Cloud-based Parallel Implementation of SLAM for Mobile Robots

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Abstract. Simultaneous Localization and Mapping (SLAM) for mobile robots is a computationally expensive task. A robot capable of SLAM needs a powerful onboard computer, but this can limit the robot's mobility because of weight and power demands. We consider moving this task to a remote compute cloud, by proposing a general cloud-based architecture for real-time robotics computation, and then implementing a Rao-Blackwellized Particle Filtering-based SLAM algorithm in a multi-node cluster in the cloud. In our implementation, expensive computations are executed in parallel, yielding significant improvements in computation time. This allows the algorithm to increase the complexity and frequency of calculations, enhancing the accuracy of the resulting map while freeing the robot's onboard computer for other tasks. Our method for implementing particle filtering in the cloud is not specific to SLAM and can be applied to other computationally-intensive tasks.

1 Introduction

The Internet of Things (IoT) promises to bring Internet connectivity to devices ranging from simple thermostats to highly complex industrial machinery and robots. Many potential IoT applications involve analyzing the rich, large-scale datasets that these devices produce, but analytics algorithms are often computationally expensive, especially when they have to scale to support vast numbers of devices. Cloud services are thus attractive for doing large scale offline and real-time analytics on the data produced in IoT applications. This paper investigates a computationally-expensive robotics application to showcase a means of achieving complex parallelism for real-time applications in the cloud.

Parallel implementations of real-time robotics algorithms mostly run on multicore machines using threads as the primary parallelization mechanism, but this bounds parallelism by the number of CPU cores and the amount of memory in a single machine. This degree of parallelism is often not enough for computationally expensive algorithms to provide real-time responses. Parallel computations in a distributed environment could give a cost-effective option to provide low latency while also scaling up or down depending on the processing requirements.

Simultaneous Localization and Mapping (SLAM) is an important problem in which a mobile robot tries to estimate both a map of an unknown environment and its position in that environment, given imperfect sensors with measurement error. This problem is computationally challenging and has been studied extensively in the literature. Here we consider a popular algorithm called GMapping, which builds a grid map by combining (noisy) distance measurements from a laser range finder and robot odometer using Rao-Blackwellized Particle Filtering (RBPF) [1, 2]. It is known to work well in practice and has been integrated into robots like TurtleBot [3]. The algorithm is computationally expensive and produces better results if more computational resources are available.

We have implemented GMapping to work in the cloud on top of the IoTCloud platform [4], a framework for transfering data from devices to a cloud computing environment for real-time, scalable data processing. IoTCloud encapsulates data from devices into events and sends them to the cloud, where they are processed using a distributed stream processing framework (DSPF) [5]. In our GMapping implementation, laser scans and odometer readings are sent from the robot as a stream of events to the cloud, where they are processed by SLAM and results are returned to the robot immediately. The algorithm runs in a fully distributed environment where different parts can be run on different machines, taking advantage of parallelism to split up the expensive computations.

Our main contribution is to propose a novel framework to compute particle filtering-based algorithms, specifically RBPF SLAM, in a cloud environment to achieve high computation time efficiency. In the following sections, we first discuss related work before introducing background on the IoTCloud framework and the SLAM algorithms. Then we show how to design and implement parallel RBPF SLAM in IoTCloud, before concluding with results and discussion.

2 Related Work

Kehoe et al. [6] summarize existing work and architectures for cloud robotics, and our architecture is similar to several of them. A key difference is that we are proposing a generic streaming architecture coupled with other big data platforms to build applications. Hu et al. [7] describe some of the challenges in cloud robotics such as communication constraints. Chitchian et al. [8] exploit multicore and GPU architectures to speed up particle filtering-based computations, while Gouveia et al. create thread-based implementations of the GMapping algorithm with good performance gains [9]. In contrast, our approach takes advantage of distributed environments with multiple multi-core machines. The C2TAM [10] framework considers a similar problem of moving some of the expensive computation of SLAM to a cloud environment. They use a visual SLAM algorithm called Parallel Tracking and Mapping (PTAM) [11] which uses a video camera. In contrast to C2TAM, we propose a generic scalable real-time framework for computing the maps online with significant performance gains. Zhang et al. [12] use the CUDA API to run part of GMapping (specifically the Scan Matching step) on GPUs to improve performance, and Tosun et al. [13] address particle filter-based localization of a vehicle with multicore processors. But neither of these is a multi-node cloud implementation as we consider here. Gouveia et al. [14] distribute the computation of GMapping among robots in the same environment. We instead focus on bringing this data to the cloud and processing it in a scalable and robust manner, exploiting (potentially) unlimited cloud resources.

