A Task Analysis Approach to Quantify Bottlenecks in Task Completion Time of Telemanipulated Maintenance

Henri Boessenkool[1,2], Jeroen G.W. Wildenbeest[3,4], Cock J.M. Heemskerk[3], Marco R. de Baar[1,2], Maarten Steinbuch[2], David A. Abbink[4],

Abstract—Telemanipulation techniques allow for human-in-the-loop assembly and maintenance tasks in otherwise inaccessible environments. Although it comes with limitations in achieved performance - required strict operator selection and extensive training are widely encountered - there is very little quantitative insight in the exact problems operators encounter during task execution. This paper provides a novel hierarchical task analysis approach to identify the most time-consuming subtask elements and to quantify the potential room for performance improvement during telemanipulated maintenance tasks. The approach is illustrated with a human factors case study in which 5 subjects performed six generic maintenance tasks, using a six degree of freedom master device connected to a simulated task environment. Overall it can be concluded that the proposed Three Phased Task Analysis is a useful tool to guide improvements since it is able to relate high-level problems (e.g. large variability) to behaviour on lower task-levels. For the case study, the largest potential for improvement was found for specific subtasks characterized by complex contact transitions and precise control of tool orientation, and in the reduction of variation of the task execution.

Index Terms—Remote maintenance, Tele-operation, human factors, task performance, task analysis.

1 Introduction

When human interventions are required in hostile environments, telemanipulation is needed. An example is the envisioned teleoperated maintenance for the experimental nuclear fusion plant ITER [1], which is foreseen to require challenging maintenance in an environment with high radiation levels and toxic materials. Efficient maintenance is one of the key factors to the success of ITER and other future fusion plants: maintenance limits the uptime of the plant and should be executed in the shortest possible timeframe [2]. In general, the performance of such remote task execution is limited (long execution time, limited accuracy, errors) and prone to high workloads [3], [4], even though operators passed a very strict selection procedure and an extensive training period [3]. This illustrates how difficult and challenging execution of remote maintenance is.

While many efforts have been made to improve task execution by for example proper design of the telemanipulation device (improved transparency through hardware [4], [5], [6], and control [7], [8], [9]), improved visual feedback (e.g. stereoscopic viewing, augmented visual feedback [10], [11]), and guidelines for the design of the task environment (e.g. the Design for Assembly approach [12], [13]: captive bolts, mechanical alignment features, grip features, etc.), there is still limited insight about what exactly complicates task execution and how this is reflected in the task execution. For example, are the long execution times the result of slow motions, inefficient motion coordination or errors and restarts? Currently, most valuable contributions to understand complicating factors in remote maintenance tasks are high level and assumption-based [4]: an expected specific cause (e.g. limited transparency, 2D viewing, sense of presence) is manipulated, and subsequently task performance is experimentally evaluated with high-level metrics, usually execution time. Although such an approach can quantify overall improvements, it can't give insight into the underlying behaviour that causes these improvements, such as: timing, variability, repeatability, trajectories and exerted forces. Insight in the relation between high-level task execution and low-level kinematic and dynamic description of operator behaviour would be very useful to guide possible directions for further improvements. Furthermore, it enables to see 'high-level' research results in the context of achievable improvements on a skill-based level.

Task analysis can be a powerful tool to give insight in task execution and to identify potential improvements in human-machine interaction [14]. Although widely used in other fields (e.g. surgery [15], [16]), it is, to the knowledge of the authors, hardly used for (non-medical) teleoperated task execution. In a previous study by the authors, a high-level task analysis was performed on logbook and video data of real executed remote maintenance tasks at the operational fusion facility JET (the closest comparison to the envisioned maintenance at ITER) [17]. The high-level results provide insight in the overall execution time of tasks and effects of the operator's level of experience on time performance. Detailed task analysis of subtasks was however not possible with

[1] *DIFFER - Dutch Institute for Fundamental Energy Research, P.O. Box 6336, 5600 HH Eindhoven, the Netherlands, www.differ.nl*
[2] *Eindhoven University of Technology, Dept. of Mechanical Engineering, Control Systems Technology Group, P.O. Box 513, 5600, MB Eindhoven, Netherlands.*
[3] *Heemskerk Innovative Technology BV, Mijnbouwstraat 120, 2628 RX Delft, the Netherlands, http://www.heemskerk-innovative.nl*
[4] *Delft University of Technology, Department of BioMechanical Engineering, Faculty 3me, Mekelweg 2, 2628 CD Delft, The Netherlands.*

the available logbook data and would require additional detailed video analysis. Although the available unique operational logbook and video data is a very valuable source for task analysis, it also has some limitations. Since the data does not origin from a measurement in a controlled laboratory environment, it contains inherent uncertainties (e.g. deviations from task protocol, unclear waiting times), complicating reliable analysis. Furthermore, besides task-completion-time, no objective data is available about the skill level execution like performed trajectories and exerted forces. To gain more insight in how to improve teleoperated maintenance, it is important to perform more detailed task analyses which study the relationship between high-level tasks performance and low-level kinematic and dynamic data.

The main objective of this paper is to determine and illustrate a task analysis approach to identify which aspects of teleoperated maintenance tasks are bottlenecks in terms of task completion time - and to quantify the potential for improvement. A case study with six fundamentally different tasks, selected to cover a wide spectrum of possible tasks, will be used to show that the proposed approach is a general approach to compare and assess task execution. A key element of a systematic approach in this study is the application of a controlled Virtual Reality task environment, ensuring repeatability and facilitating the detailed measurement of a large amount of task execution variables. Specifically, we will carry out six representative, complex tasks, and analyse in detail the duration of those tasks and the complications associated with. The task completion time, and the variety therein, are used as a proxy for the task complexity and potential room for improvement. The complex tasks will be broken down to well specified atomic tasks. The variation of the task completion time of these atomic tasks can then be associated with specific skill-based behaviour (e.g. trajectories, contact forces, etc.) measured with the VR system.
The selection of suitable task analysis techniques will be presented in section 2, along with a survey on task definition/selection. Section 3 describes the human factors case study in detail, with section 4, 5 and 6 describing the results, discussion and conclusions.

2 Task Analysis

2.1 Selection of Task Analysis Techniques

Since the early 1900s, the field of ergonomics developed, enabling better description and analysis of human involvements in systems with the aim to discover more efficient ways to perform tasks. A main contribution to the field has been the development of task analysis approaches to help focus research and solutions (see Kirwan and Ainsworth [14] for a review). The most used and most generic approach is the Hierarchical Task Analysis (HTA) [18], that decomposes high-level tasks (goals) into a hierarchy of subtasks (sub-goals), and relates these to the corresponding required conditions. One of the key features of HTA is that the hierarchical structure enables the analyst to focus on crucial aspects of the task within the context of the overall task [14], for example by focusing on the largest error variance [18]. Furthermore, HTA can serve as a framework which provides justification and boundaries for other specific task analyses approaches, like procedure analysis, workload assessment, task frequency analysis, time and motion studies, etc. A large amount of theoretical and procedural literature exists about HTA (e.g. [18], [19]) and the method is applied to a wide range of applications, e.g.: interface design and evaluation, allocation of function, and supervisory control of complex systems. Examples of specific analysis of skill-based tasks can be found in the medical field to assess and evaluate surgeons technical skills [15] or to evaluate new techniques, protocols and instruments by assessing task performance [16]. For analysis on skill level, HTA can be combined with other more detailed analysis techniques like: activity sampling [14], time-line analysis [14], or time-action analysis [16]. Providing objective data about number and duration of performed actions, the proportion of time spent on different activities, and efficiency of actions. Additionally, observational techniques can be applied to obtain data about behaviour aspects of the task execution [14], preferably by using a checklist or a set of criteria, e.g. the 'global rating scale' [20], to make the assessment process more objective.

