Avalon: Building an Operating System for Robotcenter

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Abstract—This paper envisions a scenario that hundreds of heterogeneous robots form a robotcenter which can be shared by multiple users and used like a single powerful robot to perform complex tasks. However, current multi-robot systems are either unable to manage heterogeneous robots or unable to support multiple concurrent users. Inspired by the design of modern datacenter OSes, we propose Avalon, a robot operating system with two-level scheduling scheme which is widely adopted in datacenters for Internet services and cloud computing. Specifically, Avalon integrates three important features together: (1) Instead of allocating a whole robot, Avalon classifies fine-grained robot resources into three categories to distinguish which fine-grained resources can be shared by multi-robot frameworks simultaneously. (2) Avalon adopts a location based resource allocation policy to substantially reduce scheduling overhead. (3) Avalon enables robots to offload computation intensive tasks to the clouds. We have implemented and evaluated Avalon on robots on both simulated environments and real world.

I. INTRODUCTION

In this paper we ask the following question: can warehouse-scale heterogeneous robots in a specific environment be managed to form a shared resource platform offered to multiple users? We call such facilities as robotcenters, which are similar to datacenters that provide resources on demand for cloud users. For instance, in a modern office building, hundreds of robots purchased from different companies are busying with their own tasks. The robots are shared by all users in the building to cooperatively complete users’ requests. Besides, they can simultaneously perform operations for environment detection and monitoring, such as face recognition, position detection and behaviors analysis.

To deploy such a robotcenter, an operating system (OS) is required to manage both robot resources and user requests. In particular, we argue that future robotcenter OS needs to have the following features: 1) it supports heterogeneous robots with different shapes and functionalities; 2) it supports flexible scalability and fast deployment; 3) it supports fine-grained resource sharing so that one robot can be shared by multiple tasks simultaneously; 4) it allows multiple multi-robot frameworks to be deployed on a group of shared robots; 5) it allows robots to offload computation to cloud-side datacenters.

Over the recent years, there have been efforts on multi-robot frameworks that can coordinate a team of robots to complete a specific task such as drawing on the sky. Unfortunately, they are unable to fulfill the above features so as not to be suitable for robotcenters yet. Specifically, current researches on multi-robot frameworks like Kiva [1] and Swarmfarm [2] are designed for a specific task in a specific environment rather than being shared by multiple users. In addition, these frameworks mainly aim to coordinate homogeneous robots [3], while robotcenters can consist of highly heterogeneous robots including Unmanned Ground Vehicle (UGV), Unmanned Aerial Vehicle (UAV) and even Unmanned Underwater Vehicle (UUV).

Recently, the RoboEarth project [4] has made a substantial contribution towards managing a group of robots. RoboEarth proposes a centralized task controller for multiple robots and enables offloading computation to cloud by introducing Rapyuta [5]. However, it encounters a main limitation: RoboEarth treats a whole robot as the minimal resource allocation unit. Thus, robots are managed in a batch mode and multiple jobs are sequentially executed on a robot. This mode is just like cluster-based supercomputers job scheduling systems that treat a whole server as the minimal resource allocation unit. Nevertheless, it is well known that batch-mode management is unsuitable for interactive jobs and usually results in poor utilization. The advent of fine-grained resource management systems such as Borg [6], Kubernetes [7] and Mesos [8] significantly change the supercomputer-styles cluster operating systems and has established a new ecosystem of system software stack for modern datacenters. Today, it is common for a typical datacenter to serve mixed workloads including latency-sensitive interactive applications and batch applications.

As shown in Figure 1, we observe that robotcenter and datacenter exhibit similar system stack. Much like the multi-robot frameworks (e.g. Kiva, Swarmfarm), there are also many computing frameworks (e.g. Hadoop [9], Spark [10]...
and TensorFlow [11]) in datacenters with different execution models such as MapReduce [12] and Bulk-Synchronous-Parallel (BSP) [13]. To allow these frameworks to simultaneously share datacenter infrastructure, prevalent datacenter OSes such as Borg, Kubernetes and Mesos leverage a two-level scheduling mechanism to fulfill fine-grained sharing for multiple computing frameworks. Datacenter Oses decouple resource allocation and task scheduling into two levels: the lower level is responsible for only fine-grained resource allocation and the higher level is responsible for task scheduling that is delegated to computing frameworks. We find that this mechanism can also be adopted for robotcenter OS.