3 Background

3.1 IoTCloud framework

IoTCloud [4][3] is an open source framework developed at Indiana University to connect IoT devices to cloud services. As shown in Figure 1, it consists of a set of distributed nodes running close to the devices to gather data, a set of publish-subscribe brokers to relay information to the cloud services, and a distributed stream processing framework (DSPF) coupled with batch processing engines in the cloud to process the data and return (control) information to the IoT devices. Applications execute data analytics at the DSPF layer, achieving streaming real-time processing. The IoTCloud platform uses Apache Storm [15] as the DSPF, RabbitMQ [16] or Kafka [17] as the message broker, and an OpenStack academic cloud [18] (or bare-metal cluster) as the platform. We use a coordination and discovery service based on ZooKeeper [19] to scale the number of devices.

In general, a real-time application running in a DSPF can be modeled as a directed graph with streams defining the edges and processing tasks defining the nodes. A stream is an unbounded sequence of events flowing through the edges of the graph and each such event consists of a chunk of data. The processing tasks at the nodes consume input streams and produce output streams. A DSPF provides the necessary API and infrastructure to develop and execute applications on a cluster of nodes. In Storm these tasks are called Spouts and Bolts. To connect a device to the cloud services, a user develops a gateway application that connects to the device's data stream. Once an application is deployed in an IoTCloud gateway, the cloud applications discover those applications and connect to them for data processing using the discovery service.

3.2 Design of robot applications

We designed a cloud-based implementation of GMapping for a real robot, the TurtleBot [3] by Willow Garage, using the IOTCloud platform. TurtleBot is an off-the-shelf differential drive robot equipped with a Microsoft Kinect sensor. An overview of the implementation is shown in Figure 2. The application that connects to the ROS-based [20] Turtlebot API is deployed in an IoTCloud Gateway running on a desktop machine, where it subscribes to the TurtleBot's laser scans and odometer readings. It converts the ROS messages to a format that suits the cloud application and sends transformed data to the application running in the FutureSystems OpenStack [18] VMs using the message brokering layer. The cloud application generates a map and sends this back to the workstation running the gateway, which saves and publishes it back to ROS for viewing.

[3] https://github.com/iotcloud

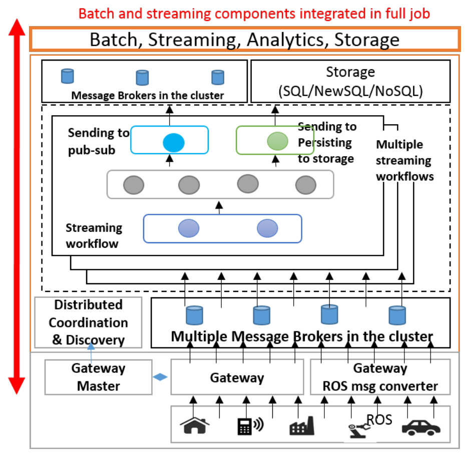

Batch and streaming components integrated in full job
Batch, Streaming, Analytics, Storage
Message Brokers in the cluster
Storage (SQL/NewSQL/NoSQL)
Sending to pub-sub
Sending to Persisting to storage
Multiple streaming workflows
Streaming workflow
Distributed Coordination & Discovery
Multiple Message Brokers in the cluster
Gateway Master
Gateway
Gateway ROS msg converter
ROS