Although a variety of task analysis techniques exist, applied to a range of applications, no specific literature was found on analysis and performance improvement of (non-medical) teleoperated task execution.

Based on the summary above we selected a combination of existing task analysis techniques which could provide relevant insight in task execution during teleoperated maintenance. In this paper, the task analysis is performed in three phases, which are based on an HTA task decomposition with three levels of detail: task level, subtask level, within subtask level. To obtain objective information on the distributions of execution time, activity sampling/time-action analysis is used in each phase (task level). The amount of variance in (relative)time duration, which could indicate task difficulty, is used to focus the analysis for the next more detailed analysis phase. On the lowest task level also signal time traces, which capture skill-based behaviour, are analysed.

2.2 Selection of a General Set of Tasks

The specific focus of this study is maintenance in hard-contact environments. Which set of generalizable maintenance tasks to select for the case study? Based on literature three possible ways to define or categorise tasks have been identified, and are discussed below: a classification in terms of general function, a human-centred classification, and a task-centred classification.

Teleoperated maintenance tasks in terms of functional perspective cover the whole range of normal hands-on maintenance; mechanical cleaning, vacuum cleaning, MIG/TIG welding, visual inspection, sawing, filing, thread tapping, dust and flake sampling, wiring loom installation, etc. [21]. For robot planning, these tasks have been subdivided into more general manipulation primitives or elemental actions; e.g. move, approach, transport, place, push, slide, grasp, release [22], [23]. A second way to describe tasks is from the human controller point of view. The human changes his control behaviour depending on the task. Well known (parts of) tasks can be performed mainly based

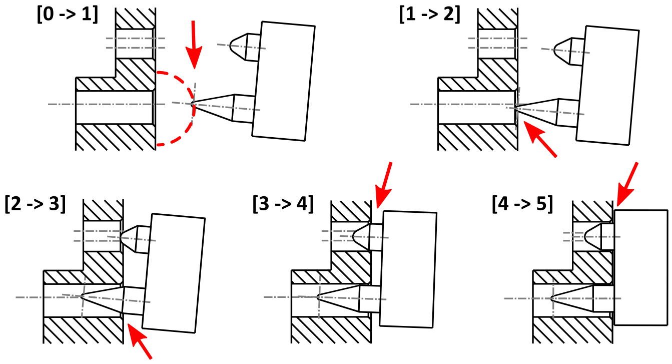

Fig. 1. Defined state transitions during an assembly task using a RH compatible alignment feature (red arrows indicate concerning thresholds, see Table 1), based on [24]. The placement strategy and task becomes different by using this kind of alignment features.

TABLE 1
Placement strategy during an assembly task: staged kinematic constraint (see Fig. 1, based on [24]

State transition	Remaining DOF's	
	Number	Type
$0 \rightarrow 1$ Component within task manipulation space, d<3cm (free space).	6	3 Translations 3 Rotations
$1 \rightarrow 2$ Component located on dowel end	6 (∼4)	3 Translations (1 Translation) 3 Rotations
$2 \rightarrow 3$ Component located on long dowel pin	5 (∼4)	2 Translations (1 Translation) 3 Rotations
$3 \rightarrow 4$ Component located on short second dowel pin	3 (∼1)	1 Translations 2 Rotations (0 Rotation)
$4 \rightarrow 5$ Component fully in contact with mating face (fully installed)	0	0 Translations 0 Rotations

on feed forward, unknown and untrained task rely more on feedback control. Furthermore, humans can intuitively adapt their neuromuscular properties to enhance task performance: from very compliant during a force task to very stiff during a position tasks [25]. An example of a task classification considering different types of (sub)tasks can be found in [26], in which four fundamental motion types for a bolt and spanner task were defined; Free air movement, Contact transition, Constrained translational movement and Constrained rotational movement. Besides the discussed human control approaches, also higher level strategy plays an important role in how tasks are executed. An example is the use of special mechanical alignment features (see Fig. 1 and Table 1), which are often used in telemanipulation situations. These alignment features support an 'assembly by constraint strategy' (systematically reduce the degrees of freedom) and enable task execution under poor feedback conditions, but they will change the way the task is executed (e.g. approach angle, final placement). Finally, a third way to characterise tasks is by their physical characteristics. Haynes et all. [27] defined a formal way of describing assembly tasks, based on the 15 fundamental contact possibilities. Mason [28] introduced the concept of compliance frame: a coordinate system related to the task and aligned with the object natural constraints. This was the basis for a hybrid control strategy which applied position control for the degrees of freedom, force control for axis orthogonal to the degrees of freedom. Bruyninckx [29] formalised and developed this approach further into the Task Frame Formalism, which has been widely used in sensor-based control.

For the case study, we decided to select 6 functional tasks (functional classification approach), to stay close to practical applications. These 6 tasks (described in the next section) were selected to have a wide variety of physical characteristics, or task frames (task-centred classification approach). This variety is reflected in the different combinations of unconstrained and constrained translational (t) and rotational (r) degrees of freedom for the (final state of the) tasks. The taskcentred classification was used because it is a formal way to describe and distinguish tasks and is allows analysis of task execution related to different task axes.

3 A Case Study

3.1 Subjects

Five right-handed subjects participated to provide data for the task analysis. The subjects had a mean age of 24.6 year, with a standard deviation of 3.5 year. Their experience with telemanipulation varied; 2 subjects (subjects 1 and 2) had 30-40 hours experience, 1 subject (subject 3) had around 5 hours experience and 2 subjects (subjects 4 and 5) had no experience with telemanipulation.

3.2 Task Description

The subjects performed six basic telemanipulation tasks which were selected to cover a wide variety of characteristics according the defined categorization. The six tasks are (see Fig. 2):

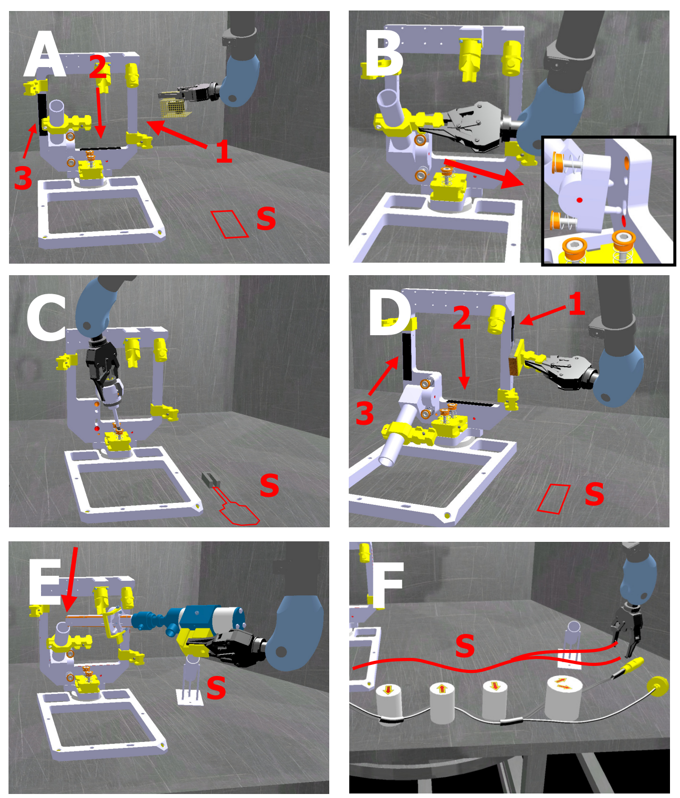

Fig. 2. The six experimental tasks; A-Visual inspection, B-Assembly, C-Bolting (Fig. 3), D-Polishing, E-Peg-in-hole, F-Cable placing. Start position of the tool is marked by S.

