Serverless Multi-Query Motion Planning for Fog Robotics

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***Abstract*— Robots in semi-structured environments such as homes and warehouses, sporadically require computation of high-dimensional motion plans. Cloud and fog-based parallelization of motion planning can speed up planning, but allocating always-on high-end computers for sporadic computations can be less efficient than a new class of "serverless" computing that can be allocated on-demand. This paper proposed parallelizing the computation of sampling-based multi-query graph-based motion planner based on asymptotically-optimal Probabilistic Road Maps (PRM*) using the simultaneous execution of 100s of cloud-based serverless functions. We explore how to overcome inherent limitations of serverless computing related to communication and bandwidth limitations using different work sharing techniques and provide proofs of probabilistic completeness and asymptotic optimality. In experiments on synthetic benchmarks and on a physical Fetch robot performing a sequence of decluttering motions, we observe up to a 50x speedup relative to a 4 core setup with only a marginally higher cost. Additional results and videos can be viewed at *https://sites.google.com/berkeley.edu/graph-based-serverless-mp/home*.**

I. Introduction

Many robotics applications, from home automation to warehouse order fulfillment, benefit from access to a fast motion planner that allows the robot to interact in a physical space. For robots in cluttered environments that have many degrees of freedom, planning can be computationally challenging [1] and, depending on the complexity of the robot and scenarios, these compute times can be highly varied. Having an always-on high-end computer, whether on-premises or in the cloud, can be an inefficient use of resources [2]. Consider a robot tasked with cleaning desks in an office space (see Fig. 1). Due to the variability of obstacles in an office scenario, the robot is required to replan motions for each desk. When decluttering a single desk, instead of replanning for every pick and place operation, it should reuse computations. Moreover, mobile manipulators like the Fetch often need to recompute motion plans even in the same environment due to variations in positioning of the frame of the manipulator arm based on inaccurate driving wheels or obstacles blocking navigation. In this example, compute demands vary dramatically between the navigation to a desk and the decluttering of a desk. Computing motion plans to move between rooms is relatively inexpensive as finding paths in a 3-dimensional space for the robot to track is cheap, whereas, planning manipulator arm motions to grasp objects requires solving 6-dimensional or higher problems that require exponentially more computation. Similarly in a warehouse or a factory, robots have to plan manipulator arm trajectories for many motions in a single work cell.

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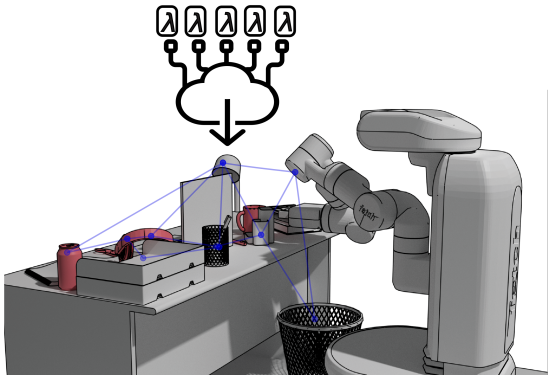

Fig. 1. A mobile manipulator robot organizes and declutters a desk with a sequence of motions computed through on-demand parallel computation with serverless fog robotics. In this scenario, after the robot approaches the desk, it picks and places the objects shown in red. Every decluttering sequence, even for the same desk, requires a new motion plan computation due to changes in the obstacle environment, either due to changes of objects that will be left alone, or due to inaccuracy or blocked approaches to the desk. To quickly start the sequence of tasks, the robot computes a single graph (shown in blue) of obstacle-free motions using 100s motion-planning serverless functions (aka *lambdas* λ) for a short duration. Once computed, the robot follows motions between points on the graph. Since serverless computing is billed in 100 ms units, the proposed approach costs the same whether using 1 serverless computer for 500 seconds, or 500 serverless computers for 1 seconds.

To get cost effective computation we propose using serverless cloud-based computing which allows developers to register functions in the cloud (that take in arbitrary input and return arbitrary output) without having to manage the infrastructure associated with executing these functions [3]. As serverless computing is focused on single-function execution, it is often called Function-as-a-Service (FaaS). Functions run on-demand on various cloud, fog, and edge systems, and are billed in small time units (e.g., 100 ms [4]). Demanding computational workloads in motion planning for home, office, and warehouse scenarios is often intermittent due to time spent in low-dimensional navigation problems, performing actual motions, or being offline. As such, the computational requirements match well with the serverless paradigm of elastically scaling compute resources to minimize cost and meet demand. Although each compute unit in a serverless scenario is limited in its computational capabilities, we propose an efficient parallel algorithm that can take advantage of the simultaneous availability of a 100s of compute units to achieve large speedups. We refer to a single execution of a serverless function as a *lambda*.

