphasis towards discrete tasks.

Case study 2: Aircraft assembly

The task selected was the installation of a large component to a passenger aircraft wing. The

first stage of the analysis was for the researcher to familiarise themselves with the task, this was achieved through study of standard operating procedures and inspection of a completed installation. The main data collection was conducted by ethnographic methods consisting primarily direct observations of operators completing the task, talk-throughs of the task, and unstructured interview questions. Observations of task completion primarily served as task familiarisation and to record physical functions. During observations operators were asked to talk through their actions and decisions as they worked, specifically with regards to their decisions they were asked to describe how they came to decisions and what information influenced this process. Alongside this operators were asked occasional unstructured questions as cues to better reveal their thought processes, actions and plans.

Main data collection was conducted during normal working conditions at the product flow line and took place over four visits during which the task was observed six times. Information was recorded manually on paper from which a HTA was constructed which was subsequently validated by operators for accuracy. From this each individual sub task was analysed with operator input to determine which skill classifications corresponded with the sub task (two examples are shown in tables 2 and 3).

[tables 2 and 3 near here]

The initial HTA identified 107 unique sub tasks; subsequent DTA determined that 8 were purely cognitive/sensory tasks, 34 required visual judgement, 26 required tactile judgement, one required acoustic judgement, and 25 cases of decision making. The output of this analysis was successful in identifying and distinguishing physical functions used by operators. Whilst the concept of identifying categories of pre-defined actions lacked the precision of Bullock et al's (2013) system, it was possible to classify information of manipulations of multiple actions with relative efficiency. Further analysis in concert with automation experts would be able to identify the automation challenges, where the 'crux' of

full automation may exist, and highlight subtasks which may share certain characteristics. The success of the methodology in capturing the perceptual skills of operator was mixed; on the one hand the methodology appeared well suited to classify and distinguish between forms of visual judgement. However with regards to tactile judgement the classification system lacked the necessary resolution to distinguish between tasks. This presents a potential area for subsequent work. With regards to the cognitive functions of decision making and communication, separating the acquisition of information from the purely cognitive functions allows system designers better determine whether a decision can be automated or should remain a human task. Additionally it allowed decisions which may appear very different because of their context and sensory source be recognised as essentially the same style of decision. For example, two subtasks identified appear at first glance to be very different however they both share the same cognitive function: estimating extent of correction required of a variable. They differed only in perceptual factors: one depended upon tactile judgement and the other visual. With regards to the implications for automated solutions in this instance, the analysis suggests that if the perceptual or sensory obstacles can be overcome then a similar subroutine can be used for both subtasks.

Dual methodology approach

The two contrasting methodologies already outlined are intended to map the physical, perceptual and cognitive faculties used by operators and so inform system designers of the capability requirement for each component subtask. They have been designed to be used independently as standalone tools to capture discrete and continuous skills but also in conjunction to provide a holistic skill capture of tasks composed of both.

Taking a Dual Methodology Approach (DMA) is relatively straight forward if subtasks can be clearly identified as either discrete or continuous, one can simply apply

whichever methodology is suitable. However the definitions of continuous and discrete skills lie at the extremities of a gradual scale within which most tasks would reside towards the middle. Tasks with discrete goals, composed of discrete skills may still require continuous skills in order to counteract external factors which may hinder the completion of the discrete elements of the task. For example: landing an aircraft requires completion of discrete tasks in order to achieve the goal of stopping safely, however the pilot must still make continuous, reactionary adjustments throughout to achieve the desired outcome. Therefore, what is required is a combined methodology which recognises and accurately captures both the discrete and continuous elements *within* an individual subtask. A comprehensive DMA methodology is outlined below which seeks bridge the gap between discrete and continuous tasks by incorporating ConTA within an overall DTA. An industrial case study investigating the tacit skills of steel polishing operators was conducted to evaluate the practicality and effectiveness of the dual methodology approach.