A) Visual inspection: Move with the robot hand to the hand-held camera start position (S), grasp the camera (grip feature), move to and inspect plane 1, 2 and 3, respectively, and bring the camera back to the start position (S). Inspection of the planes was defined as the identification of the randomly placed small white characters on the black planes (for more detail, see [30]). Collisions should be avoided. Subtasks: Move, grasp, transport. Physical characteristics: unconstrained (3t,3r).

B) Assembly task; Move with the robot hand to the tube assembly, grasp the tube assembly (yellow grip feature), transport the tube assembly to the destination and place the tube assembly fully aligned. The task was finished when the subject assessed the placement to be successful. The actual success of the trial was assessed later on during the analysis. Notice that a placement strategy as mentioned in Table 1 and Fig. 1 was not explicitly mentioned. Subtasks: Move, grasp, transport, place. Physical characteristics: constrained (3t,3r).

C) Bolting: Move with the robot hand to the bolt runner (S), grasp the bolt runner, move to the bolt head, rotate the bolt a quarter of a turn and return the bolt runner (S). Subtasks: Move, grasp, transport, place, push. Physical characteristics: unconstrained (2r), constrained (3t,1r).

D) Polishing: Move with the robot hand to the polisher (S), grasp the polisher (yellow grip feature), move to and polish plane 1, 2 and 3 respectively (see red arrows and black planes), and bring the polisher back to the start position (S). Polishing was finished when the black planes (each subdivided into 8 sections) had disappeared completely. The opacity f of the black plane subsections changed from 0 to 1 according to the next equation:

$$f(F,V) = \left(\sum_t F_{friction} \bullet V_{abs-polisher} \right) \bullet K_{effort}$$

with $0 \leq f \leq 1$, and a fixed gain K_{effort}.
Subtasks: Move, grasp, transport, place, apply pressure + slide. Physical characteristics: unconstrained (2t,1r), constrained (1t,2r).

E) Peg-in-hole: Move with the robot hand to the welding tool (S; placed in a stand), grasp the welding tool, move the welding tool to the tube and insert it completely. Subtasks: Move, grasp, transport, slide. Physical characteristics: unconstrained (1t,1r), constrained (2t,2r).

F) Cable-placement: use the robot hand to grab the cable from the table (S) and wrap the cable around the markers as indicated (see Fig. 2F). Subtasks: Move, grasp, transport, place, release, (repeat until finished). Physical characteristics: -

The initial position of the master and the slave device was identical for all tasks.

3.3 Experimental Setup

The experiment was performed using a Haption Virtuose™ 6D master device (in top-down configuration) [31] and a simulated slave and environment, available in the Remote Handling Study Centre (RHSC) at FOM DIFFER. The master device provides a 6 DOF workspace with force feedback. Virtual Reality (VR) technology was used to simulate the slave robot in an ITER-like environment. The virtual Benchmark tool [32] — designed to contain a reference set of representative ITER remote handling maintenance tasks – was chosen as task environment. A rigid body simulator, based on Nvidia PhysX™ technology, was used to emulate real-time contact interaction, providing realistic feedback to the human operator [33]. A position-error control architecture was implemented between the master and slave. The master-slave control loop and physics simulation ran on 200-500Hz, depending on the complexity of the scene. The subject was provided with visual feedback from the remote (VR) environment via a computer screen (22inch, resolution: 1680x1050) placed 1.5 meter in front of the subject. Besides an overview, 4 camera views were provided on the left side of the screen, showing (from top to bottom) the hand-held camera view, a top view and the views of cameras on the left and right slave arm (Fig. 3).

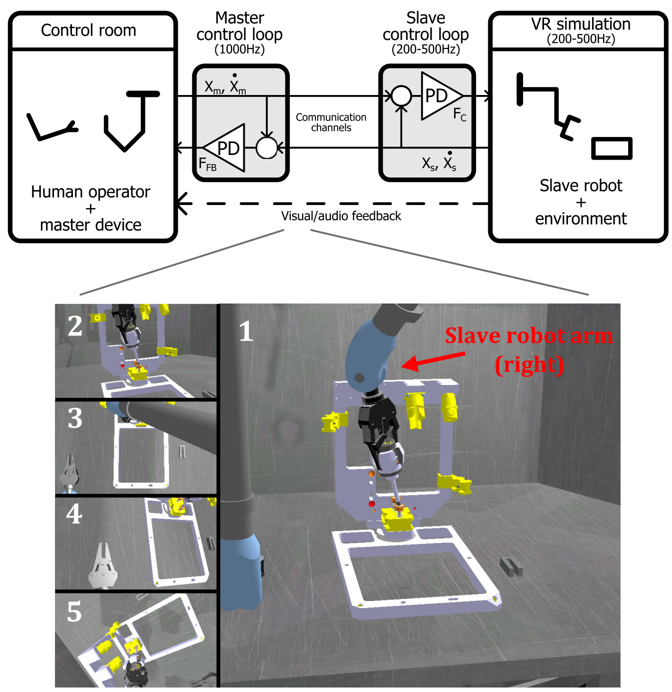

Fig. 3. Top: Schematic representation of the telemanipulation setup used for the experiments. The human operator controls the simulated slave robot by manipulating a 6DOF master device (Haption Virtuose™). The human operator gets visual, haptic and auditory feedback from the remote environment. Bottom: Screenshot of the visual feedback provided to the subjects; main view (1), front view (2), top view (3), camera on left/right arm (4/5). The overlay with white and red characters is not visible for the subjects.

3.4 Experiment Design & Data Analysis

At the start of the experiment, all subjects performed a general training session to get used to the telemanipulation system. This general training comprised the learning of master and slave workspace limits, position indexing of master with respect to slave and gripping/releasing of objects. After this general training, the subjects trained the six different tasks until they reached steady performance. The actual experiment consisted of 4 repetitions for each task. The complete experiment took around 2 hours.

3.4.1 Measured Variables & Metrics

To analyse how the teleoperated tasks are executed, a vast amount of variables was recorded during the experiment, all sampled at 200Hz. Based on the recorded data, a number of metrics was calculated to determine the task performance:

- Task completion time (tct). The time it takes for a subject to complete the (sub)task.
- Normalised task completion time (ntct). Completion time of a (sub)task normalised to the fastest subject trial.