Based on the observation, we propose a robotcenter OS design – Avalon. To our best, it is the first system that applies two-level scheduling for managing multiple robots. Specifically, Avalon allocates fine-grained robot resources to different multi-robot frameworks and delegates control over scheduling to the task allocator of each multi-robot framework. Achieving this is challenging for two key reasons:

- Unlike computing and storage resources in stationary servers, a robot’s resources have different characteristics and not all of them can be shared by multiple frameworks. Therefore, a careful resource classification is required for distinguishing which resource can be shared so as to enable multiplexing robots among multi-robot frameworks to improve robotcenter utilization.

- Prior multi-robot systems usually pre-allocate robots for a specific known task. However, like datacenters, robots in a robotcenter can be allocated on-demand and dynamically, which raises a significant challenge for robot resource allocation.

To address these challenges, We make the following contributions:

- **Fine-grained resource sharing.** We classify robot resources into three categories: computation resources (CR), sensory resources (SR) and action resources (AR). This classification, allows a robotcenter OS to know which resource can be shared and how frameworks use them. Based on the knowledge, we propose an efficient resource allocation policy to share CR and SR across multi-robot frameworks.

- **Location-based resource offers.** To address the allocation on-demand challenge, datacenter OSes usually use the locality principle to improve resource allocation. In contrast, Avalon adopts a location-based resource management method. Specifically, we design a location based resource allocator that uses a cost function based on the distance between an operation’s position and each robot’s position. We also design a range filter to reduce the number of resource offer list. By doing so, Avalon allows multi-robot frameworks to schedule without considering spatial cost, thereby resulting good system scalability.

- **Open source prototype.** To demonstrate the feasibility of our design, we implemented Avalon based on a datacenter OS Mesos [8] which supports Linux 4.4.0 and ROS indigo. It is worth noting that Avalon supports robots to offload their computation to the cloud, which is a promising direction for the future Cloud-Edge computing mode [14]. Furthermore, due to the compatibility with ROS, Avalon can leverage more than 3000 open source packages to help developers build multi-robot frameworks. We will also open source Avalon.

We evaluate Avalon on a Gazebo-simulated multi-robot system and on a turtlebot robot in real world. Experimental results show that Avalon is able to enable one robot to be shared by multiple tasks and improves CPU utilization average by 3.68 times (up to 7.51 times).

### II. BACKGROUND AND MOTIVATION

Traditional multi-robot frameworks usually treat a whole robot as resource allocation unit. In fact, different applications pose different resource demands. Thus in this section, we will conduct experiments to demonstrate that one robot has the potential to be simultaneously shared by multiple applications, which implies the feasibility of our proposed robotcenter OSes.

Assume that there are three multi-robot frameworks, each of which consists of a data-driven analysis task, a machine learning task and a SLAM task respectively. More description on these tasks are as below:

- **Data-driven analysis task:** This task regards robots as mobile sensors It collects perception data from each robot by accessing sensory resources [15], [16]. In our experiments, we choose a monitoring workload, which receives image data of a turtlebot robot and sends the data to cloud server continuously.

- **Machine learning task:** This task requires strong real-time constraints and a lot of computing resources. It improves robots’ intelligence by learning knowledge from sensory data about environments. In our experiment, we choose an image recognition workload that consists of a 34-layer convolutional neural network (CNN) called resnet34 [17], which offloads on-line training part to the backend cloud servers and only performs inference on the robot.