Proposed paradigm for the capture of mixed type tasks

The DMA is built around a refined and expanded DTA with the primary addition being a category for continuous task elements within individual discrete subtasks. This category is used alongside the other skill classification categories to indicate that the subtask contains continuous task and be linked to a separate CTA concerning that specific subtask (for example, different subtasks which require differing continuous skills may be labelled within the DTA as CTA1, CTA 2, etc.).

For this second iteration of DTA some more subtle refinements were made comprising of the addition of two new skill categories and new taxonomy of decision making skills. The first new skill category is Motor Program: this category is for describing whether a physical action is '*open loop*' thereby movements are performed without modification in

response to perceptual feedback, or whether and action is '*closed loop*' thereby physical movements are modified. At this stage it is important to define the difference between discrete closed loop actions and continuous skill which is one of scale. A discrete closed loop task may involve a minor adjustment while completing a rigidly ordered task (for example, calibrating the force required when lifting a weight), whereas continuous skills involves deploying specific actions in response to perceived stimuli. The second new skill category is Pacing: this category is for describing whether the operator performs at their own pace (*internal pacing*) or must 'keep up' with the wider system (*external pacing*). This is important when considering the viability and requirements of an automated solution with a systems integration context. The final refinement is the addition of taxonomy of decision making skills which is intended to increase the overall resolution of skill capture. The taxonomy is based upon the nature of the possible decision outcomes; specifically the types are derived from Stevens' (1946) "Levels of Measurement" and are outlined below:

- Nominal – options have no numerical connection (e.g. red, blue, green)
- Ordinal – options can be ranked (e.g. 1st, 2nd, 3rd)
- Interval – options have a degree of difference with an arbitrary zero point (e.g. -5C, 0C, 5C, 10C)
- Ratio - options have a degree of difference with a natural zero point (e.g. 1kg, 2kg, 3kg)

As with DTA and ConTA individually, an industrial case study was conducted to assess the DMAs effectiveness and practicality in capturing human skill: manual steel polishing.

Case study 3: Steel polishing

Similar ethnographic methods utilised in the previous case study (talk-throughs and observations) were used again for the latest case study exploring manual steel polishing. Data

was collected during normal working hours whilst ensuring minimal intrusion upon normal working conditions. Four current and experienced operators were observed and interviewed over four sessions of ranging up to 6 hours. The researcher also conducted some elements of the task themselves providing additional introspective insight. As with the previous case study, a HTA was first constructed which served as a structural basis for the skills analysis proper. For subtasks which appeared to include elements of continuous skills a ConTA was constructed via talk-throughs and informal operator questioning for each unique subtask. An extract from the DTA is shown in table 4 whilst the corresponding ConTA is shown in table 5.

[tables 4 and 5 near here]

Recognition of both the discrete and continuous elements within subtasks whilst also recognising their differing contributions to task performance provided a more holistic view of the skills being employed. Specifically within mixed task types the ConTA complemented the DTA by providing information about how perceptual information is being used; for example, in all of the three ConTA's related subtasks the DTA identified pressure based tactile feedback while the accompanying ConTA showed how it is used to monitor the pressure being applied to the surface and counteract torque. Additionally the DTA complimented the ConTA by giving the 'information flow' captured by the ConTA context.

The modifications of the DTA methodology can be considered successful in increasing the resolution of the skill capture. The addition of the motor program category was able to highlight crucial differences between otherwise similar tasks; for example differing strategies employed by operators during two different stages of polishing: 'rough mopping' and 'disking', during the former operators would polish an area and then inspect it, whilst in the latter the operator would constantly monitor the condition of the surface and adjust their polishing accordingly. From an automation perspective these represent two vastly different

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approaches: the first represents a 'pre-programmed' physical action followed by a quality check whilst the latter represents a continuous feedback and adjustment of the polishing action. Whilst it is possible to identify these opposing strategies with traditional task analysis methods the advantage of the DMA is that output from the ConTA also makes salient that the critical factor which facilitates successful performance is visual monitoring of the surface condition.