Besides task performance metrics, the following time traces were analysed for specific parts of the tasks:

- Position/rotation error. Position: Euclidean distance to the goal position. Rotation: the swing rotation error with respect to the defined task normal.
- Translational/rotational velocity. The magnitude of the translational/rotational velocity vector.
- Contact force. Magnitude of the linear/rotation force vector

3.4.2 Data Analysis

The task analysis is performed in three phases, which is later referred to as the Three Phased Task Analysis. Each phase comprises a different level of detail. Phase I regards the task level, phase II the subtask level, and phase III the within-subtask level (see Fig. 4). The task elements in the within-subtask level are called states and are defined based on physical task constraints [27]. Fig. 1 and Table 1 show an example of the state levels for the Assembly task.

The main metric used in this analysis is the task completion time since it is a general and relevant metric available for all tasks. Instead of using the absolute completion time, which is not a very useful metric to compare completely different (sub)tasks, a normalised completion time is used. Since the goal of the analysis is to find potential room for improvement, the completion time is normalised to the fastest subject trial. The difference between group average and the fastest trial gives an indication for potential room for improvement. The most detailed analysis during phase III comprises besides completion time also the analysis of signal time traces which capture skill-based behaviour. The analysis starts in phase I with 6 different tasks, phase II and III only are only discussed for the task with the largest normalised variation: the Assembly task (B).

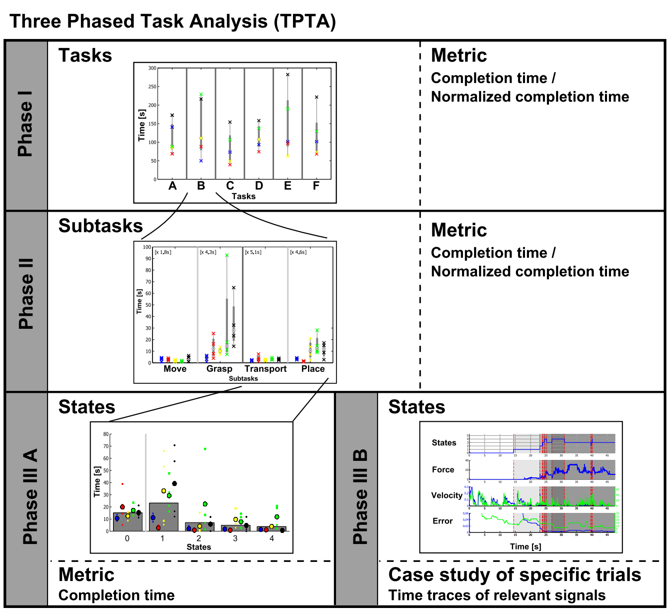

Fig. 4. The three phases of the applied Phased Task Analysis.

4 RESULTS

In section 4.1, the results for each of the six tasks are presented. Section 4.2, contains the results for the selected subtask; the Assembly Task (B), which is analysed per state in section 4.3.

4.1 Analysis Phase I - Tasks

Table 2 shows the task completion time for the six experimental tasks. The task completion times for the different

TABLE 2
Experimental results - Phase I; Task completion time per task

		Tasks					
		A	B	C	D	E	F
tct [s]	μ	**111.2**	**138.9**	**84.5**	**114.1**	**146.8**	**119.0**
	σBS	**43.7**	**79.8**	**46.8**	**33.7**	**89.1**	**62.4**
	σWS	11.2	88.1	18.6	27.9	29.3	29.2
Comparison to fastest trial							
Fastest trial		57.5s	30.7s	30.5s	57.7s	49.1s	47.9s
μ - fastest trial		53.7s	108.4s	54.0s	56.4s	97.7s	71.1s
		48%	**78%**	**63%**	49%	**67%**	60%
ntct[-]	μ	1.93	**4.52**	**2.77**	1.98	**2.99**	2.49
	σBS	0.7	**2.6**	**1.5**	0.6	**1.8**	1.3
	σWS	0.20	**2.87**	0.61	0.48	0.60	0.61

μ = mean, σBS = standard deviation between subjects, σWS = mean standard deviation within subjects, ***bold*** *= mentioned in text.*

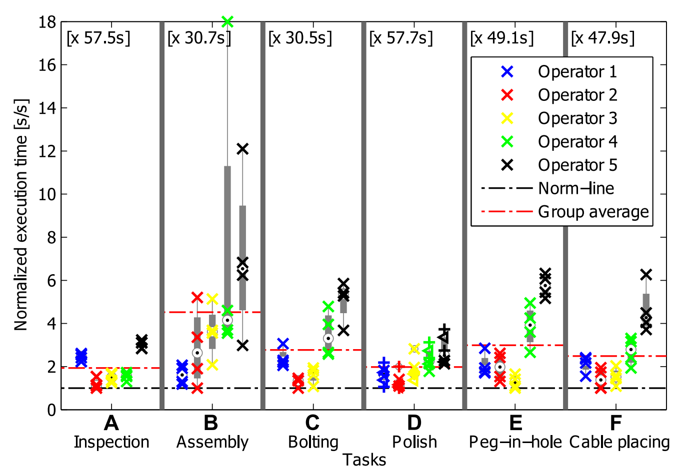

Fig. 5. Analysis phase I. Task completion time for the six tasks per operator (4 repetitions , 3x 2 repetitions for Polishing), normalised to the fastest subject trial. The potential room for improvement (group average → fastest trial) is largest for the Assembly task. The figure shows a large within-subjects variation for task B.

tasks are in the same range, with mean times between 84 to 146 seconds. A large between-subject variation is observed for all tasks, with standard deviations ranging from 33.7s to 89.1 seconds. Notable is that subjects perform for the most part consistently over the different tasks (i.e. fast subjects are fast for all tasks and vice versa). Fig. 5 shows the task completion time normalised to the fastest subject trial. The largest difference between group average and fastest trial was found for the Assembly Task (B) followed by the Peg-in-hole task (E) and the Bolting Task (C), namely 78%, 67% and 63%, respectively (Table 2). Also, these tasks show the largest normalised standard deviation (between-subject variation relative to fastest trial), 2.6, 1.8 and 1.5 respectively (Table 2).

Task B shows a relative high within-subject variation, especially when normalised to the fastest trial: a mean normalised standard deviation of 2.87 in comparison with normalised standard deviations between 0.2 and 0.61 for the other tasks (Table 2).

4.2 Analysis Phase II - Subtasks

The Assembly Task (B) shows the largest difference in task completion time between group average and fastest trial, and is analysed in more detail in this case study. Task B can be divided into four functional subtasks: move, grasp, transport and place. Fig. 6 shows the normalised task completion time for these 4 parts. The grasp and place parts show the largest difference between group average and fastest trial; respectively 95% and 88% (Table 3). The execution of the grasp subtask was characterized by a high number of failed grasps per trial; an average of 5.4 failed grasps (maximum of 27). The cause of these failed grasps was clear from observation: it appeared very challenging and time-consuming to grasp a free floating and unsteady tool with a binary gripper. The average amount of failed grasps was much lower for the other tasks, namely between 0.05 and 1.4.