- **SLAM task:** This task drives robots to execute actions in the physical world. It takes in data from sensor streams and outputs executing commands to each actuator. We choose gmapping, a laser based SLAM workload, which uses a highly efficient Rao-Blackwellized particle filter to generate grid maps from laser range data.

These experiments run on a turtlebot in real world which is connected with a four-core 8GB DRAM notebook as its computing unit. It runs a Linux host OS with kernel 4.4.0 and ROS indigo. Since the turtlebot robot can not be shared in current multi-robot frameworks, we ran the three workload one by one. For each experiment, we measured CPU utilization every 1s, for a period of 5 minutes at stable phases.

1 A public release of Avalon is available from https://github.com/xuyuan-ict/robotcenter
Figure 2 shows resource utilization for three robotics workloads. It’s clear to see that current coarse-grained resource allocation approach manages robots in an inefficient way: The gmapping workload uses 15.3% of CPU in the mapping process, while the monitoring workload occupies only 13.1% of CPU for image transfer. The image recognition is relatively better due to the 34-layer CNN consuming 51.7% of CPU cycles.

According to these experiments, we can conclude that robot resources (i.e., CPU) are seriously underutilized with current approaches. In next section, we will propose a new robotcenter OS Avalon to improve resource utilization by integrating two-level scheduling mechanism.

III. AVALON OVERVIEW

In this section, we first introduce the design overview of Avalon and present the two challenges as well as our solutions. Finally, we will show an illustrative example.

A. Design Overview

Figure 3 shows the main components of Avalon. Avalon master is a centralized task controller that monitors and maintains the connection between multi-robot frameworks and robots. Avalon supports multiple multi-robot frameworks, each of which requires to register a scheduler into the master as a framework. The Avalon master determines how many available robots (called resource offers) to be pushed to a requesting framework based on position information. Once the framework accepts the offers, it launches an executor process on robots to perform tasks. Executing process is encapsulated into Linux Container [18], which is managed by Isolation Module. Besides, each robot runs a slave daemon to communicate with the master and forward allocatable resources to the master periodically.

In such design, a robotcenter OS is divided into two levels: the master is at the lower level and responsible for only fine-grained resource allocation; the frameworks at the higher level register a scheduler into the master for task scheduling. According to this two-level scheduling design, robotics researchers could focus on developing specific multi-robot frameworks without considering co-running multiple tasks. Furthermore, it keeps Avalon simple and scalable to adapt to multi-tenant environment in robotcenters.

B. Fine-grained Resource Sharing

One challenge of the Avalon design is that a robot’s resources have different features so that not all of them can be shared. To address this issue, we classify robot’s resources into the following three categories: 
- **Computation resources (CR)**: Some robots such as humanoid robots and self-driving vehicles are equipped with powerful CPU and high-capacity memory. This kind of resources can be shared by multiple tasks.
- **Sensory resources (SR)**: Some sensors including camera, laser and GPS, are the perceptual organs of robots to perceive the physical world. This kind of resources are also shareable.
- **Action resources (AR)**: Actuators including wheel, hand and propeller, are the action organs of robots. Due to spacial limitations, this kind of resources are unshareable. For example, a robot cannot simultaneously move to position A and position B that are on opposite directions.

Based on this resource classification, we can categorize robotics workloads along three axes. For instance, for the workloads mentioned in Section II, monitoring is an SR workload, image recognition is a CR-SR workload and gmapping is an AR-CR-SR workload. This gives a chance to deploy these three workloads on one robot in a mixed mode.

For each type of resource, Avalon uses two states used and allocatable to determine whether a resource can be shared. Usually a framework may run multiple tasks and one task can apply for multiple types of resource. When resources are offered to a framework, the framework traverses the offer list to check whether the allocatable resources meet its requirement. Specifically, Avalon provides interface for the framework to take the following actions:
- If a task needs a CR execution environment, the allocated CR should be marked as used, while the remain CR of that robot will be marked as allocatable.
- If a task needs an SR execution environment, all SR of that robot will be marked as allocatable.
- If a task needs an AR execution environment, all AR of that robot will be marked as used. Because other ARs...
may incur spatial conflicts with the used AR.