Serverless computing does comes with its limitations, including: inability to directly communicate with other computers, no direct permanent storage between executions, and

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unpredictable delays in execution [5]. In the proposed method, we overcome some of these limitations, but note that future serverless computing offerings may relax these restrictions or provide systems that facilitate the computation model proposed here [6], [7]. As such, the proposed method may scale better and become more cost-effective in the future, with no change the to algorithm.

This paper proposes a method that leverages the elasticity of serverless computing to parallelize computations on-demand of complex multi-query motion plans. We show that one can flexibly allocate computational parallelism to each problem, allowing one, with marginal increase in cost, to allocate *more* parallelism to compute motion plans faster. We experiment with the Amazon Lambda FaaS solution. To overcome the inability of lambdas to communicate with each other, we set up a small coordinating server to which the lambdas connect. We show that the proposed method scales well upto 128 concurrent lambdas which suggests that serverless computing can be cost-effective for motion plan computation. The main limit to cost-effective scaling beyond 128 lambdas are startup delays of functions. To test the potential for further scaling with shorter startup delays, we control for delays in startup, and scale up to 512 concurrent lambdas with up to a 52x speedup compared to a 4-core local baseline for a Fetch robot [8] decluttering scenario and up to a 100x speedup on synthetic motion planning benchmarks.

This paper makes the following contributions:

1) a distributed parallel algorithm for computing Probabalistic Road Maps "Star" (PRM*), probabilistically-complete and asymptotically-optimal motion planner, using serverless computing
2) an implemented system of the proposed algorithm on Amazon Web Services FaaS "Lambda" environment
3) time and cost bounded allocation of resources for motion-planning for generating graphs of a given size
4) experiments in simulation and on a physical Fetch mobile manipulator robot that suggested that the proposed algorithm provides significant speedups against local baselines

II. Related Work

In this section, we provide background on sampling based motion planners and prior work on parallelizing them. We also describe serverless computing and fog robotics.

A. Sampling Based Motion Planners

Sampling-based motion planners solve motion-planning [9] problems by generating random robot configurations and connecting them into a graph of feasible motions. Planners such as PRM [10] and RRT [11] are probabilistically complete, meaning that with enough time, they will find a solution with probability 1. With attention to sampling and connection strategy, these planners can be asymptotically-optimal (e.g., PRM* and RRT* [12] and SST [13]), meaning that with enough time, they will find an optimal solution with probability 1. In some scenarios, finding a single solution to a motion planning problem or *single-query* is sufficient, while in other scenarios it can be beneficial to precompute a *multi-query* graph or road map of motions that can later be quickly search with different start and goal configurations.

Amato et al. [14] showed that sampling-based motion planners are well-suited for parallel computation. Prior work on parallelizing these motion planners explored building a single graph in shared memory with locks [15] and without locks [16], in distributed memory [17], [18], [19], and more.

B. Serverless Computing and Fog Robotics

Serverless computing has gained wide attention in recent years in both academia and industry for a wide variety of workloads [20], [21], [22]. Compared to server-based computing, where users provision and compute with virtual machines (VM) serverless computing has two key advantages. First, it abstracts away the notion of servers; users register functions with the system and define when to trigger function execution. This simplifies the deployment process as users no longer need to manually provision VMs and find the VM with the optimal CPU, memory, and network resources. Second, serverless platforms automatically adapt to workload changes; and users only pay for the compute allocated during the function execution [3]. In our setting, a robot's computing requirements sporadically spike, making serverless computing an attractive option.

Cloud-based computation for robotics shows promise in offloading compute-intensive processes from a robot's on-board computer [23] to the public cloud or servers on the Edge, allowing robots to have low-power CPUs and light-weight batteries to power them. Motion planning can be computationally challenging [1], and thus is a good candidate for cloud-based computation [24]. In prior work, Ichnowski et al. [2] showed that serverless computing of tree-based single-query motion planners has the potential to dramatically speed up motion plan computation. Tree-based planners need to replan from scratch with every new problem, even if the robot is operating in the same environment. Using a graph-based planner allows exploration from a previous motion plan to be reused to greatly reduce the amount of time required to move each object.

