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Metrics and Benchmarks for Remote Shared Controllers in Industrial Applications

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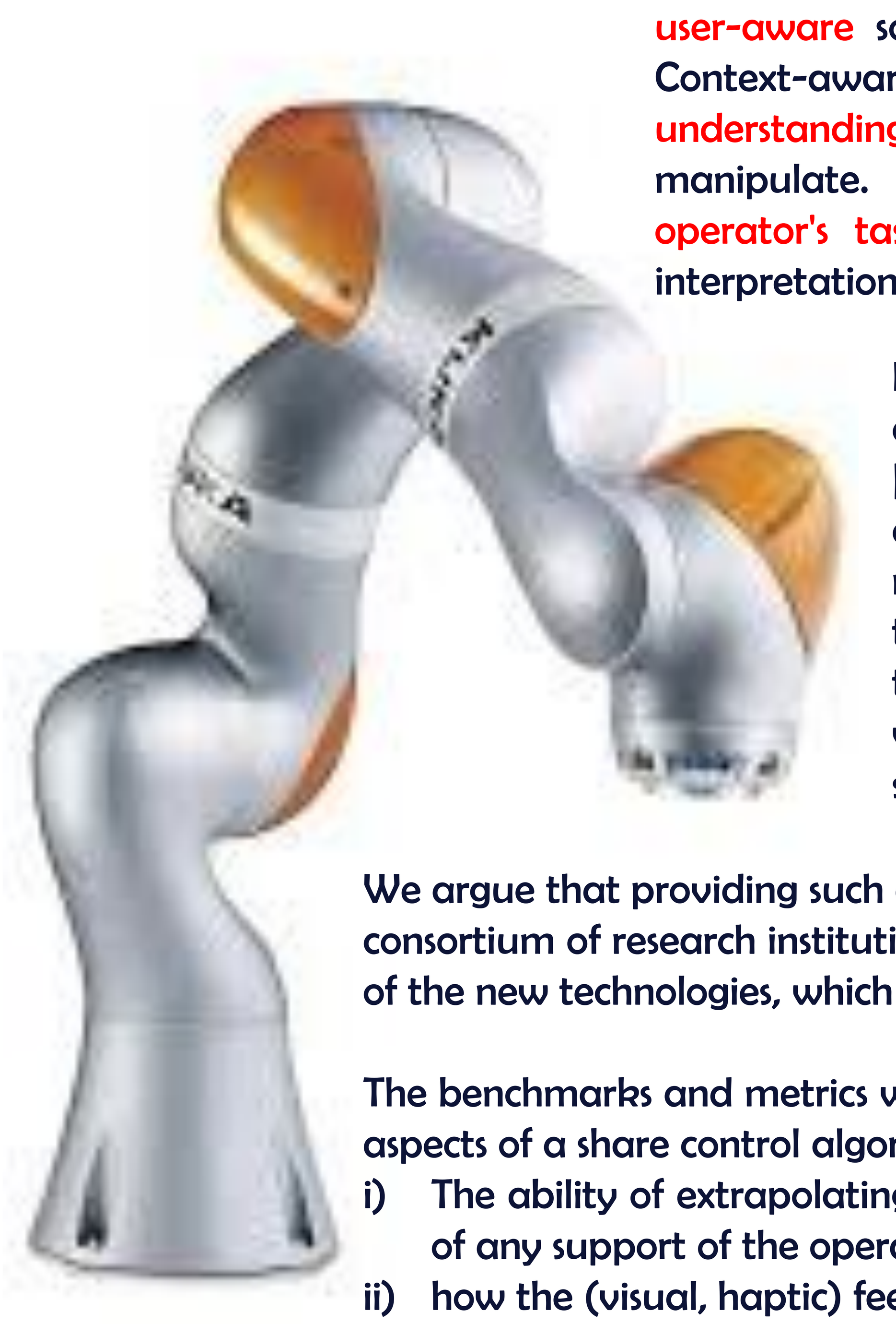
ABSTRACT

Remote manipulation is emerging as one of the key robotics tasks needed in extreme environments. Several approaches have been investigated on how to add AI components into shared controllers to improve their reliability. But the impact of novel research approaches in real-world applications can have a very slow in-take. We propose a set of benchmarks and metrics to evaluate how the AI components of remote shared control algorithms can improve the effectiveness of such frameworks for real industrial applications. We also present an empirical evaluation of a simple intelligent share controller against a manually operated manipulator in a tele-operated grasping scenario.

INTRO & BACKGROUND

The exposure of humans to hostile work environments can be reduced by means of shared controlled systems, in which the operator remotely controls a robotic platform to perform a task in such environments, e.g. [1]. One of the first industries which initially introduced the use of shared control systems was the nuclear industry but, over time, many other industries have adopted these technologies including health care, undersea, and space [2].