Fig. 1: IoTCloud Architecture

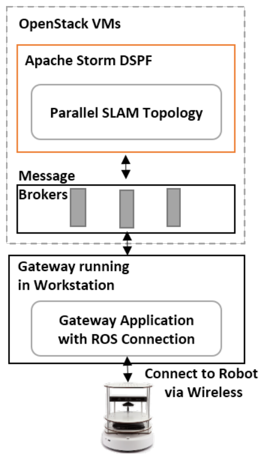

OpenStack VMs
Apache Storm DSPF
Parallel SLAM Topology
Message Brokers
Gateway running in Workstation
Gateway Application with ROS Connection
Connect to Robot via Wireless

Fig. 2: GMapping Robotics application

3.3 RBPF SLAM Algorithm

A detailed description of the Rao-Blackwellized particle filter for SLAM is given in [1, 2], but we give a brief overview here. Suppose we have a series of laser readings $z_{1:t} = (z_1, ..., z_t)$ over time, as well as a set of odometer measurements $u_{1:t-1} = (u_1, ..., u_{t-1})$ from the robot. Our goal is to estimate both a map m of the environment and the trajectory of the robot, $x_{1:t} = (x_1, ..., x_t)$. For any time t, we can sample from the posterior probability,

$$p(x_{1:t}, m|z_{1:t}, u_{1:t-1}) = p(x_{1:t}|z_{1:t}, u_{1:t-1})p(m|x_{1:t}, z_{1:t}), \tag{1}$$

by sampling from the first term on the right hand side to produce an estimate of the robot's trajectory given just the observable variables, and then sample from the second term to produce an estimate of the map using that sampled trajectory. The particle filter maintains a set of particles, each including a possible map of the environment and a possible trajectory of the robot, along with a weight which can be thought of as a confidence measure. A standard implementation of the algorithm executes the following steps for each particle i as follows:

1. Make an initial estimate of the position of the robot at time t, using the estimated position at time $t-1$ and odometry measurements, i.e. $x'^i_t = x'^i_{t-1} \oplus u_{t-1}$ where $\oplus$ is a pose compounding operator. The algorithm also incorporates the motion model of the robot when computing this estimate.
2. Use the ScanMatching algorithm shown in Algorithm 1 with cutoff of ∞ to refine x'^i_t using the map m^i_{t-1} and laser reading z_t. If the ScanMatching fails, use the previous estimate.
3. Update the weight of the particle.
4. The map m^i_t of the particle is updated with the new position x^i_t and z_t.

```
input  : pose $u$ and laser reading $z$
output: $bestPose$ and $l$
$steps \leftarrow 0$; $l \leftarrow -\infty$; $bestPose \leftarrow u$; $delta \leftarrow InitDelta$;
$currentL \leftarrow$ likelihood($u, z$);
for $i \leftarrow 1$ to $nRefinements$ do
    $delta \leftarrow delta/2$;
    repeat
        $pose \leftarrow bestPose$; $l \leftarrow currentL$;
        for $d \leftarrow 1$ to $K$ do
            $xd \leftarrow$ deterministicsample($pose, delta$);
            $localL \leftarrow$ likelihood($xd, z$);
            $steps += 1$;
            if $currentL < localL$ then
                $currentL \leftarrow localL$; $bestPose \leftarrow xd$;
            end
        end
    until $l < currentL$ and $steps < cutoff$ ;
end
```

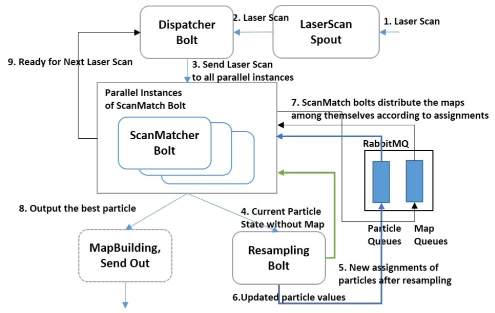
Algorithm 1: Scan Matching

After updating each particle, the algorithm normalizes the weights of all particles based on the total sum of squared weights, and then resamples by drawing particles with replacement with probability proportional to the weights. Resampled particles are used with the next reading. At each reading the algorithm takes the map associated with the particle of highest weight as the correct map. The computation time of the algorithm depends on the number of particles and the number of points in the distance reading. In general the accuracy of the algorithm improves if more particles are used.