III. Problem Statement

In this paper we parallelize the computation of a multi-query motion planning using cloud-based serverless computing.

A. Multi-query Motion Planning Problem

Let $\mathbf{q} \in \mathcal{C}$ be the complete specification of a robot's degrees of freedom (e.g., joint angles, position and orientation in space), where $\mathcal{C}$ is the configuration space, the set of all possible configurations. Let $\mathcal{C}_{\text{obstacle}} \subset \mathcal{C}$ be the configurations that are in obstacle or otherwise violate task-specific constraints, and the remaining configurations $\mathcal{C}_{\text{free}} = \mathcal{C} \setminus \mathcal{C}_{\text{obstacle}}$ is the free space. Given a start configuration $\mathbf{q}_{\text{start}} \in \mathcal{C}_{\text{free}}$ and a goal configuration $\mathbf{q}_{\text{goal}}$, the objective of motion planning is to find a sequence $\tau = (\mathbf{q}_0, \mathbf{q}_1, \ldots, \mathbf{q}_n)$

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such that $\mathbf{q}_0 = \mathbf{q}_{\text{start}}$, $\mathbf{q}_n = \mathbf{q}_{\text{goal}}$, and paths between all consecutive pairs of points in τ are collision free.

The objective of multi-query motion planning is to precompute a data structure that allows for the efficient computation of τ given changing $\mathbf{q}_{\text{start}}$ and $\mathbf{q}_{\text{goal}}$.

Given a cost function $d : \mathcal{C} \times \mathcal{C} \to \mathbb{R}^+$, let $c(\tau) = \sum_{i=0}^{n-1} d(\mathbf{q}_i, \mathbf{q}_{i+1})$. The objective of optimal motion planning is to compute a τ that minimizes $c(\tau)$.

B. Serverless Computing Environment

The robot has an onboard computer and networked access to a cloud-based serverless computing service. The serverless computing service allows for an unbounded number of concurrent executions of single functions, with the limitation that they cannot store state between executions, cannot accept inbound network connections, and have bounded runtime. The goal of serverless multi-query motion planning is to perform parallel precomputation step of multi-query motion planning, allowing for faster computation at the expense of more parallelism.

IV. Method

We propose a parallel serverless sampling-based motion planner. We start with background on PRM and PRM* algorithms, followed by a discussion of the challenges that arise from parallelizing PRM* using serverless computing. We then describe the algorithm we propose.

A. Probabilistic Road Maps (PRM) and PRM* Background

The Probabilistic Road Maps (PRM) [10] motion planner randomly samples configurations to build a graph of the connectivity of the environment. This graph is subsequently searched to find paths between any two points. PRM samples n configurations in $\mathcal{C}_{\text{free}}$ and attempts to connect k_{prm} pairs of configurations provided there is a collision-free path between them using to a local planner. In the query phase, a shortest-path search (e.g., Djikstra's) computes a path connecting start and goal configurations. PRM is probablistically complete. Karaman et al. [12] propose PRM*, with $k_{\text{prm}} \geq k^*_{\text{prm}}$, where $k^*_{\text{prm}} = e(1+\frac{1}{d})\log n$, and d is the dimension of the planning problem, PRM is asymptotically-optimal.

B. Parallelizing PRM* using Serverless Compute

Parallelizing PRM* over a serverless environment presents additional challenges compared to local methods of parallelizing PRM* [9] due to network overhead that makes it expensive to share information between lambdas. Sharing data structures [25] and nearest neighbor queries between lambdas is infeasible due to this lack of shared state.

To work around the limits of serverless computing, specifically statelessness and only allowing outbound network connections, a coordinator algorithm is defined. This coordinator runs on a separate computer that allows inbound connections and can keep state. If the robot has a public IP address, it can run the coordinator algorithm and bypass the provisioned server. However, the coordinator algorithm has low CPU and memory requirements, so it can be a lightweight cloud instance with a far lower cost than the compute intensive resources required for motion planning.