The taxonomy of decision making skills was able to accommodate all the decisions observed and provided an extra dimension of information regarding option generation within the decision making process. A specific example, the expanded taxonomy allowed the analysis to identify fundamental differences in the decision making process between selection of disk/mop shape and grade: the former requires selecting between nominal options whilst the latter requires selecting between interval options. In terms of the implication for a potential automated solution this could suggest the former would require a simpler algorithm to model the human operator's decision process due more salient differences in options compared with the more subtle differences of options on an interval scale.

Within the current case study the analysis found all the subtasks to be internally paced, however it is likely that analysis of further case studies would find mixed paced tasks, as such it is this scenario that the pacing category would improve skill capture resolution.

In conclusion the modifications and synchronisation of DTA and ConTA appear to have improved their effectiveness and increased the level of detail they can provide. Furthermore by recognising the importance of the interaction between continuous and discrete elements within tasks, the DMA provides a more holistic view of how human faculties deployed during task completion.

Discussion

As progress towards the goal of a robust, formal skill capture methodology for assessing the feasibility and implementation of intelligent automation the methodologies proposed in this paper represent a step forward. DTA supplements traditional HTA methods to provide a framework upon which to explore factors which facilitate operations, with regards to the implications for automation implementation this allows system designers to map out how an automated system would match human performance physically (FMS, GMS, Motor program), perceptually (Visual, Tactile, Auditory judgement) and cognitively (Decision Making, Communication) for discrete tasks. What DTA offers over standard HTA is a classification system which guides the analyst to identify the action-facilitating factors and thus an insight into the range and type of capabilities an automated solution would require. This was demonstrated in case study 2; within the 107 unique tasks identified DTA classified the range of human faculties being deployed from various physical manipulations, visual and tactile judgements and decision making.

ConTA frees the analysis from attempting to force an arbitrary chronological order on more fluid, context reactionary tasks, which in terms of automation implementation allows system designers to see the flow of information between the operator and the stimulus, which in turn assists the development of analogous sub routines for automated solutions. Whilst this may not provide information which cannot be revealed by an experienced analyst using traditional methods, the advantage of ConTA is that it is structured to explore the tacit decisions and actions based on sensory inputs individually, making it salient how each input influence decisions. The implication for automation design is that the designer can easily identify which sensory inputs may be of greater or lesser importance for achieving desired levels of performance. In turn each sensory input is grounded to the root parameter so the reader can also begin to model how sensory inputs triangulate. Furthermore by formally

structuring the analysis around the identification of real world parameters this can facilitate the creation of completely novel ways to monitor a parameter. For example in case study 1 it was shown that human welders monitor the heat in the weld piece tactilely by thermoreception and visually by the size of the weld pool, redness in the weld piece, yet an automated solution could simply use a thermal camera to precisely monitor the temperature.

When used in conjunction as the Dual Methodology Approach the methodologies provide a more comprehensive view of the action-facilitating factors of human performance by probing not only what human faculties are being used but also addressing how they are being used (i.e. in a rigid, discrete manner or in a fluid, continuous manner). Furthermore Shepherd (2001) reported that the practice of recording constraints the notes column of HTA lack rigor, by incorporating ConTA into DTA or even HTA it provides a simple, accessible structure in which to represent the continuous strategies employed by human operators to cope with constraints experienced during discrete task performance.

Within the automation implementation process these methodologies are ideally suited for two purposes: assessment of automation feasibility and human to automation skill transfer. With regards to the first application the use of taxonomy to reveal the action facilitating factors allows designers to approximately 'map out' potential automated solutions, including hardware capabilities, sensory systems and decision making artificial intelligence. This in turn allows system designers to assess the theoretical system's feasibility from both a technical standpoint as well as cost effectiveness. In the context of complex multifaceted tasks it can used to ascertain which parts of a task may be suitable for automation, and those which may be more suited to human operators.

With regards to the second application the methodologies are limited by the fact that they are merely theoretical frameworks upon which rely upon traditional qualitative human factors techniques such as ethnography and interviewing. Their strength lies in the

identification of critical factors which facilitate tacit human skill but they are limited in that the techniques upon which they rely cannot produce technical data regarding those critical factors within tacit skill. In order to be able to truly match human performance quantifiable data regarding these parameters must be obtained (e.g. Newtons of force required for steel polishing). Whilst arguably beyond the scope of human factors, the development of technical measurement of human skills for transfer to automation presents an important avenue for future research. It is envisioned that the methodological paradigms proposed in this paper will form the former in a two-step, multidisciplinary process; the identification of critical factors followed by technical measurement.