4 Streaming parallel algorithm design

We found that RBPF SLAM spends nearly 98% of its computation time on Scan Matching. Because Scan Matching is done for each particle independently, in a distributed environment the particles can be partitioned into different computation nodes and computed in parallel. However, the resampling step requires information about all particles so it needs to be executed serially, after gathering results from the parallel computations. Resampling also removes and duplicates some particles, which means that some particles have to be redistributed to different nodes after resampling.

Our stream workflow of the algorithm is shown in Figure 3, implemented as an Apache Storm topology. The topology defines the data flow graph of the application with Java-based task implementations at the nodes and communication links defining the edges. The different components of this workflow run in a cluster of nodes in the cloud. The main tasks of the algorithm are divided into ScanMatcherBolt and ReSamplingBolt. The LaserScanBolt receives data from



Dispatcher Bolt
2. Laser Scan
LaserScan Spout
1. Laser Scan
9. Ready for Next Laser Scan
3. Send Laser Scan to all parallel instances
Parallel Instances of ScanMatch Bolt
7. ScanMatch bolts distribute the maps among themselves according to assignments
ScanMatcher Bolt
RabbitMQ
8. Output the best particle
4. Current Particle State without Map
Particle Queues
Map Queues
MapBuilding, Send Out
Resampling Bolt
5. New assignments of particles after resampling
6.Updated particle values

Fig. 3: Storm streaming workflow for parallel RBPF SLAM.

the robot and sends it to the rest of the application. After computation, results are passed to SendOut bolts which send it back to the robot. If required, data can be saved to persistent storage as well.

A key idea behind our implementation is to distribute the particles across a set of tasks running in parallel. This particle-specific code is encapsulated in the ScanMatcher bolt, so we can control the parallelism of the algorithm by changing the number of ScanMatcher bolt instances. The Resampling bolt must wait until it receives the results of the ScanMatcher bolts. After a resampling happens, the algorithm removes some existing particles and duplicate others, so the assignments of particles to ScanMatcher tasks have to be rearranged. The directed communication required among the parallel ScanMatcher tasks to do the reassignment is not well supported by Apache Storm, so we use an external RabbitMQ message broker. All the data flowing through the various communication channels are in a byte format serialized by Kryo. The steps for a single reading as shown in Figure 3 are:

1. LaserScan spout receives laser and odometer readings via the message broker.
2. The reading is sent to a Dispatcher, which broadcasts it to the parallel tasks.
3. Each ScanMatcher task receives the laser reading, updates its assigned particles, and sends the updated values to the Resampling bolt.
4. After resampling, the Resampling bolt calculates new particle assignments for the ScanMatchers, using the Hungarian algorithm to consider relocation costs. The new particle assignment is broadcast to all the ScanMatchers.
5. In parallel to Step 4, the Resampling bolt sends the resampled particle values to their new destinations according to the assignment.
6. After ScanMatchers receive new assignments, they distribute the maps associated with the resampled particles to the correct destinations, using RabbitMQ queues to send messages directly to tasks.
7. The ScanMatcher with the best particle outputs its values and the map.
8. ScanMatcher bolts send messages to the dispatcher, indicating their willingness to accept the next reading.

Our implementation exploits the algorithm's ability to lose readings by dropping messages that arrive at a Dispatcher bolt while a computation is ongoing,

Table 1: Serial average time (in ms) for different datasets and numbers of particles.

	Particle count		
Data set	20	60	100
Simbad	987.8	2778.7	4633.84
Simbad, ScanMatching Cutoff = 140	792.86	2391.4	4008.7
ACES	180	537	927.2

to avoid memory overflow. Owing to the design of the GMapping algorithm, only a few resampling steps are needed during map building. If resampling does not happen then steps 5 and 6 are omitted. Although an open source serial version of the algorithm in C++ is available through OpenSlam[4], it is not suitable for our platform which requires Java. The algorithm described above was implemented in Java and is available in github[5] along with steps to run the experiments.