The key insight is to add an active AI component which is context- and user-aware so to make better decision on how to assist the operator. Context-awareness is typically provided by reconstructing and understanding the scene, in terms of the objects the robot has to manipulate. User-awareness is obtained by providing as input the operator's task to the AI component, so to enable a more efficient interpretation of his/her inputs through the master device.

Despite the advancements in technologies and algorithms in autonomous robotics, e.g. [5-11], and shared controllers, e.g. [1], [2], [4], many industries has not yet embraced these new approaches, but rather prefer to maintain out-of-date but reliable systems. This is due to a very simple fact: the risks for the operators and the money to be invested are not worth the benefits that a novel approach may have on paper but which has never been properly tested on an uniform and standardised benchmark.

We argue that providing such a benchmark, a benchmark approved and standardised by a consortium of research institutions and industries, will encourage industrial partners to invest of the new technologies, which will lead to a safer and efficient environments.

The benchmarks and metrics we propose in this paper are designed to evaluate mainly two aspects of a share control algorithm:

i) The ability of extrapolating contextual information from sensing the environment to be of any support of the operator
ii) how the (visual, haptic) feedback are used to influence the operator's response.

The combination of these two components should, in fact, improve the task efficiency (number of successful executions of the task), reduce the task effort (how long it will take to execute the task), and robot demand attention (the time the user utilises to interact with the interface instead of focusing on the task at hand).

BENCHMARK I
Task Efficiency

Dataset

The dataset is composed of three sets of 3D printed primitive shaped objects.

i) Visible & non-slippery
ii) Transparent
iii) Coated in wax (shiny & slippery)

Task

We aim to evaluate if the algorithm can lead the operator to robustly grasps objects. Each of the object will be presented to the robot attached to a base via a spring. By lifting the object of ten centimeters the external force generated by the spring will challenge the grasp.

Evaluation

For each object in the dataset, ten random positions that span the entire workspace will be selected and recorded. Each algorithm will be tested five times for each pose. This would provide a set of fifty trials per object, and it guarantees that the performance is not biased by the configuration of the object. The metrics will be computed at the end of the experiments as average per class and across classes.

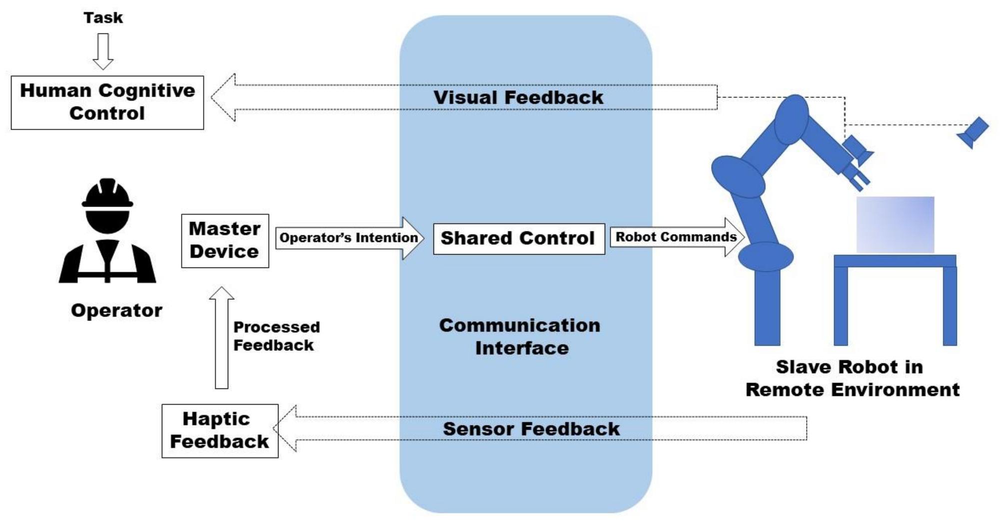


FIG. 1. Graphical representation of a remote shared control setup. The operator receives a visual feedback of the task environment (shaded blue area above the tabletop) and controls the slave robot via a master device. The operator input is translated in movements for the slave robot according to the shared control algorithm. Haptic feedback can also be provided to guide the operator according to the shared control algorithm.