The development of a more structured task analysis model for intelligent automation implementation outlined is still in its infancy and as such it is subject to some limitations. Firstly, the bulk of the data collection and analysis has been carried out by a single researcher and so the study has been unable to empirically demonstrate internal reliability of the methodology. Whilst it could be argued that task analysis is by its nature a subjective process and that it is possible for two or more differing but equally valid interpretations to exist, this is rooted in the flexibility of common task analysis methods such as HTA and CWA. As DMA is intended to be a more structured analysis tool the immediate concern of future developmental work should be the demonstration of inter-rater reliability. Secondly, the case studies presented are intended solely to evaluate the practicality of the methodology in use and were not linked to a specific automation project. Thus the next logical step in the methodology development is a test of the methodology as part of 'live' automation project to assess the contribution of the output data to actual automation design decisions. The main purpose of this paper is to introduce and outline the early development of the DMA, it is anticipated that in the course of future publications that the methodologies will evolve and these limitations resolved or reduced.

In conclusion, the primary advantage of the proposed DMA to the more generic task analysis methodologies currently proposed (HTA, CWA, GOMS) is its rigid structure which makes it more accessible to automation designers for conducting analysis, comprehension of the critical factors, and making inferences. Finally these methodologies demonstrate the value of applying human factors knowledge, beyond HTA, to capturing human skill for the purpose of implementing intelligent automation. However, human factors are only one part of what must be a multidisciplinary effort.

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Parameter	Perception	Decision	Action(s)
Size/width of the weld pool	Visual - depends upon material and thickness	Correct width	
		Too big	**Reduce current**
			Reduce filler
			Lift torch away from weld pool
		Too small	**Increase current**
			Increase filler
			Concentrate the heat
			Lowering the torch
Position of the weld pool	Visual	Evenly distributed over both work pieces	
		Skewed towards one work piece	**Adjust torch away from over-melted/towards under-melted work pieces**
	Anticipation - More heat in a work piece will mean faster melting. See: Heat in the work piece(s)	Even temperature across work pieces	
		Uneven temperature across work pieces	**Adjust torch away from over-melted/towards under-melted work pieces**
Shape of the weld pool	Visual	Flat	
		Concave	**Increase filler**
		Convex	**Decrease filler**
Heat in the weld pool	Visual - indicated by width of weld pool	see: Size/width of weld pool	
	Tactile	Weld pool "nips" the filler rod	
		Too much resistance to filler rod	**Increase current**
			Concentrate the heat
			Lowering the torch
		Too little resistance to filler rod	**Reduce current**
			Lift torch away from weld pool
Gap between work pieces	Visual	Gap size consistent	
		Gap getting larger	**Reduce current**
			Increase filler
		Gap getting smaller	**Increase current**
			Reduce filler

Heat in the work piece(s)	Anticipation - position of the work piece		
	Anticipation - thickness of work piece		
	Visual - indicated by width of weld pool	see: Size/width of weld pool	
	Visual - red glow on work piece	No red glow	
		Red glow	**Reduce current**
			Lift torch away from weld pool
	Tactile - feel the heat on the hand	Feel heat	**Reduce current**
		No feeling of heat	**Lift torch away from weld pool**
Misc	Auditory	"Nice crackle"	
		Change of pitch	*Depends on other stimuli*
		Pop	**Lift torch away from weld**
			Stop weld

Table 1

HTA	Task	FMS	GMS	Visual judgement	Tactile judgement
3	**Primary rigging**				
3.1	Rotate component A to 0 degrees (T)			Spatial - track position of component A	
3.2	Recheck component C alignment (see 1.1)				
3.3	Attach component D				
3.3.1	Place component D on track beam 3				
3.3.1.1	Place component D on aft end of component E	Grasp (T)	Place		
3.3.1.2	Secure with locating screws by hand (x4)	Precision grasp and screw	Place		Pressure - detect when sufficiently fastened.
3.3.2	Place component D on track beam 4				
3.3.2.1	Place component D on aft end of component E	Grasp (T)	Place		
3.3.2.2	Secure with locating screws by hand (x4)	Precision grasp and screw	Place		Pressure - detect when sufficiently fastened.