5 Results and Discussion

The goal of our experiments was to verify the correctness and practical feasibility of our approach, as well as to measure its scalability. All experiments ran in FutureSystems [18] OpenStack VMs each having 8GB memory and 4 CPU cores running at 2.8GHz. Our setup had 5 VMs for Apache Storm Workers, 1 VM for RabbitMQ and 1 VM for ZooKeeper and Storm master (Nimbus) node. For all the tests the gateway node was running in another VM in FutureSystems. Each Storm worker instance ran 4 Storm worker processes with 1.5GB of memory allocated. We used the ACES building data set [21] and a small environment generated by the Simbad [22] robot simulator for our experiments. ACES has 180 distance measurements per laser reading and Simbad has 640 measurements per laser reading. For the ACES dataset we used a map of size 80x80m with 0.05 resolution, and for Simbad the map was 30x30m with 0.05 resolution.

A sample result from ACES is shown in Figure 10. Since GMapping is a well-studied algorithm, we did not extensively test its accuracy on different datasets, but instead focused on the parallel behavior of our implementation. We measured parallel speedup (defined as serial time over parallel time, i.e. T_s/T_p) by recording the time required to compute each laser reading and then taking an average. We tested the algorithm with 20, 60 and 100 particles for each dataset. The serial time was measured on a single FutureSystems machine, as shown in Table 1, and the parallel times were measured with 4, 8, 12, 16 and 20 parallel tasks.

The parallel speedups gained for the ACES and Simbad datasets are shown in Figure 4. For ACES, the number of points per reading is relatively low, requiring relatively little computation at the the ScanMatcher bolts, which results in only a modest parallel speedup after 12 particles. On the other hand, Simbad has about 4 times more distance measurements per reading and produces higher speed

[4] https://www.openslam.org/ [5] https://github.com/iotcloud/iotrobots

gains of about a factor of 12 for 20 parallel tasks with 100 particles. While not directly comparable because we test on different datasets with different resources, our parallel speed-ups are significantly higher than those of [9], e.g. up to 12x compared with up to about 2.6x, illustrating the advantage of implementing in a distributed memory cloud versus the single node of [9].

However, ideally the parallel speedup should be close to 20 with 20 parallel tasks, so we investigated factors that could be limiting the speedup. Figure 5a shows I/O, garbage collection, and computation times for different parallel tasks and particle sizes. The main culprit for limiting the parallel speedup appears to be I/O: when the number of parallel tasks increases, the compute time decreases, but because of I/O overhead the speedup also decreases. The average garbage collection time was negligible, although we have seen instances where it increases the individual computation times. Additionally, the resampling step of the algorithm is done serially, although since this is relatively inexpensive compared with Scan Matching, it is not a significant source of speedup loss.

Another factor that affects parallel speedup is the difference in computation times among parallel tasks. Assume we have n ScanMatcher tasks taking $t_1, ..., t_m, ..., t_n$ seconds, where t_m is the maximum among these times. In the serial case, the total time for ScanMatching is $T_s = t_1 + ... + t_m + ... + t_n$, while for the parallel case it is at least t_m because Resampling has to wait for all parallel tasks to complete. The overhead introduced because of this time imbalance is $t_{overhead} = t_m - T_s/n$, which is 0 in the ideal case when all tasks take the same time. Figure 5b shows the average overhead for the Simbad dataset compared with the total time. The average overhead remained almost constant while the total time decreased with more parallel tasks, restricting the speedup.

