Research Challenges and Progress in Robotic Grasping and Manipulation Competitions

Yu Sun, Joe Falco, Máximo A. Roa, and Berk Calli

***Abstract*—This paper discusses recent research progress in robotic grasping and manipulation in the light of the latest Robotic Grasping and Manipulation Competitions (RGMCs). We first provide an overview of past benchmarks and competitions related to the robotics manipulation field. Then, we discuss the methodology behind designing the manipulation tasks in RGMCs. We provide a detailed analysis of key challenges for each task and identify the most difficult aspects based on the competing teams' performance in recent years. We believe that such an analysis is insightful to determine the future research directions for the robotic manipulation domain.**

***Index Terms*—Grasping; Dexterous Manipulation; Performance Evaluation and Benchmarking**

I. Introduction

ROBOTIC grasping and manipulation as a research field had tremendous growth in the last decade. Researchers have made significant progress in different areas that prevented robots from reliably handling household items, mechanical parts, and packages. The progress in robotic grasping and manipulation has shown new application promises that led to a renewed interest in robotics from the general public, industry, and government agencies. Nevertheless, the growth and progress have not been even. Some challenges receive a great deal of well-deserved attention because they are either obvious or standing in the way of big commercialization potential. Some challenges might not be as popular and remain unsolved for decades, but they could be crucial for many applications. Some challenges may have changed or vanished because a new kind of hardware becomes available or an engineering solution became adequate. A comprehensive overview of the major challenges not only helps us analyze the history of the robotic grasping and manipulation field, but also allows us to determine future research directions. We should keep track of the challenges, their changes, and the progress made to solve them. Competitions rooted in real-life applications could be an ideal vehicle for this purpose.

This paper discusses recent progress in the robotic manipulation field based on the recent Robotic Grasping and Manipulation Competitions (RGMC)[1]. For defining the RGMCs, we designed over 40 grasping and manipulation tasks that reflect realistic scenarios in service robotics and industry. Each task has a detailed setup and requirement description and scoring rules. The task details can be found on the competition webpages [1]–[4] and [5], [6]. This paper presents the challenges and the progress of the competing teams, identifies critical areas preventing better performance in robotic manipulation, and provides observations regarding future research directions.

II. Background

A. Related Robotic Grasping and Manipulation Benchmarks

Establishing experimentation methodologies that allow comparison across different research groups is still a pending challenge in robotics. The large variety in robotic platforms, setups, and software implementations poses numerous difficulties to achieve common experiment protocols. Even the pressure to publish plays a role in this lack of comparison, as applying the benchmarking protocols is a thorough and time-consuming process, which is sometimes neglected under the pressure of publication deadlines. In this sense, initiatives such as the Reproducible Articles (R-articles) of the IEEE Robotics & Automation Magazine (RAM) [7] aim to encourage easy reproduction of results via adopting and/or presenting detailed experiment protocols. Several initiatives of benchmarks for grasping and manipulation have been proposed, focusing on different levels of the manipulation system:

Mechanism level: In these types of benchmarks, the intrinsic capabilities of the mechanisms (often times end-effectors) are considered and measured. A benchmarking protocol for assessing and comparing the grasping abilities of robotic hands is presented in [24]. The benchmark in [25] assesses the robustness and resilience of the robotic hands by determining the impulsive conditions that break their grasp and their mechanism itself. A detailed list of procedures for analyzing the mechanical properties of the robotic hands is given in [26]. A specific benchmark for compliant hands is provided in [27].

Algorithm level: These benchmarks evaluate the performance of a specific algorithm in the robotic manipulation pipeline. The benchmarks in [28], [29] assess the performance of grasp planning algorithms. In [30], the force control capabilities of the system are analyzed. A platform-independent method for quantifying the motion planning performance is presented in

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[1]Certain commercial entities and items are identified in this paper to foster understanding. Such identification does not imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the materials or equipment identified are necessarily the best available for the purpose.