Algorithm 1 Coordinator Algorithm: A packet in the work queue is a group of vertices to be connected to the graph

```
G = (V = ∅, E = ∅)
work_queue = initWorkQueue(packet_size)
for lambda_id in num_lambdas do
    work = work_queue.pop()
    initializeLambda(lambda_id, work, seed)
while not done do
    for lambda in lambdas do
        Receive new edges E_l from lambda
        E = E ⋃ E_l
        Send next work packet to lambda
    if work_queue empty then
        Send done to all lambdas and return graph to robot
```

Algorithm 2 Lambda Algorithm

```
i = 0
(start_index, end_index) = work
nn = nearest neighbor structure
rng = random_state_generator(seed)
while not done do
    while i < end_index do
        q_rand ← rng.sample()
        if q_rand ∈ C_free then
            i = i + 1
            if i > start_index then
                Update k_prm
                for q_near in nn.near(q_rand, k_prm) do
                    E_l = connect(q_rand, q_near)
        nn.add(q_rand)
        Send E_l to coordinator
    work ← poll coordinator
```

C. Serverless Algorithm

To parallelize the computation of the PRM and minimize communication costs, Alg. 1 exploits the determinism of pseudo-random number generators to create a deterministic sequences of points when provided with a particular seed. As long as all lambdas are initialized with the same random seed, they will sample the same set of points. The sampling stage of the PRM* algorithm is orders of magnitude faster than the nearest neighbor queries and the connection of edges. For instance sampling and validating 1000 points for an 8 dimensional space took 0.063 seconds, whereas connecting the edges for the above samples took 6.194 seconds. The key trade-off in this algorithm is to perform repeated fast sampling instead of slow communication of samples. As size of the graph increases, and the amount of serial sampling work decreases as a proportion of the total work, Amdahl's law [26] tells us that the theoretical maximum parallel efficiency goes up.

In Alg. 2 all the lambdas perform the sampling step for the

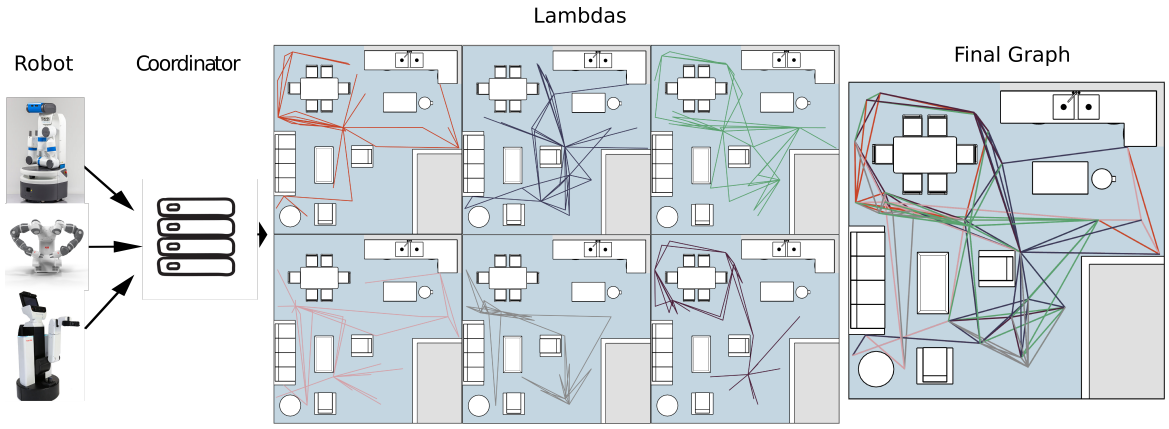

Fig. 2. A central coordinator handles initializing lambdas and maintains open connections to them to allow communication between lambdas. Note that the coordinator need not be a very large instance as it performs a network bound task. Multiple robots can also reuse a single coordinator for maximum efficiency. Each of the 6 lambdas in the center connect a subset of the edges in the sampled vertices. These edges are sent to the coordinator which combines them into the complete graph on the right.

required graph size. Vertices get unique IDs using a counter. These IDs are shared between the coordinator and lambdas implicitly through the common seed in the sampling process. This allows lambdas to send edges to the coordinator using vertex IDs instead of d-dimensional state, resulting in lower bandwidth communication.

Vertex IDs are divided into work packets using different work sharing methods (Sec. IV-D). A work packet has start and end vertex IDs that indicate the range of vertices to be connected to the rest of the graph. Each lambda in Alg. 2 is initialized with its first work packet and immediately begins vertex sampling and edge connection. Once the vertices have been connected, any new edges are sent to the coordinator (Alg. 1) which responds with either another work packet or a termination message.