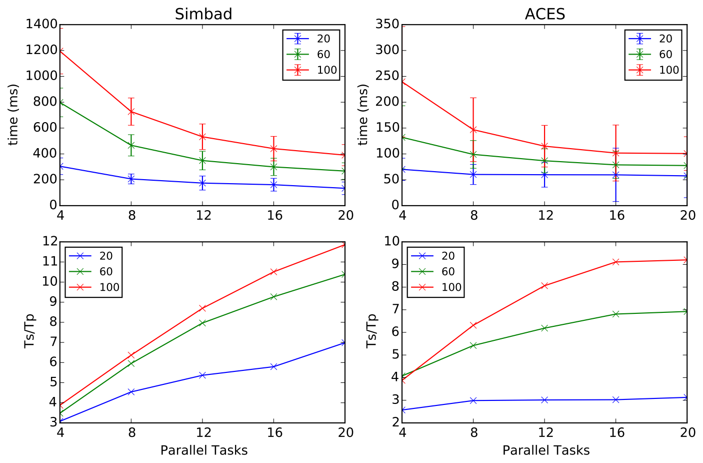
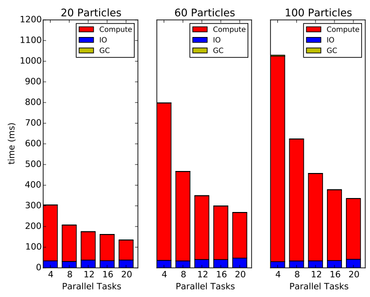
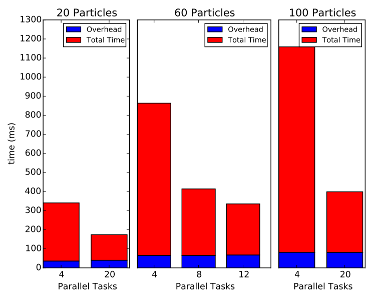


Fig. 4: Parallel behavior of the algorithm for the Simbad dataset with 640 laser readings (left) and the ACES dataset with 180 readings (right). For each dataset, the top graph shows mean times with standard deviations and the bottom graph shows the speedup.



(a)



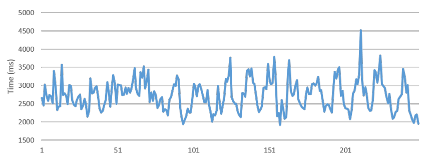
(b)

Fig. 5: Overhead on the Simbad dataset: (a) I/O, garbage collection, and Compute time. (b) Overhead of imbalanced parallel computation.

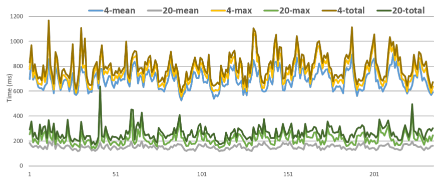
To further investigate the behavior of the algorithm, we plotted the computation times for each reading, as shown in Figures 6a and 6b. There are high peaks in the individual times in both serial and parallel algorithms. This is caused by the while loop ending in line 5 of Algorithm 1, which can execute an arbitrary number of times if the cutoff is ∞. We have observed a mean of about 150 and standard deviation around 50 for number steps executed by the ScanMatching algorithm for Simbad, although sometimes it is as much as 2 to 3 times the average. This is especially problematic for the parallel case because even one particle can significantly increase the response time. An advantage of nondeterministic particle-based algorithms is that if there are a sufficiently large number of particles, cutting off the optimization for a few of them prematurely does not typically affect the results, and we can easily increase the number of particles if needed to compensate for these premature cutoffs. We also observed that these large numbers of steps typically occur at later refinements with small delta values, where the corrections gained by executing many iterations is usually small.

We thus changed the original algorithm shown in Algorithm 1 to have a configurable cutoff for the number of steps and performed experiments by setting the maximum number of steps to 140, which is close to the empirical average. We found that maps built by this modified algorithm were of comparable quality to the originals. The resulting time variations for two tests are shown in Figure 6c. Here we no longer see as many large peaks as in Figure 6b, and the remaining peaks are due to minor garbage collection. Figure 7 shows the average time reduction and speedup after the cutoff. As expected, we see an improvement in speedup as well, because the parallel overhead is now reduced as shown in Figure 9 after cutoff at 140 steps. This shows that cutoff is an important configuration parameter that can be tuned to balance performance and correctness.