TABLE I
ROBOTIC COMPETITIONS INVOLVING MANIPULATION

Competition/Challenge	Years	Tasks*		Focus**				Description
		Fi	Fr	Gr	Ma	As	Mm	
RoboCup@Home [8]	2006-2021	X	X	X	X		X	Domestic service tasks, different fixed challenges each year
DARPA Robotics Challenge [9]	2012-2015	X		X	X		X	Disaster response scenarios
RoCKIn [10]	2014, 2015	X		X	X		X	Two tracks: RoCKIn@Home (domestic environment) and RoCKIn@Work (factory environment)
European Robotic Challenge (EuRoC) [11]	2014-2017		X	X	X		X	Reconfigurable manufacturing cells, shop floor logistics and manipulation, and plant servicing and inspection
Amazon Picking Challenge (APC) [12]	2015-2016	X		X	X			Logistics scenario, retrieving items
IROS Robotic grasping and Manipulation Competition (RGMC) [5], [6]	2016-2017, 2019-2020	X		X	X	X		Different tracks: service, manufacturing, and logistics
Cybathlon arm prosthesis race [13]	2016, 2020	X		X	X			Solution of everyday tasks using arm prostheses
Amazon Robotics Challenge [14]	2017	X		X	X			Logistic environment, as evolution of APC [12], pick and stow items
ICRA Mobile Manipulation Challenge [15], [16]	2017, 2019	X		X			X	Navigate, pick and place items
World Robot Challenge (WRC) [17]	2018, 2021	X		X	X	X		Three categories: industrial scenarios (agile manufacturing), service robotics (home and convenience stores), and disaster robotics (inspection and maintenance in a plant)
IROS Fan Robotic Challenge [18]	2018	X		X	X			Pick up and manipulate a Spanish fan
IROS Mobile Manipulation Hackathon [19]	2018		X	X	X		X	Freely-chosen application to showcase both mobility and manipulation
RoboSoft Competition [20]	2018-2021	X		X	X			Industrial, surgical or domestic scenarios in the manipulation track
Smart City Robotics Challenge (SciRoc) [21]	2019, 2021	X		X	X			Different episodes, or challenges, in domestic and logistic scenarios
OCRTOC, Open Cloud Robot Organization Challenge [22]	2020, 2021	X		X	X			Table reorganization problem, tested in a remote lab
Real Robot Challenge [23]	2020-2021	X		X	X			Grasping and in-hand manipulation tasks in a remote platform

*Tasks: Fi: Fixed, Fr: Free
**Focus: Gr: Grasping, Ma: Manipulation, As: Assembly, Mm: Mobile manipulation

[31]. Object segmentation and pose estimation data sets and benchmarks are commonly used in the robotics and computer vision community, with recent examples in [32], [33].

System level: These benchmarks consider the task performance of a robotic system as a whole, fully integrated autonomous solution (perception, planning, control). The box and blocks test in [34] assesses the pick-and-place performance of a robotic system. Similarly, pick-and-place abilities in logistics scenarios are evaluated in [35]. Inspired by the Amazon Picking Challenge, a shelf picking benchmark is presented in [36]. In-hand manipulation performance is quantified in [37]. Assessment for various challenging manipulation tasks such as cloth [38], bimanual [39] and aerial [40] are also provided as system-level benchmarks.

B. Related Competitions and Challenges

The robotics community has a long history in organizing competitions and challenges. Over the last decade, there have been multiple competitions that involve robotic manipulation in different degrees of complexity, pushing forward the research in the field. The competitions focus on different aspects, such as pure grasping, manipulation, assembly, or even mobile manipulation, as summarized in Table I. In terms of tasks, those competitions adopt two approaches:

- Completing a fixed set of tasks: the environment, objects, and rules are defined in advance. Thus, the tasks provide an objective measure of progress intra-edition, i.e., comparison of performance of different teams, and inter-edition, i.e., measuring progress across different years on the same set of tasks. The disadvantage of this approach is that teams usually over-engineer their solution (or work around the rules) to fulfill the intended task.
- Demonstration of a freely-chosen application: this open format allows the teams to demonstrate their strengths in a self-selected scenario, usually following very general constraints, e.g., using a common robotic platform or demonstrating tasks that include prescribed components. The disadvantage is that demonstrations are hardly comparable among them.

The Robotic Grasping and Manipulation Challenge (RGMC) uses system level benchmarks and defines a fixed set of tasks in each track to be solved using a robot manipulator. The descriptions of the tasks are provided in the next section.