The algorithm maintains the probabilistic completeness and asymptotic optimality of PRM*. The common random seed ensures that all lambdas generate the same sequence of vertices $(v_1, \dots v_n)$. Similarly, the sequence of edges $(e_1, \dots e_n)$ is identical to the serial version of PRM* as each lambda generates the same edge-set for its vertices. Since the same vertices and edges are present in the graph as in the serial algorithm, Alg. 1 inherits probabilistc completeness and asymptotic optimality from PRM*.

D. Work Sharing

We define 5 work sharing methods:

No Work Sharing Each lambda uses a packet size of $\frac{\text{num\_vertices}}{\text{num\_lambdas}}$. This requires no communication with the coordinator and lambdas will terminate after processing the first work packet and sending edges to the coordinator.

Cyclic Work Sharing Each lambda processes vertices that have the property that $\text{vertex\_id} \mod \text{num\_lambdas} = \text{lambda\_id}$. This requires all lambdas to sample nearly all vertices, but distributes work more evenly.

Synchronous Work Sharing After sending edges to the coordinator the lambda blocks communication until a new work packet is received. This can result in idle time between two work packets but ensures that work is distributed evenly.

Asynchronous Work Sharing Lambdas poll the coordinator for a work packet shortly before processing the current work packet. This reduces network overhead and lambda idle time as packets are readily available in the network queue of the lambdas, but comes with the tradeoff of less even distribution of work than the synchronous method.

Equal Work Amount Per Packet The cost to add a new vertex to the PRM graph goes up with the number of vertices since k^*_{prm} grows. Small packet sizes in previously discussed work sharing methods make the distribution of work between lambdas more even, however, this leads to additional communication costs. Packets that have an equal amount of work instead of an equal vertex count can result in good work distribution without additional communication.

To find the optimal packet sizes to send to each lambda the work per vertex was estimated. The time spent connecting edges for each vertex is proportional to the number of edges that have to be checked for collision which is determined by k^*_{prm}. Since k^*_{prm} is proportional to $\log n$, the work to connect each vertex should grow as $\log n$. To test this hypothesis, the connection time was measured (in Fig. 3), and the resulting graph roughly matched a log-distribution.

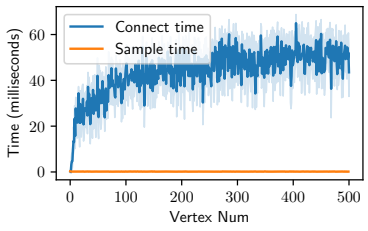

Fig. 3. The blue line refers to the edge connection time for the vertex and the orange line refers to the sampling time for the same vertex. The sampling time is much lower than the edge connection time. The edge connection time roughly follows a log function

This log-like work distribution is leveraged by creating variable size packets with the property that the log-sum of the vertex IDs in them are equal. Under the assumption that the relative time to connect each vertex is approximately proportional to the log of its vertex ID, this creates packets that have the same approximate amount of work. This method does not require any communication with the coordinator.

V. Experiments and Results

We experiment with the proposed system on SE(3) synthetic benchmarks from OMPL [27] and physical Fetch decluttering tasks, running on the Amazon AWS Lambda serverless computing environment. The coordinating server runs on a c5.xlarge instance (two 64-bit Intel Xeon cores) in the same region as the lambda processes. All experiments are run for 11 trials while varying the random seed.

A. Work sharing comparison

To compare the different work sharing methods discussed, we generate a graph of 17000 vertices and approximately 700000 edges with each work-sharing method while varying the number of lambdas and number of packets sent. We compare all methods across two metrics: total cost of the serverless execution and the termination time of the algorithm. The first row of graphs on Fig. 4 show the results for all scenarios.

Comparing the relative performance of asynchronous and synchronous methods across different scenarios, we observe from Fig. 4 that asynchronous work sharing outperforms synchronous work sharing in both cost and end time for nearly all packet sizes due to the lower communication overhead. This supports the hypothesis that communication costs exceed repeated sampling costs in a serverless environment.

Comparing the performance of different packet sizes within the asynchronous method, we observe that a moderate packet size performs the best in terms of end time—too small of a packet size results in high communication costs on the coordinator, while too large of a packet size results in uneven work distribution that causes some lambdas to straggle. However, the cost of execution monotonically decreases with increasing packet size. This is because the slowest-to-complete lambda determines the end time of the algorithm, while the aggregate execution time determines the cost. A large packet size results in fewer packets that allows a greater proportion of lambdas to finish early due to the low work allocated to them which brings down the overall cost.