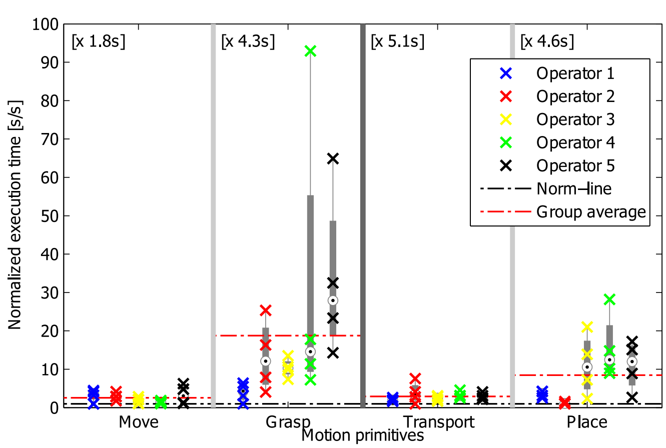

Fig. 6. Analysis phase II. Task completion time for the four subtasks of the Assembly Task (B), per operator (4 repetitions). The potential room for improvement (group average → fastest trial) is largest for the grasp and place subtasks (see also Table 3). In Fig. 7-8 the transport and place subtask are analysed in more detail.

TABLE 3
Experimental results - Phase II; Task completion time per subtask - Task B: Assembly task

		Subtasks			
		Move	Grasp	Transport	Place
tct [s]	μ	4.7	80.3	15.1	38.8
	σBS	1.6	57.7	3.7	27.1
	σWS	2.3	66.0	5.7	22.5
Comparison to fastest trial					
Fastest trial [s]		1.8	4.3	5.1	4.6
μ - fastest trial		2.9s	76s	10s	34.2
		61%	**95%**	66%	**88%**
ntct[s]	μ	2.5	**18.8**	2.9	**8.5**
	σBS	0.9	**13.5**	0.7	**5.9**
	σWS	1.3	**15.4**	1.1	**4.9**

*μ = mean, σBS = standard deviation between subjects, σWS = mean standard deviation within subjects, **bold** = mentioned in text.*

4.3 Analysis Phase III - States

The 'grasp' subtask showed the largest variation in time performance, but since observations already revealed the

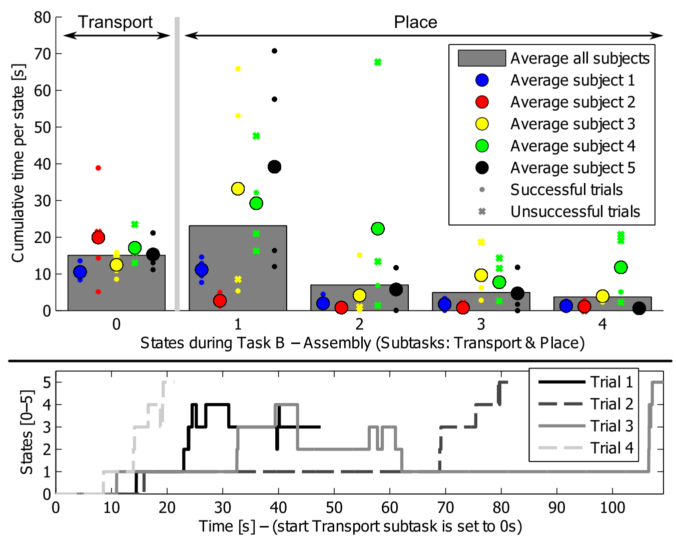

Fig. 7. Analysis phase IIIA - Assembly task (task B). Top: Cumulative time per state for each subject repetition. States 0 (transport) and state 1 require the most time. Bottom: Typical example of states (Fig. 1/ Table 1) during the transport & place subtasks of the Assembly Task (four repetitions of subject 3). State 5 means fully placed. Note that not always the final state 5 is reached. Also note that state 0 and 1 require most time and are therefore identified as possible candidates for improvement (viz. decreased duration).

TABLE 4
Experimental results - Phase IIIA; Task completion time per state for the state 'transport' (state 0) and 'place' (state 1-4) of the Assembly task (task B)

		States				
		0	1	2	3	4
tct [s]	μ	**15.1**	**23.1**	7.0	4.9	3.8
	σBS	3.7	**15.5**	8.8	3.8	4.7
	σWS	5.7	15.8	9.0	4.2	2.7

*μ = mean, σBS = standard deviation between subjects, σWS = mean standard deviation within subjects, **bold** = mentioned in text.*

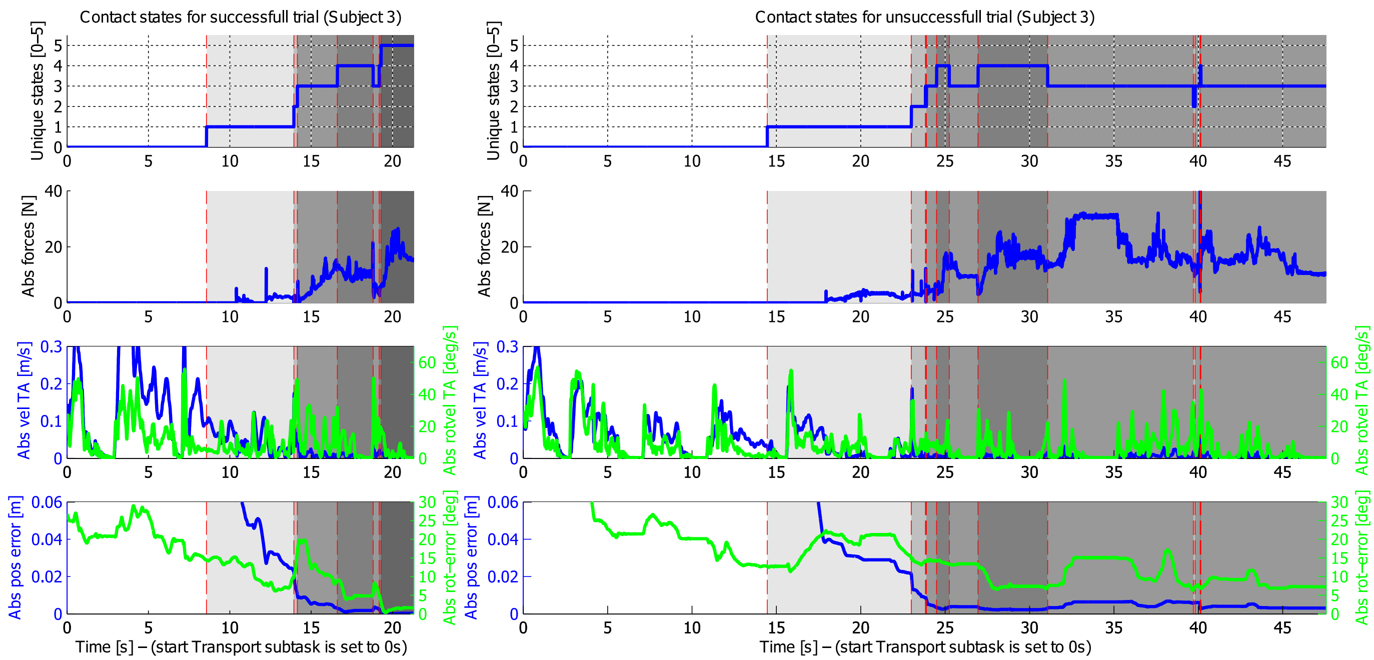

Fig. 8. Analysis phase IIIB - Assembly task (task B). Time traces capturing skill-based behaviour (absolute forces, absolute linear/rotational velocity and absolute positional/rotational alignment error) of two typical trials of subject 3. For a successful trial (left): alignment errors with respect to the target are gradually reduced, while contact forces are relatively low and smooth. On the contrary, the unsuccessful trial (right) shows large rotational error in particular (shown in green), suggesting the rotation is difficult to control.