III. TASK DESIGNS

To evaluate robotic systems' capability, we have designed over 40 real-life tasks based on our knowledge of the research challenges in robotic grasping and manipulation. All these tasks have detailed protocols, rules, and scoring policies. For instance, the task descriptions and rules of the 2016 and 2017 RGMCs can be found in [5]. Each competition comprises challenges that span a large set of robotic manipulation

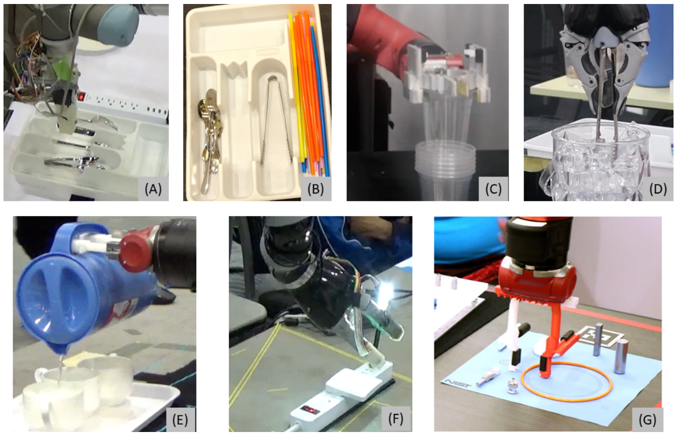

Fig. 1. Task setups based on perception challenges. Description of the tasks is provided in Table II.

TABLE II
TASKS REFLECTING PERCEPTION CHALLENGES

Research challenges	Tasks
Shiny objects	-Pick up silverware (Fig. 1a) -Pick up a a polished spoon for stirring (Fig. 1b) -Pick up metal tongs to get ice cubes (Fig. 1b) -Pick up metal pegs for insertion -Locate insertion holes on task board
Translucent objects	-Pick up transparent cup lid (Fig. 1c) -Pick up ice cubes (Fig. 1d) -Pour a certain amount of water into a cup (Fig. 1e)
Precision/accuracy	-Insert electrical connectors (Fig. 1f) -Insert pegs, fasteners (Fig. 2f) -Insert gears (Fig. 3b) -Insert/route belts (Fig. 1g)

capabilities with varying difficulty levels. Easier tasks are expected to be solved by most teams, while some challenging tasks are not expected to be fully accomplished by any of the teams. Such variety in difficulty serves multiple purposes: Easier tasks encourage participation and constitute a starting point for new robotics researchers. Challenging tasks aim to differentiate the most successful teams while encouraging robot/algorithm design and integration innovation. Limited by natural constraints of the competition settings (e.g., timeline, space, and equipment), the tasks are carefully composed to appeal to a large group of researchers and research interests. Therefore, some of the tasks that were selected in a certain year might be replaced by others in the following years, even though the teams did not fully accomplish them.

Here we present the tasks in the RGMCs according to the research challenges associated with them. There are plenty of unsolved research challenges in perception, grasping, manipulation, and mechanical design trade-offs for both real-time service tasks as well as for manufacturing/assembly tasks [41].

A. Research Challenges in Perception

Perception is critical to most robotic grasping and manipulation tasks. A significant amount of work has been dedicated to solving various challenges in robotic perception and, over the years, we have seen great improvement, especially after depth cameras became widely accessible and high-precision tactile sensors became less expensive. However, many challenges remain unsolved, and while designing our competitions we highlight these challenges to gauge progress.

1) Objects with shiny surfaces: Computer vision has a long-standing difficulty in dealing with shiny objects. Because of the reflection, some shiny surface areas cannot be well-perceived by vision sensors. The missing areas make segmentation and pose estimation difficult, and drop the success rate of grasping and manipulation algorithms. In RGMCs, we have several objects with shiny surfaces, such as the silverware sets, 2017 RGMC (Fig. 1a) and spoons and tongs, 2019/2020 RGMCs (Fig. 1b). Also, parts such as the plastic assembly base (task board) and metallic components in manufacturing tasks (Fig. 1g) can present perception difficulties.

2) Translucent or transparent objects: Translucent objects are also very challenging for robotic vision. In all four RGMCs, we have translucent to-go cups and lids (Fig. 1c). We have also introduced a pile of ice cubes for a picking task in the last two RGMCs. In general, the sensing aspect of the ice cube picking task is more challenging than the sensing for picking up a to-go cup and a lid, since the to-go cups and lids are standalone objects on the table, and they occupy a significant space to approximate their pose. On the other hand, the ice cubes are randomly piled up in an ice bucket (Fig. 1d), and determining the pose of an individual ice cube among other (also translucent) ice-cubes within a translucent ice bucket is a very challenging task. In 2017 RGMC, the competition requested to pour a certain amount of water into a cup. Estimating the amount of water in the cup also provides a significant challenge since it is transparent (Fig. 1e). There are currently no translucent or transparent objects used for the manufacturing tasks.

3) Tasks requiring high precision or accuracy: Tasks with tight tolerances usually require the perception part of the system to be precise. For typical peg-in-hole problems such as plugging a Universal Serial Bus (USB) light into a socket (Fig. 1f), a robot would need to use vision to precisely localize the socket. To compensate for the inaccuracies of the localization, an exploration algorithm or a failure recovery approach is often times needed. Using force sensors to guide corrective motions is a common example of such exploration strategies.