C. Location-based Resource Offers

Prior multi-robot systems are usually deployed for a specific task with pre-allocated robots. In robotcenters, however, robots are allocated on-demand and dynamically, which raises a significant challenge for robot resource allocation.

Dynamic resource allocation in datacenters is also very challenging. Datacenter OSes usually allocate resources and do scheduling based on data locality which means assigning computation tasks close to their data. However, the locality principle cannot directly be employed in robotcenters because robots can move. Thus, Avalon needs a new resource allocation policy to efficiently allocate resources to multiple frameworks.

To address this issue, we propose a location-based resource allocation policy. In particular, the Avalon master has a pluggable allocator module to offer a list of allocatable resources to frameworks. The allocator module takes spatial constraint as an important utility. If available robots are far from the position where a framework task takes place, then the Quality of service (QoS) cannot be guaranteed since it takes long time for the robots to move from current positions to the operation position.

To improve the efficiency of location-based allocation policy, we implement a range filter in Avalon allocator module (Algorithm 1): when a framework is registered with master, the selected operation position and search radius will be sent to the allocation module. Avalon calculates the distance from each robot position to the framework operation position to form a score attached to related slave ID of a robot. If robots locate in search area, it means that these robots are all allocatable for the framework. The allocator module reorders the allocatable list by scores in an ascending order and then pushes several closest robots to the frameworks.

\begin{algorithm}
\caption{Location based Reorder}
\begin{algorithmic}
\Input \\
\Comment{A set of robots to be scheduled at time t} \(R^t\)
\Comment{A set of frameworks at time t} \(F^t\)
\Comment{The position of ith robot} \(pos^i\)
\Comment{The position selected by jth framework} \(pos^j\)
\Comment{The search radius selected by jth framework} \(r^j\)
\Begin \\
\While{\(F^t \neq 0\)}
\While{\(R^t \neq 0 \text{ and } F^j \text{ is available}\)}
\State calculate \(score^i = distance(pos^i, pos^j)\)
\If{\(score^i \leq r^j\)}
\State push in list \(l\)
\EndIf \\
\EndWhile \\
\EndWhile \\
\End \\
\end{algorithmic}
\end{algorithm}

We note that distance may not be a perfect utility in some complex environments because obstacles and speeds also affect allocation. However, using distance is easy to implement and requires little computation. In addition, based on the two-level scheduling design philosophy, frameworks will choose suitable robots from the offer list by their own task schedulers.

D. Put It All Together

Figure 4 depicts an illustrative example of how Avalon fulfills the design of fine-grained resource sharing and location-based resource offers to allow resources shared by multiple frameworks. The steps are shown as follow:

1) Two robots (Slave 1 and Slave 2) report their available resources and position to the Avalon master;
2) Framework 1 is registered with the master and sends the selected position and search radius to the master;
3) The master sends a robot offer list to the framework based on algorithm 1;
4) The scheduler of Framework 1 chooses proper robots from the offer list by its own task allocation policy;
5) The master simultaneously deploys the task 1 and task 2 from Framework 1 to robot slave 1 and slave 2;
6) Assume that the position and search radius selected by Framework 2 are the same with that of Framework 1, the master will offer the remain CR and all SR in slave 1 and all SR in slave 2 to Framework 2;
7) Finally, the Avalon master deploys two tasks requiring SR in the two slaves.

IV. IMPLEMENTATION

We build an Avalon prototype on Linux with off-the-shelf ROS packages. We use Linux containers to isolate each execution process. Linux containers can reduce the complexity of configuring CPU quotas, memory limits and I/O rate limits, which makes Avalon easily scale up and down.

We have implemented Avalon in C++ with an efficient actor-based asynchronous programming library called libprocess [19]. To allow Avalon to flexibly access multi-robot frameworks, our implementation exposes C++ and Python interfaces to bind applications with scheduler and executor.
(see Figure 3). These two languages are well adapted in most ROS relevant applications.