origin of this variation, the third analysis step of this cases study will examine the 'place' subtask in more detail. To incorporate task-context, also the preceding subtask 'transport' is included in the analysis. Fig. 7 (bottom) shows the course of states during the task execution for 4 repetitions by a typical subject. The top part of the figure summarises the cumulative time per state for each subject repetition, which is part of Analysis Phase IIIA. The most time was spent in state 1 (position long dowel in place) and state 0 (move with tool to target place), see Fig. 1 and Table 4. The most variation in execution time was found for state 1.

Fig. 8 shows, for a successful and an unsuccessful placement from the same subject, five relevant measured variables (Phase IIIB) related to the different states. During the successful trial, the position and rotation errors with respect to the target were gradually reduced. During the unsuccessful trial, especially the rotation error stayed large. In general, the successful trial was much faster and more smooth, with lower contact forces, and an increasing progress.

5 Discussion

We proposed a Three Phased Task Analysis to systematically analyse six representative virtual remote maintenance tasks at three levels of detail. In the first phase the distributions in task completion times were analysed for each of the six tasks, each of which could then be analysed at the level of abstract subtasks (e.g., move, grasp, transport) in the second phase, which in turn could each be analysed at a signal-level (e.g., forces, positions, rotations) in the third phase. This allows a coherent analysis of elementary operator behaviour underlying the observed differences in time-to-complete at phase II or phase I. In this paper, the task with the largest potential improvement (phase I), was chosen for further analysis in phase II and III to identify opportunities for improvement. The experimental results will be discussed per analysis phase.

5.1 Task Analysis Phase I

The average task completion time over all subjects for each of the six tasks was comparable (Table 1), which was the intention when designing the experiment. However, some subjects completed tasks substantially faster than other subjects, and with less variability. The better subjects (1,2,3) were generally faster for each of the six tasks than the other subjects (4,5), who also showed much more variability between identical repetitions of the task (Fig. 5). An additional observation from Fig. 5 is that some tasks evoked this variability much more than others: Task D (Polishing) showed the smallest difference in completion time between the fastest and the slowest subject (a factor of 2.1), whereas task B (Assembly task) showed the largest (a factor 4.6). If the fastest subject trial is taken as ultimate reference, the highest potential improvement could be reached for task B (Assembly task): on average 108s or 78%.

5.2 Task Analysis Phase II

What is the origin of the observed variation in phase I? The subtasks that comprise each of the six tasks were analysed in more detail in phase II. For this paper, the Assembly task (task B) was selected as an illustrative case because it showed the highest variation (relative to the fastest trial). Task B consists of the 4 subtasks move, grasp, transport and place, of which grasp and place showed the largest variation. Based on the observations during the 'grasp' subtask, it is expected that the use of a tool stand (to constrain the tool) and the use of a non-binary gripping interface, will reduce the execution time and its variation drastically. Regarding the other subtasks of task B, the highest potential improvement – with the fastest subject trial as benchmark – is found for the place subtask: on average 34s or 88%. A better understanding of the origin of this variation in execution time requires analysis on a more detailed level.

5.3 Task Analysis Phase III

In Phase III the 'transport' and 'place' subtasks were analysed in more detail by looking at the defined 5 different states within these two subtasks (Fig. 1). Analysis Phase IIIA shows that 28% and 43% of the total transport + place time was required for state 0 (transport) and 1 (alignment pin between 3 to 0 cm of the entrance) respectively. State 1 showed also the highest variation in execution time, so appears most difficult. This can be explained by the fact that this part of the task requires positional accuracy, but the mechanical alignment features are not assisting yet, so all 6 degrees of freedom need to be controlled. In the later states, the mechanical guiding features assist during the placement by reducing the remaining degrees of freedom systematically. By design, the used guiding feature mainly assists with constraining the translations, leaving the rotations largely unconstrained.

Phase IIIB gives more insight at a signal-level to understand the elementary operator behaviour. The difficulty of rotations is reflected in the plotted time series of an unsuccessful trial (see Fig. 8); the rotation error stays large (e.g. in state 4) and appeared difficult to control. This figure indicates the fidelity of the use of VR for the detailed analysis of the task-understanding and execution of a single operator. In principle, this could be extended to a variety of operators.

For task B, the mechanical alignment feature could easily be changed to also assist for the orientation [24], but the current design is more representative for similar type of tasks for which orientation is important and mechanical rotation guiding features are difficult to implement (peg-in-hole tasks, cable placement, etc.).

5.4 General

The main opportunity for performance improvement identified during the three phases of the task analysis is the reduction of the overall large variation in task execution (reflected in e.g. the task completion time). Particularly for fine positioning, which appeared difficult and time-consuming (especially without mechanical alignment features). Literature implies that an important part of the observed variability is related to operator skills and aptitude. Operational experience at JET stressed the important role of appropriate operator skill and aptitude: only a small percentage of humans has the required skills and aptitude to become a good master-slave operator [3]. This experience corresponds with other human factors research which identified three different groups of learners (e.g. [34]); high performers (at the start of the training already high performing), low performers (doing poorly at the outset and only marginally improving throughout the training), and transitional performers (starting poorly, but improving rapidly early in training). The common practice to deal with this is strict operator selection, which in this case would imply selecting operator 1, 2, or 3 [3]. There remains, however, a substantial amount of between-subject variability (and within-subject variability), which was also found during real executed maintenance performed by experienced operators at JET, where even between highly experienced operators statistically different task completion times were observed [17].

Besides the differences between subjects, also a high variation within subjects was found for identical task repetitions. Although more extensive training is likely to decrease this variation, an in-depth task analysis comparing experienced versus novice operators during remote maintenance in JET showed that even experienced operators exhibit considerable variability during similar tasks [17]. The results obtained in analysis phase I and literature imply that human task execution has inherent variation in execution time, and apparently training can only partly decrease that.

Potential ways to improve the performance are a more transparent telemanipulation system (vision/haptics) or operational assistance by augmented visuals/haptics. The first option is the more conventional approach and does not show direct possibilities for innovation. Instead of focusing on improvement of natural feedback and obtaining a sense of being there, the authors aim to develop a sense of feeling what to do [35], for which the second option could be promising. Can we assist the human operator in such a way that less skilled operators can perform as skilled operators? For example by visual assistance and/or by providing guiding forces to assist the orientation during state 4 (or more general, to the degrees of freedom which are left unconstrained by the task)? Experiments in a simplified setting showed promising results for applying guiding forces during a bolt-and-spanner task and an insertion task [26], [36].