4) Other challenges: Service track objects are provided to teams prior to competitions depending on type and difficulty. This time can range from hours to days. The teams usually utilize this time to collect data and learn models for object identification, segmentation, and planning. While developing techniques to model the objects in a short amount of time under a semi-controlled environment is a challenge, obtaining prior models of the objects significantly reduces the perception and planning difficulties of the task. If the objects are unknown (no learning data or models), the tasks could be much more difficult. However, for real service applications, learning object models is typically not feasible. In the case of the manufacturing track, design data is typically known, so all components and Computer Aided Design (CAD) data are provided to teams weeks in advance to the competition.

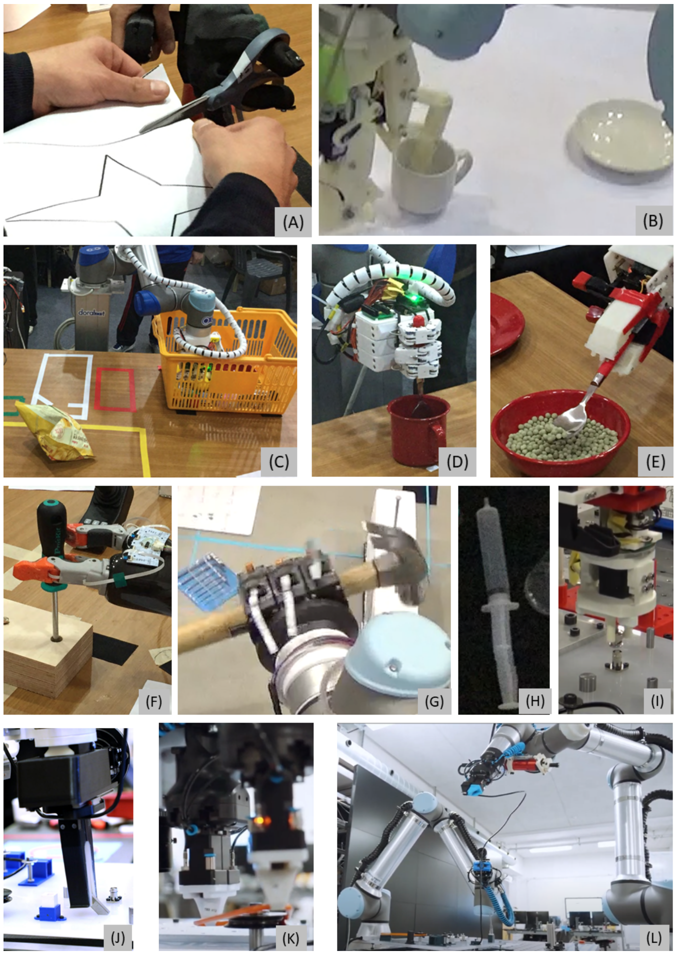

Fig. 2. Tasks reflecting grasp challenges. Description of the tasks is provided in Table III.

At the start of the competition all teams are given updated CAD data that reflects changes in the challenge tasks from the practice tasks, which imitates challenges associated with product changes in batch type production runs.

Table II summarizes the tested perception challenges and the tasks reflecting them in the RGMCs.

B. Research Challenges in Grasping

1) Grasping with imperfect perception: Perception errors cause most failures in grasping. If the object's pose is estimated seriously wrong, the robot could knock over the object or push it away, end up with an unstable grasp, or completely miss the object. For end-to-end approaches, even if there is no separated pose estimation step, the noise in perception layers still dramatically affects the grasp results. Unfortunately, it is almost impossible to have "perfect" perception. Noise can always find a way to creep in. So grasping approaches should be prepared to deal with perception uncertainties. In RGMC, most tasks require robots to handle a bad grasp caused by perception errors since many tasks have challenging objects.