Avalon has been evaluated in both simulation environment and real world. We will open source Avalon soon. Next, we will present three implementation issues.

A. Core Process

All tasks are executed as processes in Linux containers. There are three types of core processes in Avalon (Figure 3): Master process, Slave process and Framework process. We will show how these three processes work as follows:

1) **Master**: The master is the main controller module that polls events pool to trigger both frameworks and slaves. It maintains a dataset to record the status and resources of each robot (Slave). Once detecting a new framework is registered, the master will launch the allocator module to determine which slaves are available. In addition, the master also detects the executor status to allocate a next task or perform fault tolerance.

2) **Slave**: The slave is installed in robots. Its responsibility is to monitor host robot’s status and resources and communicate with the master. For computation resources (CRs), the slave detects allocatable CRs by system calls. For SR and AR, the slave obtains the information through robots themselves or user-input parameters. The resource parameters have the following structure

```
--sr_res="Sensor:Function;..."
--ar_res="Actuator:Function;..."
```

which is an unordered collection of key/value pairs. Note that the same key with different values would be grouped into one tuple (eg. kinect:ImageGen,LaserGen). Furthermore, the slave obtains a robot’s position from odometry topic published by ros node. Due to various topic names in different ros package, user should tells the slave module where to listen. In simulation environment, the slave also needs to know the namespace and coordinate transform between map and each robot.

3) **Framework**: The framework is responsible for choosing proper robots from a resource offer list and scheduling tasks on these robots. One framework usually has multiple tasks. To find proper robots, the framework should provide operation position and search range to the master. In a simulation environment, framework can select positions in the rviz GUI by publishing message into click point topic for visualization.

B. Access Interface

Table I summarizes the Avalon scheduler and executor API functions. The “callback” columns list functions that frameworks must implement and “actions” columns list which they could invoke.

The Scheduler interface binds functions with the state estimator and task allocator modules in multi-robot framework in the Figure[3]. Because a multi-robot framework may receive goals from multiple customers, setFilter and setPosition could be invoked to update the framework parameters for different positions. Then we implement resourceOffers to allocate each task in one goal to specific robot after requesting offers. The statusUpdate monitors task status from slaves at runtime. If a framework does not respond an offer for a sufficiently long time, Avalon will rescind the offer and reallocate the resources to other frameworks.

The Executor interface binds functions with the task executor modules. Frameworks could directly control robots through rostopic and rosservice API, or execute a roslaunch file in a container environment. The killTask function is used for a scheduler to kill one of its tasks. This will be useful when a robot encounters some emergency situations and needs to stop its actions.

C. Communication Protocols

Avalon’s communication protocols consist of two parts: *internal communication protocol* and *external communication protocol*. The internal communication protocol covers communication between Avalon processes. It is implemented by Google’s protocol buffers [20] for flexibility and efficiency. The external communication protocol defines the data transfer between slave-slave processes running in a ROS environment and slave-framework processes.

Avalon uses scheduler and executor to communicate with a non-Avalon process running either on the slave or in the framework. These two internal interfaces provide an asynchronous I/O mechanism to report initialized information of framework and slave processes to master. Since tasks are executed in ROS context, executors provide converts to transform a data message from the external communication format (serialized ROS message) to the internal communication format (Protobuf message) and vice versa.

Meanwhile, Avalon also implements computing offloading through external communication protocol. Specifically, cloud infrastructure can be registered with master as CR-only slaves, enabling multi-robot frameworks receive powerful computing resource pools from master. Since the computing environment is a ROS node, frameworks are able to launch multiple nodes within both servers and robots and coordinate with each other using ROS interprocess communication. It is worth noting that this approach can set up Cloud-Edge computing mode, which helps robots to offload heavy computation to local edge servers or remote cloud datacenters.
V. EVALUATION

We evaluated Avalon through two experiments on a turtlebot robot in real world. Our first experiment aims at showing how one robot’s resources can be shared by three workloads to improve utilization. Then we measured the communication overhead between two Avalon instances running on different machines. The experimental results can help us to make decision for offloading in the Cloud-Edge computing mode.