5.5 Task Analysis Approach

The applied three phased task analysis appeared to be an insightful approach to analyse task execution and quantify task performance and potential room for improvement. In this paper the detailed analysis was only applied to the Assembly Task, but the methodology is applicable to any other task. Depending on the starting point, the number of phases can be adjusted. Furthermore, other metrics than task completion time could be used, depending on the task.

The current analysis and solution-direction focus on task performance in the sense of technical skills, but it is important to note that other aspects of operator competence like knowledge, decision making and team skills are also important for overall task performance in real situations. In the surgical field, the performance assessment of skill based tasks showed nevertheless that dexterity or technical proficiency of the surgeons/trainees is of biggest importance [20].

The experimental task was performed in a simulated environment, which has the benefit of repeatability (more control over secondary factors which could disturb the experimental results), accessibility of variables for measurement and it gives freedom in task design. The use of VR appeared very useful and insightful, and the results seem in line with the (limited) available literature describing hardware tests. To be sure to incorporate all real life effects, the results or implications should be validated in hardware tests in a later stage.

A limitation of the study is the absence of real experienced operators for the system. The subjects who participated in this study followed a training (0.5h), but that is relatively short compared to typical learning curves for these types of teleoperation tasks, which can last years [3]. The fact that the subjects are relative novice operators could make the inherent difficulties of the tasks even more clear. A study in the medical field which analysed a non-clinical point-to-point task, reported for example much higher variability in task-relevant motion components for novice surgeons compared to experienced surgeons [37]. On the other hand, it could be the case that some of the found difficulties would be less an issue for experienced operators since they could be (partly) by-passed with a learned strategy. For complex tasks, these effects could have been substantial, but since the defined tasks are rather basic, novice behaviour is expected to be a good trigger for task difficulties. Tasks and task aspects with high observed variability in task completion time, like e.g. contact transitions and the control of tool orientation, should therefore be an important focus during operator training.

The results of this case study illustrate the strengths of the proposed Three Phased Task Analysis, however, due to the low number of subjects in this case study (n=5), no hard conclusions can be drawn from the current dataset.

5.6 Future Work

In this paper, six fundamental tasks were defined and investigated using the Task Analysis Phase I, but the full three-phased analysis was presented only for task B, selected because of its large variability between and within operators. To be able to generalise these findings on telemanipulated task performance beyond the observed task B, future work should include further analysis of the other five tasks. This future work should include a larger number of test subjects to increase the reliability of the data.

Besides data gained during (exploratory) virtual reality experiments, like described in this paper, the Three Phased Task Analysis should also be applied to operational data from real-life teleoperated maintenance. Although the availability of measurement signals is maybe less in reality when compared to VR - which will limit the level of detail in the third analysis phase - real data will reveal the actual task difficulties the best. VR can then be used to (re)do specific detailed task analyses up to signal level.

To allow for the detailed phased task analysis of real executed maintenance, the conventional logbook methods of just logging timestamps for tasks is insufficient [17]. Task analysis phase II & III require detailed timing data up to seconds-resolution (e.g. extracted from video data) and phase IIIB requires forces and positions of master and slave device to be logged, which we recommend to automatically add/link to the logged video data.

The gained insight in underlying causes for degraded task performance will be used to explore the impact of support systems that aid the operator with augmented visual or haptic guidance. The main improvements are expected from providing the operator with haptic orientation guidance during the fine positioning phase of grasp and place tasks.

6 Conclusion

In this paper, we proposed a novel hierarchical analysis approach to identify and quantify potential room for performance improvement in remote nuclear fusion maintenance. The approach consists of three phases: a set of general tasks was analysed in the first phase, followed by an analysis on subtask level in the second phase, and finally, specific difficulties per subtask were identified in the third phase. To explore the utility of this approach, a data set was generated in a virtual environment with a small number of relative inexperienced operators, since it was not possible to have the three real operators from JET participating. Five subjects performed six fundamental 6-DoF remote maintenance tasks with a haptic master device and a virtual slave and environment.

The main conclusion of this paper is that the proposed Three Phased Task Analysis can be used to identify and quantify potential improvements and is able to relate high-level problems (e.g. large variability) to behaviour on lower task-levels. This is illustrated by the case study results for the small dataset:

- Teleoperated task execution is characterised by inherently large between- and within-subject variance.
  - Variance between and within subjects in task-completion-time is specifically large for tasks which require accurate control of forces in one or more DoFs (Assembly, Bolting, Peg-in-Hole).
  - With the fastest trial as a reference, operators can (theoretically) reduce the task-completion-time by 48-78%.
- Analysis phase II (subtask level) allows to identify sources of variance.
  - Variance in time for the Assembly Task originates mostly from grasping and placing (and not from moving and transporting).
  - Grasping appeared specifically difficult for the Assembly task; the amount of failed grasps is much higher compared to other tasks, which was caused by slipping away of the not fixed component.
- Analysis phase III pinpointed specific difficulties of the states within the subtask:
  - Transition from free-space to contact proves the be most critical, as shown by the large amount of time spent in this state.
  - Rotational errors are most difficult to control as unsuccessful placement is characterised by high rotational errors.

Based on the case study results, it is a promising option to improve specific (low-level) difficulties in task execution with specific performance enhancing methods (e.g. visual/haptic assistance during contact transitions, haptic guidance to improve orientation accuracy during assembly tasks). By detailed analysis on subtask level, such specific methods can be designed and their (absolute) effectiveness evaluated. Future research will apply the Three Phased Task Analysis approach on larger VR and real-life telemanipulated maintenance datasets, to obtain reliable results on potential room for task performance improvement. These results will be the basis for further research on the applicability of support systems that aid the operator with augmented visual and haptic guidance.

Acknowledgments

This work supported by European Communities was carried out within the framework of EFDA (WP10-GOT RH) and the EUROfusion Consortium and has received funding from the Euratom research and training programme 2014-2018 under grant agreement No 633053. The views and opinions expressed herein do not necessarily reflect those of European Commission.