2) Objects with challenging shapes and surfaces: Even with perfect vision, some objects can still be challenging to pick up or manipulate. It could be because there is a minimal good surface area for grasping. Curved and narrow surfaces

TABLE III
TASKS REFLECTING GRASP CHALLENGES

Research challenges	Tasks
Objects with challenging shapes and surfaces	-Cut a piece of paper using a pair of scissors (Fig. 2a) -Transfer a cup on its saucer (Fig. 2b)
Grasp in clutter	-Pick and place objects from a shopping basket (Fig. 2c) -Pick up silverware from a silverware organizer (Fig. 1a)
Regrasp	-Assemble fasteners -Use a spoon to stir water in a cup (Fig. 2d) -Use a spoon to pick up peas (Fig. 2e)
Grasp for manipulation	-Hammer a nail (Fig. 2g) -Stir water with a spoon (Fig. 2d) -Assemble/disassemble electrical connectors (Fig. 2i) -Insert pegs (Fig. 2j) -Insert/screw fasteners (Fig. 2f) -Insert/mesh gears (Fig. 3b) -Insert/rout belts/wires (Fig. 2k,l)
Grasp for in-hand manipulation	-Fully extend and fully press syringe (Fig. 2h) -Grasp and use scissors to cut a piece of paper to half along a line (Fig. 2a) -Pick up ice cubes using tongs (Fig. 1d)

are challenging to grasp. For example, the curved finger rings of a pair of scissors pose a significant challenge to a robotic hand (Fig. 2a). Holding and manipulating scissors with them are both very difficult. Another challenging task is to pick up a saucer with a cup on it with one hand, since it is difficult to hold the edge of the saucer and balance the unknown torque generated by the cup's weight (Fig. 2b).

3) Grasping objects in clutter: Picking up an object in clutter is quite challenging. Its neighbor objects could block the robotic hand and pose planning difficulties, since usually a gripper would need to grasp on two sides of the object, and the hand approaches from another side. One task that reflects this challenge is picking objects from a shopping basket and placing them in defined areas (Fig. 2c). Grasping objects in clutter for manipulation is more challenging since the object would need to be held in a certain way to provide needed manipulability [5] and interactive force [42]. Therefore, the grasping points and orientations for manipulation are more limited than for picking. When objects are in clutter, a robotic hand may not be able to reach and grasp the object in the desired way. For example, in the stirring water task (Fig. 2d), and pea-picking using a spoon task (Fig. 2e), the spoons are in a silverware organizer and they are difficult to pick up.

4) Regrasping: A robot may pick up an object in one grasp but may need to change to a different grasp for manipulation. Then the robot would need to regrasp the object after it is picked up. As mentioned before, in both stirring and pea-picking tasks, the grasp of the spoon should be adjusted after it is picked up. In the task of putting on or removing a bolt from a nut with a nut driver, since multiple turns are required, a robotic hand would need to regrasp the nut driver to overcome the rotation limit of the wrist (Fig. 2f). Due to the number of fasteners, making regrasp operations efficient is challenging.

5) Grasping for manipulation: For some manipulations, an object should be grasped in a certain way so that the manipulation can be performed efficiently and the object has less chance

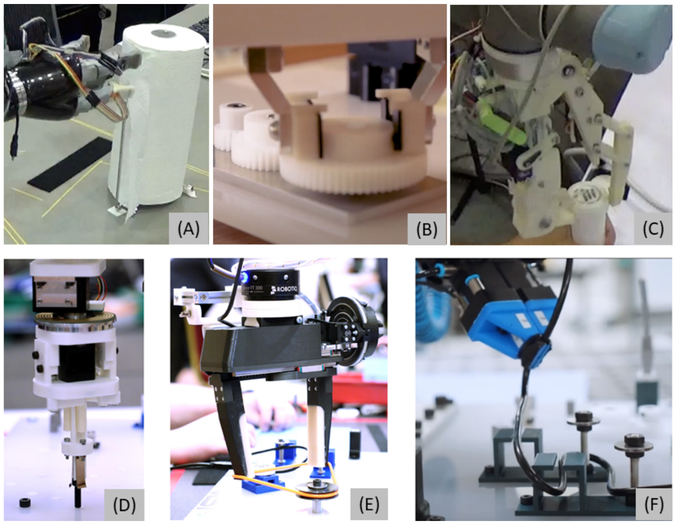

Fig. 3. Tasks reflecting manipulation challenges. Description of the tasks is provided in Table IV.

TABLE IV
TASKS REFLECTING MANIPULATION CHALLENGES

Research challenges	Tasks
Manipulation with imperfect perception	-Solve peg in hole with a wood board -Assemble/disassemble electrical connectors -Insert pegs (Fig. 2j) -Insert/screw fasteners (Fig. 3d) -Insert/mesh gears (Fig. 3b)
Manipulation that needs accurate prediction	-Open a water bottle cap and pour water into a to-go cup -Pour water from a pitcher into a cup (Fig. 1e) -Tear a paper towel (Fig. 3a) -Open a bottle with a locking safety cap (Fig. 3c) -Threading flexible belts (Fig. 3e) -Routing wires (Fig. 3f)

of being dropped during the operation [43], [44]. We have designed nail hammering (Fig. 2g) and water stirring tasks to gauge if the team considers the manipulation requirements in grasp planning. Performing force-based manipulation for insertions requires adequate grasping force to avoid movement of the object within grasp and ultimate insertion failure (Fig. 2j). In addition, grasping non-rigid objects to effectively control their shape, as in threading belts on pulleys (Fig. 2k) and wire routing (Fig. 2l), is a very challenging problem.