No-work-sharing outperforms asynchronous and synchronous methods on cost for various packet sizes, however the cheapest asynchronous method is usually cheaper to run. The reason is that no work sharing can be reframed as synchronous work sharing with a large packet size (that results in a single packet for each lambda to process), and large packet sizes result in reduced costs. However, no-work-sharing suffers from a worse end-time than asynchronous methods due to the poor work distribution. Cyclic work-sharing methods perform worse on both metrics than other methods because cyclic work-sharing requires every lambda to sample nearly all vertices in the graph, which adds up to increased costs and worse end times.

Finally, log-based work sharing (using packets with equal work) on the Fetch scenarios for high numbers of lambdas (128 or above) finishes as quickly as the asynchronous work sharing method and has nearly the same cost as no-work-sharing with fixed packet sizes: the absence of communication lowers the cost while the approximately equal work in each packet allows for the quicker end times. Additionally, the cost of log-based work sharing is only slightly greater than no-work-sharing. However, at lower numbers of lambdas and for certain scenarios (like the SE(3) simulations), log-based work sharing is outperformed by asynchronous work sharing methods. This is likely due to large deviations from the predicted log-growth of work for SE(3) scenarios that causes an uneven work distribution.

B. Scaling with Lambdas

We then experiment to measure the speedup provided by more lambdas. Ideal scaling means that a doubling of lambdas leads to a halving of runtime. However, due to startup and network overhead, and repeated sampling work, real-world scaling incurs performance penalties.

Fig. 4 compares 4- and 8-core local baselines (running PRM* on the robot's CPU) against Alg. 1 running on 16 to 128 lambdas. Scaling beyond 128 lambdas is difficult with the current serverless offering due to startup overhead—simultaneously starting up 256 lambdas takes 5s, which is nearly the runtime of the algorithm on 128 lambdas. We hypothesize that this startup delay will be eliminated in the future [6], [7], and also simulate lambdas starting without the delay. We show results for 128*, 256*, and 512* lambdas that simulate no delayed startup with an asterisk.

To quantify the speedup of the algorithm, we measure the parallel efficiency of k lambdas which can be defined as $\frac{\text{time for m lambdas}}{\text{time for k lambdas}} \cdot \frac{m}{k}$ where m refers to the number of lambdas being compared against. A parallel efficiency of 1 indicates ideal scaling.

Fig. 4 shows that using 128 lambdas has a mean parallel efficiency of 0.77 as compared to 4 cores. As the number of lambdas increases, we observe that the proportion of time spent in sampling and startup increases and causes the efficiency to drop. When controlling for startup overhead, we observe that the algorithm continues to scale to 512 lambdas. 512 lambdas on the Fetch scenarios has an end time of only 2.9s compared to the 157.2s end time of a 4-core local baseline, a 52x speedup. SE(3) scenarios scale even better with 512 lambdas finishing in 1.43s compared to the 153.5s of the 4-core local baseline, a 106x speedup.

C. Choosing Optimal Parameters

In a real-world scenario people are most interested in cost and end time. We measure the tradeoffs that between the two, and plot the cost of execution in USD against the time to obtain the solution across all lambda counts in Fig. 4. The ideal position for a point on the graph is in the bottom-left, corresponding to lowest end time (left) and lowest cost