References

[1] "ITER - the way to new energy," http://www.iter.org, accessed: Nov, 2016.
[2] D. van Houtte, K. Okayama, and F. Sagot, "ITER operational availability and fluence objectives," *Fusion Engineering and Design*, vol. 86, no. 6-8, pp. 680–683, oct 2011.
[3] S. Collins, J. Wilkinson, and J. Thomas, "Remote Handling Operator Training at JET," in *prepint Proceedings ISFNT*, no. 13, 2013.
[4] J. Y. C. Chen, E. C. Haas, and M. J. Barnes, "Human Performance Issues and User Interface Design for Teleoperated Robots," *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1231–1245, nov 2007.
[5] G. Christiansson and F. C. T. van der Helm, "The Low-Stiffness Teleoperator Slave - a Trade-off between Stability and Performance," *The International Journal of Robotics Research*, vol. 26, no. 3, pp. 287–299, mar 2007.
[6] P. Lambert, H. Langen, and R. Munnig Schmidt, "A Novel 5 DOF Fully Parallel Robot Combining 3T1R Motion and Grasping," in *Volume 2: 34th Annual Mechanisms and Robotics Conference, Parts A and B*, vol. 2. ASME, 2010, pp. 1123–1130.
[7] D. Lawrence, "Stability and transparency in bilateral teleoperation," *IEEE Transactions on Robotics and Automation*, vol. 9, no. 5, pp. 624–637, 1993.
[8] P. Hokayem and M. Spong, "Bilateral teleoperation: An historical survey," *Automatica*, vol. 42, no. 12, pp. 2035–2057, dec 2006.
[9] C. Lopez Martinez, I. Polat, M. van de Molengraft, and M. Steinbuch, "Robust High Performance Bilateral Teleoperation Under Bounded Time-Varying Dynamics," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 1, pp. 206–218, 2015.
[10] J. P. McIntire, P. R. Havig, and E. E. Geiselman, "Stereoscopic 3D displays and human performance: A comprehensive review," *Displays*, vol. 35, no. 1, pp. 18–26, jan 2014.
[11] Z. Ziaei, A. Hahto, J. Mattila, M. Siuko, and L. Semeraro, "Real-time markerless Augmented Reality for Remote Handling system in bad viewing conditions," *Fusion Engineering and Design*, vol. 86, no. 9-11, pp. 2033–2038, feb 2011.
[12] C. J. M. Heemskerk, M. de Baar, B. Elzendoorn, J. Koning, T. Verhoeven, and F. de Vreede, "Applying principles of Design For Assembly to ITER maintenance operations," *Fusion Engineering and Design*, vol. 84, no. 2-6, pp. 911–914, jun 2009.
[13] N. Sykes, S. Collins, A. Loving, V. Ricardo, and E. Villedieu, "Design for high productivity remote handling," *Fusion Engineering and Design*, vol. 86, no. 9-11, pp. 1843–1846, oct 2011.
[14] B. Kirwan and L. Ainsworth, *A Guide To Task Analysis*. CRC Press, sep 1992.
[15] S. K. Sarker, A. Chang, T. Albrani, and C. Vincent, "Constructing hierarchical task analysis in surgery," *Surgical Endoscopy and Other Interventional Techniques*, vol. 22, no. 1, pp. 107–111, 2008.
[16] J. Minekus, P. Rozing, E. Valstar, and J. Dankelman, "Evaluation of humeral head replacements using time-action analysis." *Journal of shoulder and elbow surgery*, vol. 12, no. 2, pp. 152–7, 2003.
[17] H. Boessenkool, J. Thomas, C. Heemskerk, M. de Baar, M. Steinbuch, and D. Abbink, "Task analysis of human-in-the-loop tele-operated maintenance: What can be learned from JET?" *Fusion Engineering and Design*, vol. 89, no. 9-10, pp. 2283–2288, oct 2014.
[18] N. Stanton, "Hierarchical task analysis: developments, applications, and extensions." *Applied ergonomics*, vol. 37, no. 1, pp. 55–79, jan 2006.
[19] A. Shepherd, "HTA as a framework for task analysis." *Ergonomics*, vol. 41, no. 11, pp. 1537–52, nov 1998.
[20] K. Moorthy, "Objective assessment of technical skills in surgery," *BMJ*, vol. 327, no. 7422, pp. 1032–1037, nov 2003.
[21] A. Rolfe, "A perspective on fusion relevant remote handling techniques," *Fusion Engineering and Design*, vol. 82, no. 15-24, pp. 1917–1923, oct 2007.
[22] J. Felip, J. Laaksonen, a. Morales, and V. Kyrki, "Manipulation primitives: A paradigm for abstraction and execution of grasping and manipulation tasks," *Robotics and Autonomous Systems*, vol. 61, no. 3, pp. 283–296, mar 2013.
[23] A. Owen-hill, J. Breñosa, M. Ferre, J. Artigas, and R. Aracil, "A Taxonomy for Heavy-Duty Telemanipulation Tasks using Elemental Actions," *International Journal of advanced robotic systems*, vol. 10, pp. 1–7, 2013.
[24] R. Subramanian and J. Palmer, "ITER Remote Handling Code of Practice_2E7BC5_v1.2," Tech. Rep., 2009.
[25] W. Mugge, J. Schuurmans, A. C. Schouten, and F. van Der Helm, "Sensory weighting of force and position feedback in human motor control tasks." *The Journal of neuroscience : the official journal of the Society for Neuroscience*, vol. 29, no. 17, pp. 5476–82, apr 2009.
[26] H. Boessenkool, D. A. Abbink, C. J. Heemskerk, F. C. van der Helm, and J. G. Wildenbeest, "A Task-Specific Analysis of the Benefit of Haptic Shared Control During Telemanipulation," *IEEE Transactions on Haptics*, vol. 6, no. 1, pp. 2–12, 2013.
[27] L. S. Haynes and G. H. Morris, "A formal approach to specifying assembly operations," *International Journal of Machine Tools and Manufacture*, vol. 28, no. 3, pp. 281–298, jan 1988.
[28] M. T. Mason, "Compliance and Force Control for Computer Controlled Manipulators," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 11, no. 6, pp. 418–432, 1981.
[29] H. Bruyninckx and J. De Schutter, "Specification of force-controlled actions in the "task frame formalism"-A synthesis," *IEEE Transactions on Robotics and Automation*, vol. 12, no. 4, pp. 581–589, 1996.
[30] H. Boessenkool, D. Abbink, C. Heemskerk, M. Steinbuch, M. de Baar, J. Wildenbeest, D. Ronden, and J. Koning, "Analysis of human-in-the-loop tele-operated maintenance inspection tasks using VR," *Fusion Engineering and Design*, vol. 88, no. 9-10, pp. 2164–2167, oct 2013.
[31] "Specifications sheet Haption Virtuouse 6D," http://www.haption.com, accessed: Feb, 2014.
[32] C. Heemskerk, B. Elzendoorn, A. Magielsen, and G. Schropp, "Verifying elementary ITER maintenance actions with the MS2 benchmark product," *Fusion Engineering and Design*, vol. 86, no. 9-11, pp. 2064–2066, oct 2011.
[33] C. Heemskerk, M. de Baar, H. Boessenkool, B. Graafland, M. Haye, J. Koning, M. Vahedi, and M. Visser, "Extending Virtual Reality simulation of ITER maintenance operations with dynamic effects," *Fusion Engineering and Design*, vol. 86, no. 9-11, pp. 2082–2086, oct 2011.
[34] J. Huegel, O. Celik, A. Israr, and M. K. O'Malley, "Expertise-based performance measures in a virtual training environment," *Presence*, vol. 18, no. 6, pp. 449–467, 2009.
[35] J. Flach and J. Holden, "The Reality of Experience: Gibson's Way," pp. 90–95, 1998.
[36] J. van Oosterhout, J. G. W. Wildenbeest, H. Boessenkool, C. J. M. Heemskerk, M. R. de Baar, F. C. T. van der Helm, and D. A. Abbink, "Haptic Shared Control in Tele-Manipulation: Effects of Inaccuracies in Guidance on Task Execution," *IEEE Transactions on Haptics*, vol. 8, no. 2, pp. 164–175, apr 2015.
[37] I. Nisky, M. Hsieh, and A. Okamura, "Uncontrolled manifold analysis of arm joint angle variability during robotic teleoperation and freehand movement of surgeons and novices." *IEEE transactions on bio-medical engineering*, vol. 61, no. 12, pp. 2869–81, dec 2014.