6) Grasping for in-hand manipulation: In-hand manipulation is still a very challenging research area. We have designed several tasks that would require some in-hand manipulation after grasping. These include extending and pressing a syringe (Fig. 2h), cutting paper with a pair of scissors (Fig. 2a), and using tongs to pick up ice cubes (Fig. 1d), but they have not been satisfactorily solved so far.

Table III summarizes the tested grasp challenges and the tasks reflecting them in the RGMCs.

C. Research Challenges in Manipulation

Manipulation motions can usually be generated with motion planning and motion control. In general, the challenges in manipulation are caused by imperfect perception and the lack of capability to predict a motion's outcome. Both can be extremely challenging. In RGMCs, since the objects are provided to the teams beforehand (at least for several hours), they can model the objects and their behaviors to a certain extent, which dramatically reduces the challenges. However, several tasks remain challenging because either the tolerance is tight or the behaviors are difficult to model. For instance, peg-in-hole tasks and tightening or loosening bolts (Fig. 3d) require purposeful motions. Tearing up a paper towel (Fig. 3a) and pouring water (Fig. 3b) require the robot to predict the kitchen roll motion and water flowing speed in response to a motion. Opening a bottle with a locking safety cap (Fig. 3c) is a task that requests the robot to predict a pressing outcome. Since it is repeatable, it is easier to model than water and cloth.

Assembling flexible belts and routing wires, while difficult, becomes more achievable with practiced routines and the use of CAD data. Table IV summarizes the tasks reflecting those challenges in the RGMCs.

IV. RESULTS AND PROGRESS

Each year, seven to ten teams passed the initial screening and participated in the competition. Teams are from world-renowned research groups in universities, prominent startups, and large corporations. We can see that their improvement in performances aligns with the progress made by the robotics research community over the same period of time. Though their performance might not represent the absolute best solutions available at the time, their successes and struggles in the RGMCs reflect research progress and remaining challenges.

A. Overview

In the four RGMCs, twenty-three tasks have been used to measure the contestant's performance in the service track, some used in multiple years with stricter requirements toward achieving real-world application. In the beginning, in 2016, the teams were allowed to predefine the locations of the objects with little to no randomness. Then in 2017 and afterward, the teams were only allowed to define object regions based on the robot's workspace and the organizers randomly placed the objects in those regions. In 2016 and 2017, only the best possible result for every task was counted, while in 2019 and 2020, the total score of five trials was counted. In 2019, the total allowed time was 90 minutes, while in 2020, the total allowed time was 60 minutes. The manufacturing track was first introduced in 2017, and teams were allowed to set the position of the task board and kit layout, and optional random placement provided bonus points. The dominant solution was the use of lead-through programming. To encourage the use of perception, in 2019 and 2020 randomized placement was required and CAD data was supplied as an option for extracting locations of assembly components on both the task board and kit layout relative to a coordinate frame. While the 2017 task board contained only insertion and fastening operations, the 2019 and 2020 task boards introduced wire routing and belt on pulley operations. The supplemental document[2] provides

[2] https://rpal.cse.usf.edu/competition_iros2021/Supplemental-RA-L-RGMC.pdf

details of the tasks, the best scores, unsolved tasks, and performances of the RHGM teams based on the data and organizers' observation.

B. Research Progress and Challenges in Perception

1) Objects with shiny surfaces: In 2016, teams were struggling with silverware due to their shiny surfaces. In 2020, several teams could reliably segment a shiny spoon from other spoons and estimate its pose for grasping. They managed the reflection by controlling the lighting using multi-flash, similar to the technique in [45]. Objects with shiny surfaces may not be a significant challenge if the object model is known and its location variation is limited.

2) Translucent or transparent objects: Translucent objects still pose a significant challenge to perception, especially for randomly stacked objects such as ice cubes in a bucket. No team was able to finish the picking ice cube task. For the pouring task, all teams completed it using hard-coded pouring motions. We do not think any team could estimate the water level in the receiving cup when the water is transparent. Even though several promising pouring approaches are available, none of the teams used them. So, when an object is truly transparent, alternative perception other than vision could be used. On the other hand, randomly stacked translucent objects are still very challenging.