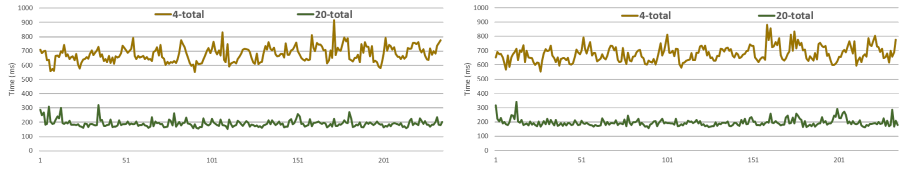
Figure 8 presents the difference in calculations when we conducted the resampling step for every reading with the Simbad dataset. When the number of particles is high, the overhead is large. When we have more parallel workers, the map distribution happens simultaneously using more nodes, which reduces



(a) Serial time



(b) Parallel without cutoff



(c) Two trials of parallel with cutoff at 140 steps

Fig. 6: Computation time across individual readings, for Simbad and 60 particles.

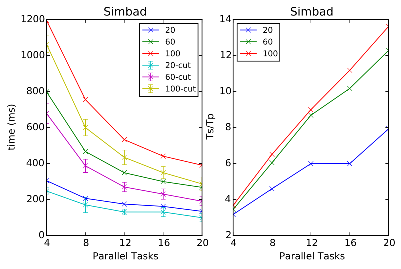


Fig. 7: Average time and speedup for Simbad with cutoff at 140

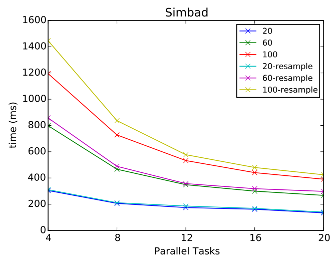


Fig. 8: Resampling overhead with Simbad

the I/O time. The original serial algorithm for Turtlebot runs every 5 seconds. Because the parallel algorithm runs much faster than the serial version, it can be used to build a map for a fast-moving robot. In particle filtering-based methods, the time required for the computation increases with the number of particles. By distributing the particles across machines, an application can utilize a high number of particles, improving the accuracy of the algorithm.

6 Conclusions & Future Work

We have shown how to offload robotics data processing to the cloud through a generic real-time parallel computation framework, and our results show significant performance gains. Because the algorithm runs on a distributed cloud, it has access to potentially unbounded memory and CPU power. This allows the system to scale well, and for example could build maps in large, complex environments needing a large number of particles or dense laser readings.

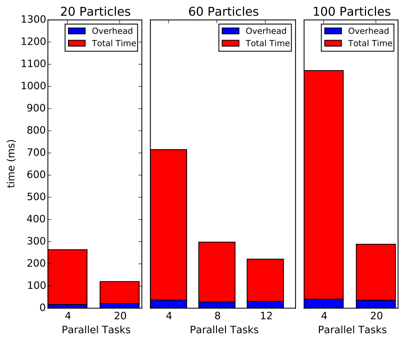


Fig. 9: Parallel overhead with cutoff at 140

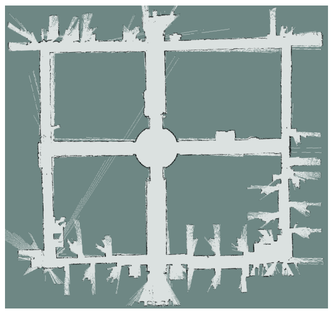


Fig. 10: Map of ACES

There are many possible enhancements to our system. We addressed the problem of imbalances in particle computation times by simply discarding particles that exceed a hard computation limit, which works well for this particular algorithm but may not for others. Also we have observed fluctuations in processing time caused by virtualization, multi-stream interference and garbage collection. In the future we would like to address these fluctuations with a generic approach such as running duplicate computation tasks. Also, we have observed that result broadcast and gathering in the streaming tasks takes considerable time, so reducing I/O would also significantly improve performance.

Reducing programming complexity is also an interesting direction. Modern distributed stream processing engines expose low-level APIs, making developing intricate IoT applications quite complex. Future work should propose higher-level APIs to handle complex interactions by abstracting out the details. Distributing state between parallel workers currently requires a third node, such as an external broker or a streaming task acting as an intermediary. A group communication API between the parallel tasks would be a worthy addition to DSPF. Extending our work to abstract out a generic API to quickly develop any particle filtering algorithm would also be interesting.

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