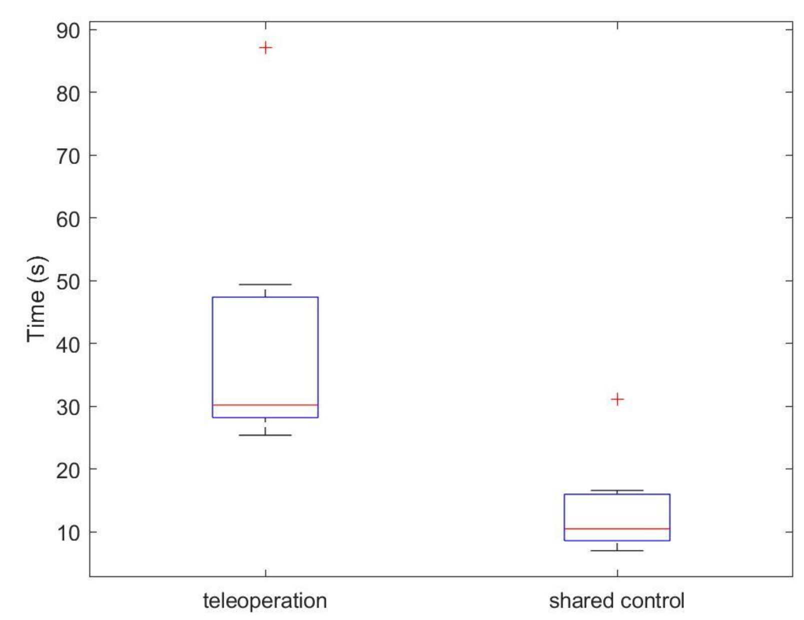


FIG. 4. Time effort (in seconds) for teleoperating a robot manipulator for a grasping task. We tested 10 participants. The plot shows the average completion time to reach and grasp 5 objects with standard Cartesian controller (blue) and a simple shared controller (red). The empirical results show that the shared controller outperforms the baseline controller in guiding the robot towards the grasp.

BENCHMARK II
Pick & Place

Dataset

i) Soft & deformable.
ii) Metallic & slippery.
iii) Composed objects.

Task I

Pick a single object and place it into a basket area.

Task II

Pick an object from a clutter scene with objects from the same class of the dataset, and place it to a basket until there are no more objects.

Task III

Pick an object from a clutter scene with objects sampled across categories, and place it to a basket until there are no more objects.

Evaluation

Task I: each object will be placed in ten random positions that span the entire workspace and the positions recorded. *Task II & Task III:* ten random clutter scenes with ten objects each will be selected and recorded. Each algorithm will be tested five times for each object or scene to generate fifty trials per object/scene not biased by the pose the objects. The metrics will be computed for each task individually at the end of the experiments as average per class and across classes.

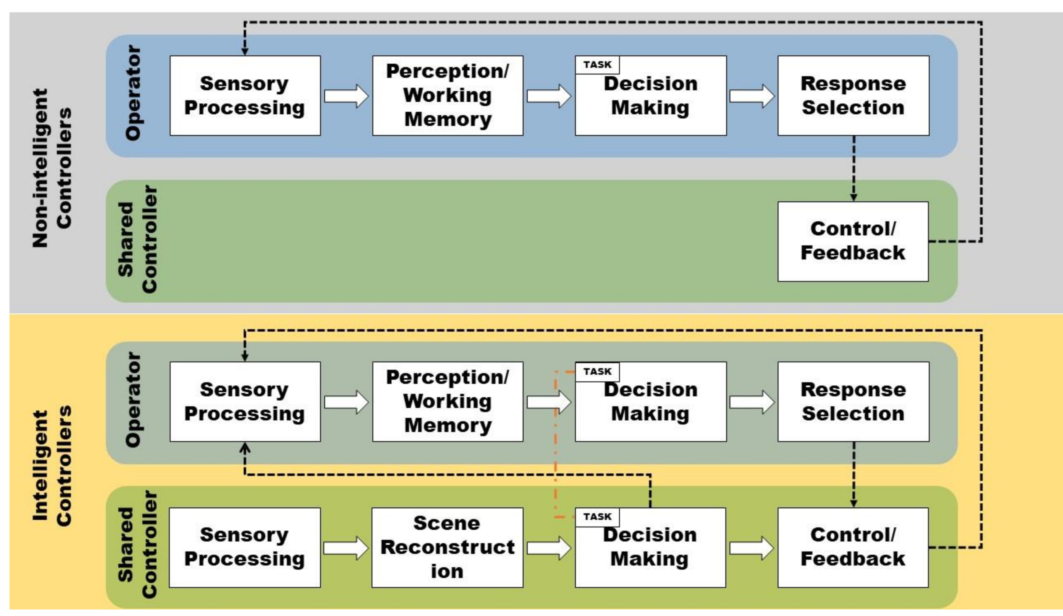


FIG. 2. A four-stage model of human/robot information processing. The top row (grey) shows a classical, non-intelligent shared controller, which simply maps the master's movements into the slave's movements. No context- or user-awareness is provided. The bottom row (yellow) shows the same model for an intelligent shared controller that is context-aware thanks to a scene reconstruction of the task space, and user-aware thanks to a shared task which will allowed the algorithm of interpreting the operator's intentions, through his/her responses, in a more helpful way. Modified from [12].