3) Tasks requiring high precision or accuracy: In plugging a USB light into a socket task, several teams were able to finish the task. Some teams are slower than others. But in general, the peg-in-hole problem is not a significant challenge if both models are known.

C. Research Progress and Challenges in Grasping

1) Grasp with imperfect perception: Teams in RGMCs have gradually incorporated approaches to handle perception uncertainties, since they found that it was one of several major reasons that make their solutions slow and unreliable. It is a significant challenge that requires both research and engineering work.

2) Objects with challenging shapes and surfaces: Teams have explored several options and made good progress. Several teams tried an automatic tool-change approach that allows them to swap grippers. Several grippers were designed and made to deal with challenging shapes and surfaces. Some others developed a gripper that incorporates multiple fixtures. They can flip or rotate so that the right fixture is in contact with the object. Many smart and inspiring designs have come out, but they are tailored and calibrated on known objects. It is a significant challenge for cases with unknown objects or under unseen situations.

3) Grasp objects in clutter: RGMCs only have several tasks with objects in clutter, and the level of cluttering is moderate. On the one hand, we observed the teams made progress over the years in dealing with closely lying objects. But on the other hand, we also observed that cluttered environments still slowed down their performance dramatically. So it is still a challenge, and we would expect it is more difficult if the objects are unknown and the situations are new.

4) Regrasp: Many tasks require the robot to adjust the grasp after picking up an object. We have observed many teams put down the object and used the setup to position or orient the object in a certain way and then regrasped it. Many of the pick-place-regrasp routines are well crafted and impressive. However, teams have been avoiding in-air regrasp even it would be more efficient. Adjusting a grasp or regrasping in the air is still very challenging.

5) Grasp for manipulation: Several tasks require grasp planning while considering manipulation requirements. We have mostly seen that teams predefine several grasp points based on their experiences and simulations. As far as we know, teams have avoided computing and searching for proper grasp points on the fly. The approach would fall apart if the objects are unseen or different from the provided models. For known objects, the predefined grasp point approach seems sufficient.

6) Grasp for in-hand manipulation: In-hand manipulation remains the biggest challenge, where teams have been unable to complete tasks that utilize scissors, syringes, and tongs. These tasks, in most cases have been removed from RGMC due to their high difficulty.

D. Research Progress and Challenges in Manipulation

1) Manipulation with imperfect perception: Many teams have no problem dealing with tasks testing manipulation with imperfect perception. In general, the available object models and setups and tactile/force sensors allow teams to complete those tasks successfully.

2) Manipulation that needs accurate prediction: Teams did little in predicting the outcomes of a manipulation action. Most manipulation motions were generated based on obstacle avoidance. As far as we know, they have avoided modeling dynamics. They usually created a list of possible outcomes and matched a set of predefined motion strategies to those outcomes. This approach is not sufficient when dealing with flexible objects and fluids, since a finite enumeration of the states of those objects is usually not feasible. Even though the teams have not provided satisfactory solutions, we believe that recent research progress could be used to solve some of the challenges [46], [47]. Table V summarizes the tested challenges and the progress in the RGMCs.

V. Discussion and Future Directions

This paper provided an overview of the tasks and challenges proposed in the RGMCs. Different from many evaluation setups in the literature, competitions such as RGMC usually require participants to run demos at a certain time and to complete tasks in a limited amount of time. In addition, participants usually do not have total control of the setup, making the competition setup realistic to real-world applications.

Over the years, we have seen that tasks that were initially deemed as hard, have been solved using different ingenious approaches. Especially in the first editions, teams tried to solve the most difficult challenges with highly-engineered solutions. But with progress made in research, we have seen less and less hard-coded routines, less use of predefined grasp points, which have led to solutions becoming more effective and reliable. For software, the most significant challenges identified by