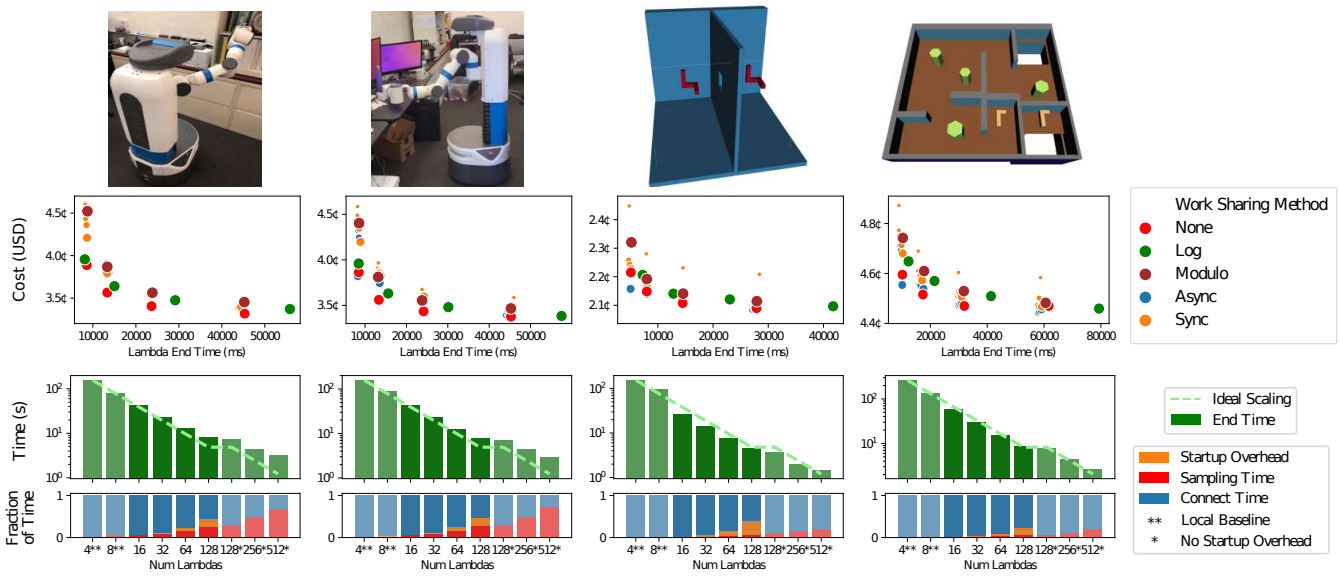

Fig. 4. Experiments are run on real-world decluttering scenarios (with the Fetch robot) and on synthetic benchmarks. The first row for each scenario depicts the tradeoff between cost and end-time that a user can make: the size of the dot indicates the number of packets sent. Higher numbers of lambdas always finish quicker but have a marginally higher cost; and the best work-sharing method is scenario dependent. In general, asynchronous work sharing performs better than synchronous work sharing, and less communication results in a lower total cost. The second row for each scenario shows time scaling of the algorithm with increasing number of lambdas: as the number of lambdas increases the startup overhead and sampling time costs dominate the overall computation that causes a reduction in parallel efficiency.

(down). This means that if a point is on the below and left of any neighbors, it is a strictly better choice.

Using this insight, one can traverse the graphs in Fig. 4 to pick optimal parameters for a specific application. For the Fetch scenario, the log-based work-sharing method is to the bottom-left of the asynchronous and synchronous work sharing methods due to its low cost. However, in these scenarios, no-work-sharing is marginally cheaper than the log-based method with the penalty of a higher end time. Thus depending on the unit economics of the application, the choice can be made between log-based work sharing and no-work-sharing. In this example, no-work-sharing is suitable where the unit economics don't allow a marginally higher cost for quicker end times, otherwise log-based work sharing is preferable. Similarly, lower lambda counts can result in a lower unit cost, but at the penalty of much worse end times.

Another perspective involves viewing idle time on the robot as lost opportunity cost. If the opportunity cost can be quantified, then the time saved by using a more expensive work-sharing method or more lambdas can translate to cost savings. For example, in the Fetch scenario, the log-based method is faster than no work sharing by 0.2s, but costs \$0.001 more. If 0.2s of robot idle time is worth more than 0.001, then log-based work sharing method is superior due to the additional work that can be performed by the robot.

VI. Conclusion

We propose using cloud-based serverless computing to rapidly compute a probabilistically-complete and asymptotically-optimal road map for multi-query motion planning. Serverless computing provides a nearly unbounded source of parallelism that we exploit by dividing vertices to connect across lambda functions. Each lambda samples the same vertex sequence by initializing the sampler with a common seed and connects a subset of edges.

In experiments with a Fetch robot, the proposed serverless computing speeds up motion planning computation by up to 52x compared to local baselines while costing \$0.035 to build a graph (that can be reused for multiple motions), suggesting this approach can be used to speed up sporadically computationally-intensive motion-planning problems while being more cost effective than an always-on high-end computer. Additionally, we provide guidelines for applications to simultaneously optimize for Dollar-cost and end-time by varying the work sharing method and the number of lambdas.

In future work, we plan to explore different approaches to sharing information between serverless processes, taking advantage of recent developments in serverless computing [6], to achieve lower startup overhead, faster point-to-point communication, and reduce bottlenecks on scalability.

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