BENCHMARK III
Assembly

Dataset

The dataset is composed of a set of 3D printed primitive shapes and a peg board for the respective shapes.

Task I

A CAD model of the peg board will be available to the algorithm and its pose will be kept fixed throughout the experiments. We will present a single object from the dataset to the robot in a pre-defined region of the dexterous workspace of the robot manipulator. A point cloud from a pre-defined single view will be collected from the eye-in-hand camera to localise the object in an expected region. The operator will need to pick the object and push it through the correct hole in the peg board.

Evaluation

Each trial will be composed by twelve objects (i.e. three for each shape). The objects will be presented to the operator in a random order which will be recorded. Ten trials per algorithm will be performed. The metrics will be computed as an average over the ten trials.

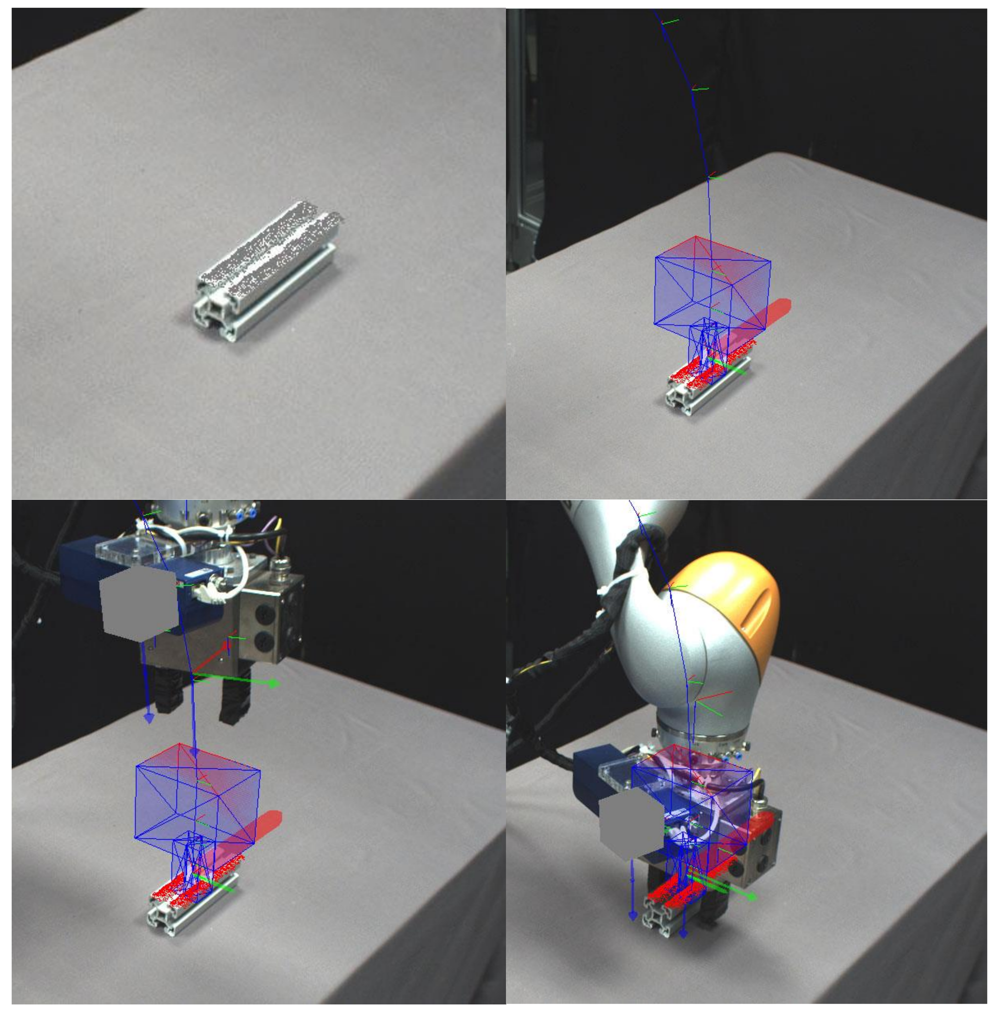


FIG. 3. An example of an intelligent shared controller. First image on top: a point cloud is collected to process the workspace. Second image on top: a grasp suggestion with a relative trajectory is visualised to the operator. Third and fourth images in the bottom row: the operator drives the robot towards the object following the suggested trajectory until the operator decides to send the command to close the gripper and grasp the object.

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