TABLE V
PERCEPTION CHALLENGES AND PROGRESS

Research challenges	Progress
Shiny objects	Mostly solved for standalone objects if their models are known.
Translucent objects	Still very challenging for randomly stacked translucent objects.
Requiring high precision or accuracy	Largely manageable if the objects are known. Implementations are incorporating force control and CAD data.
Grasp with imperfect perception	It is the major reason that solutions are slow and unreliable. It is a significant challenge that requires research and a lot of engineering work.
Objects with challenging shapes and surfaces	It remains a significant challenge even though special-purpose grippers and fingers are designed.
Grasp objects in clutter	It is still a challenge, and we would expect it is more difficult if the objects are unknown and the situations are new.
Regrasp	Many teams developed impressive pick-place-regrasp routines, but adjusting a grasp or regrasping in the air is still very challenging.
Grasp for manipulation	For manipulating known objects in a known condition, the predefined grasp point approach seems to work well. However, this approach would fall apart if the objects are unseen or the conditions are new.
Grasp for in-hand manipulation	In-hand manipulation remains the most difficult challenge, as it requires accurate prediction of the motion effects and suitable control of the end effector.
Manipulation with imperfect perception	The available object models, design data, and tactile/force sensors allow teams to complete those tasks successfully.
Manipulation that needs accurate prediction	Teams have avoided modeling dynamics for prediction, even though recent research progress could be used to solve some of the challenges.

the teams are related to perception. The arrival of learning-based approaches has facilitated solving tasks that use known objects, as they can be readily available for system training. The generality of such approaches to be applicable to familiar and fully unknown objects is still a large challenge. Learning-based approaches have been also lately used for defining grasping configurations, thus avoiding the reliance on predefined grasp poses. For motion planning, most teams relied on open libraries, such as the Open Motion Planning Library (OMPL) [48] or MoveIt [49], and using Robot Operating System (ROS) [50] in most cases as middleware. These openly-available resources enable teams to more efficiently create solutions.

We saw that some of the RGMC tasks still represent a significant challenge. The most clear example are tasks requiring some degree of in-hand manipulation, which were effectively removed from the last RGMC editions. This reflects the state of industry, where most end-effectors are two-finger grippers that are used for pick-and-place tasks. Industrial applications usually prefer to design special fingertips for grasping different types of objects, or using a robot accompanied by a tool changer that endows the robot with the ability to switch end-effectors for performing multiple tasks. The promised generic dexterity of multi-finger end-effectors still seems more a research topic rather than a viable commercial solution, mainly due to the higher mechatronic and control complexity and higher cost associated with multi-finger grippers.

There has been a significant increase in manufacturing track solutions that utilize CAD data. Typically, perception or force solutions are used to localize the task board with subsequent localization of part assembly points on the task board using CAD data. Improvements to the CAD pipeline could result in improved data formats to transmit dimensions, geometric features, relative part positions, mating descriptions, and tolerances from CAD systems. In addition, the inclusion of force-based assembly parameters within a CAD system, which could be best specified by a designer who is most familiar with the mechanical properties of the parts to be assembled, should be considered. Methods for automatic robot program generation using this data should also be considered.

In terms of robotic devices, participants have used a full range, from experimental robotic hands and arms to off-the-shelf robot arms and simple parallel grippers. Hardware for perception is nowadays relatively standard, with depth cameras dominating the landscape, although different teams have been using other types of sensors (stereo cameras, laser-based perception, in-hand cameras). Integration of different hardware and software components remains, however, a large challenge, requiring hours of dedication to reach a stable and robust execution during the demonstrations. In most RGMC editions, teams had to transport their own equipment to the competition locations. The pandemic required the 2020 edition to be a fully online competition, which greatly alleviated the logistics for participation of teams around the world. Moving toward a standard remote lab for testing different approaches for solving a set of tasks seems like a reasonable approach to enhance comparability and reproducibility of results in robotics in the near future.

New robot designs provide improved methods for fast lead-through programming using direct interactions between the operator and the robot. Teams leveraging these solutions typically score well by programming the most difficult high scoring tasks first, to accumulate as many points as possible within a given time frame. Competition format changes to discourage solutions that only use lead-through programming could include: a required part assembly order, less tasks per board, and unknown task board offset and part variations.

Several successes have ensued RGMC teams. Dorabot [51], for instance, participated in the 2016 and 2017 RGMC competitions with prototypes of their dexterous modular robotic three-fingered hand, which is now a product. Focused on robotic logistic solutions, the company now has products including a five-fingered hand, and mobile manipulators. Robotic Materials [52] emerged as a startup out of the University of Boulder following the RGMC 2016/2017 competitions, and participated in RGMC 2019/2020 competition using their prototype smart gripper, which integrated position, force, and depth camera sensing modalities. Their work on this gripping system continues with the development of easy-to-use programming interfaces aimed at small- and medium-sized manufacturers. Southern Denmark University [53] research focuses on the development of a flexible workstation for automated assembly tasks that can be used commercially. Their generalized solution is proving to be robust and streamlined, achieving the first ever perfect score in the 2020 RGMC Manufacturing Track.

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