A. Resource Sharing

Experimental settings: To evaluate the primary goal of Avalon, which is allowing diverse multi-robot frameworks to share a robot efficiently, we ran a mix of three workloads described in Section II: gmapping (CR-SR-AR), monitoring (SR) and image recognition (CR-SR). Specifically, we launched three frameworks and the master in a local server (assume each workload is from different multi-robot frameworks). A four-core 8GB RAM turtlebot is registered with the master as a CR-SR-AR slave, offering resources to each framework. For performance metric, we measured CPU utilization for a period of 5 minutes at stable phases through perf tool [21].

Results: The effectiveness of Avalon would be proved by two facts: Avalon achieves higher utilization than traditional multi-robot systems (MRSs) and workloads finish within acceptable time limits. Our results show both effects, as detailed below.

Figure 5 shows the fraction of CPU running time allocated to each workload at different phases. Assume both gmapping and image recognition workloads request [2CPU, 4GB RAM] computing resource. At the first 165 seconds, turtlebot moves around and maps the physical world from laser range data. Meanwhile, a monitoring workload receives image data from turtlebot’s kinect sensor continuously, which improves the CPU utilization up to 69.66%. After 165s, the third framework is registers with master and launches the image recognition workload into the turtlebot. The CPU utilization of a mix of three workload increases to 98.38% quickly. Compared with the results with workloads in traditional single-task mode, Avalon can improve the CPU utilization by 3.68 times (up to 7.51 times). We also show that the task finish time is acceptable in our video.

B. Computation Offloading

Experimental settings: We used the same configuration of the turtlebot from Sec. V-A and a local server with 4 cores and 8 GB RAM. The connection between the turtlebot and the local server was covered with a 2.4 GHz band wireless network in Beijing ICT CAS, and remote servers were deployed in Tencent datacenter located in Guangzhou, China. We show four communication paths analyzed for 6 data sizes as follows:

- C2C: Container to container where both running in the same machine;
- R2LC: Container to container where one is hosted in the robot and the other in the local server;
- R2RC: Container to container where the other is executed in the remote cloud server;
- F2S: Communication between framework and slave which both hosted in the local server.

Note that C2C, R2LC and R2RC use an external communication protocol, which transfers string messages within ROS environment, while F2S is implemented by an internal communication protocol.

Results: Figure 6 shows the round-trip time of four communication paths with 6 data sizes. First, C2C is the smallest constraint of Avalon’s throughput which takes lowest overhead shared by different frameworks. Second, Avalon introduces an overhead of 100 [ms] for data sizes up to 1MB (see F2S in the figure), due to the task queuing and internal communication overhead. Third, external communication (R2LC and R2RC) is the biggest bottleneck of Avalon’s throughput, which is caused by the variable wireless network performance. When data size increases to 1MB, the overhead of R2RC brings a sharp rise. Thus, when determining which task can be offloaded to remote cloud, we should consider the package size and real time constrains of tasks.

VI. CONCLUSION AND FUTURE WORK

This paper envisioned future robotcenter ecosystem that comprises multiple heterogeneous robots and proposed Avalon, which is inspired by datacenter OS such as Mesos and Borg Avalon is a two level scheduling robotcenter OS that enables multi-robot frameworks to share fine-grained resources. We implemented Avalon on both Gazebo simulator and real world. Our experiments demonstrated that
Avalon is able to achieve high utilization through fine-grained resource sharing in robotcenter environment without substantial modifications in multi-robot frameworks. Moreover, Avalon supports offload computation intensive tasks into cloud servers, which makes sense to the Cloud-Edge computing mode.

Finally, we believe a robotcenter OS is needed for enabling the development of a future multi-robot ecosystem. However, there are still a lot of open and challenging problems. We would like to researchers to pay more attention to this field from operating system perspective.

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