Table 2: Please note that categories not used have been omitted.

HTA	Task	FMS	GMS	Visual judgement	Tactile judgement	Decision making	Ergonomic issues
5.2	Install component F						Posture - for the entirety of the component F installation the operator has to bend over (approx 30 degrees) the flap in order to access the mid cruise roller.
5.2.1	Insert washer into bolt hole	Precision grasp and push	Place		Pressure - detect when washer is correctly inserted		
5.2.2	Position component F in line with bolt hole	Precision grasp	Position				
5.2.3	Decide if within tolerance (<3mm gap, 0mm gap if movement is permitted, 1mm gap is ideal)	nil	nil	Spatial - observe gap between component A and component F		Decide if suitable gap is achieved	
5.2.4	Replace component F if necessary, repeat 5.2.2. and 5.2.3.						
5.2.5	Insert bolt	Precision grasp and push	Place				
5.2.6	Secure with nut (20Nm) (T)	Precision grasp and grasp (T)	Screw				
5.3	Rig component F						
5.3.1	Unscrew nut from component G	Precision grasp					
5.3.2	Lift locking plate (T)	Grasp (T)					
5.3.3	Rotate eccentric bearing to adjust gap between component F and 'dagger bracket' until it's <2mm but allows movement	Precision grasp and screw		Spatial - observe gap between component F and 'dagger bracket'		Decide if suitable gap is achieved	

Table 3: Please note that categories not used have been omitted.

HTA	Task	FMS	GMA	MP	Visual judgement	Tactile judgement	Decision making	Pacing	ConTA
4.5	Perform radding								
4.5.1	Perform first sweep								
4.5.1.1	Apply power to radding tool	Bi-Grasp/Precision grasp (T)		Open loop				Internal pacing	
4.5.1.2	Make contact with target edge at either extremity perpendicular to the edge and at an acute angle	Bi-Grasp/Precision grasp (T)	Place	Open loop				Internal pacing	
4.5.1.3	Move mop/cone down the edge to other extremity.	Bi-Grasp/Precision grasp (T)	Position	Closed loop		Pressure		Internal pacing	ConTA (table 5)
4.5.2	Perform second sweep								
4.5.2.1	Apply power to radding tool	Bi Grasp/Precision grasp (T)		Open loop				Internal pacing	
4.5.2.2	Make contact with target edge at either extremity perpendicular to the edge and at an acute angle	Bi Grasp/Precision grasp (T)	Place	Open loop				Internal pacing	
4.5.2.3	Move mop/cone down the edge to other extremity.	Bi-Grasp/Precision grasp (T)	Position	Closed loop		Pressure		Internal pacing	ConTA (table 5)
4.5.3	Perform final sweep								
4.5.3.1	Apply power to radding tool	Bi Grasp/Precision grasp (T)		Open loop				Internal pacing	
4.5.3.2	Make contact with target edge at either extremity perpendicular to the edge and at an angle equal to both surfaces (fig.3)	Bi Grasp/Precision grasp (T)	Place	Open loop				Internal pacing	
4.5.3.3	Move mop/cone down the edge to other extremity.	Bi-Grasp/Precision grasp (T)	Position	Closed loop		Pressure		Internal pacing	ConTA (table 5)
4.6.	Determine if edge is sufficiently radded	Non-prehensile contact	Place/Smear	Closed loop	Spatial recognition		2-way nominal based decision	Internal pacing	

Table 4

Parameter	Perception	Decision	Action(s)
Pressure against edge	Tactile	Appropriate pressure applied	
		Too much pressure	**Ease off pressure**
		Too little pressure	**Apply more pressure**
Torque	Tactile	Fluctuation of torque effect	**Adapt forces applied to maintain steady movement**

Table 5