Learning Multi-paths for Edge Networks in a Stochastic Approximation Approach

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Abstract—
Millions of edge devices are now equipped with increasingly strong computing, communication and storage capabilities. It is beneficial to connect these edge devices into networks for sharing different network service workloads so that these services are close to end-users and achieve reduced network access delay. In this paper, we proposed a measurement-assisted learning algorithm to find efficient multi paths between edge nodes with the assistance of intermediate nodes serving as an edge layer for reduced delay in edge networks in a stochastic approximation approach. Our simulation results demonstrate the effectiveness of the proposed learning algorithm.

I. Introduction

With the pervasiveness of end devices and wireless networks (4G/5G/WiFi), billions of sensors and mobile devices have been connected on the Internet. End devices equipped with powerful processing units and resourceful storages have become the leading roles for generating distributed contents on network edges [1].The decentralized content generation by machine-to-machine is far beyond the centralized content centers.

Centralized content platforms, such as Clouds, CDNs, data processing and computing are mostly provisioned remotely from content service providers [2]. However, the emerging edge networking supports content generating and computing performed at network edges, which are directly referred to the end devices capable with strong abilities in computing and storage. Edge devices may play an important role in the three-tier end-edge-cloud architecture as shown in Fig. 1: end devices near users building the "end" layer for data generation of specified applications, edge devices near the backbone of the Internet constructing the "edge" layer for high performance network transport, and intelligent applications in the cloud forming the brain for data analysis and control.

In the above edge network, edge nodes can cooperate and coordinate with each other for complicated content computation and communication [3]. Nevertheless, because these edge nodes are located at the edges of the Internet, poor network conditions may prevent edge nodes from direct communication [4]. Fortunately, centralized nodes instructed with powerful resources on the core layer usually provide connections for clustered edge nodes. Therefore, edge nodes can setup different detours or alternative paths instead of direct connections with help of these

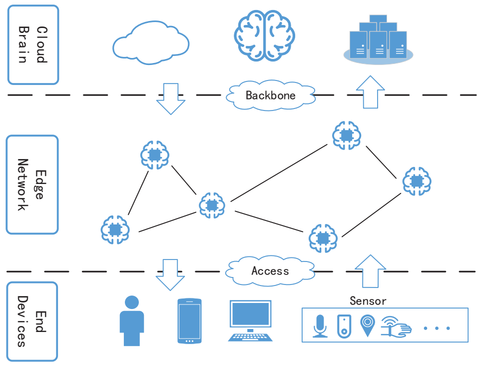
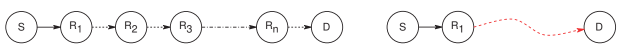


Fig. 1. An illustration of a three-tier end-edge-cloud architecture.

super nodes. In this paper, we study a measurement-assisted multi-path edge routing problem in a stochastic approximation approach, called the dynamic stochastic shortest path (DSSP), to improve the edge connections with detours.

II. Algorithm

Consider an edge-centric network denoted by $G = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ is the set of network nodes and $\mathcal{A}$ is the set of constructed links. Let $S(j)$ be the set of all successors of edge node j residing at the edge layer. Then, $S(s)$ represents the super neighbor nodes at the edge layer of source node S. An edge-to-edge path from source S to destination D in an edge network is shown in Fig. 2. Thus, edge node S and D can utilize intermediate super nodes at the edge layer to forward traffic for better performance. For convenience, we abbreviate these intermediate super nodes at the edge layer as super nodes or relay nodes.



(a) Traditional routing (b) Stochastic routing

Fig. 2. An edge-to-edge delay computation example.

Fig. 2(a) illustrates an alternative path routing example using n super nodes as relays on the forwarding routing path. Therefore, the edge-to-edge delay from source S to destination D can be represented as $T_{sd} = T_{sr_1} + T_{r_1 r_2} + \ldots + T_{r_n d}$. Source S is able to measure the exact delay T_{sr_1} of the local link accurately, while it is difficult for S to obtain the exact delays, $T_{r_1 r_2}, T_{r_2 r_3}$, et al. of those non-local links between the relays and destination D in a timely manner. Nevertheless, the delays of those non-local links can be measured by relays and summarized into probability distributions. Those delay distributions of non-local links can be further exchanged between available relays and source S. Therefore, S can compute the expected delays of the non-local overlay links to quantify their link states.

As shown in Fig. 2(b), the alternative routing path from S to D via relay node 1 is then divided into two segments: $S \rightarrow R_1$ and $R_1 \rightarrow D$. This edge-to-edge delay is computed as $T_{sd} = D^o_{sr_1} + v_{r_1}$, where $D^o_{sr_1}$ is the exact delay from S to node 1 by observations or measurements of the local link, and v_{r_1} is the expected delay of the stochastic shortest path from node 1 to D. Source S can further establish an optimization model to determine the best edge node J as chosen node 1 in order to minimize the edge-to-edge delay $T_{sd} = D^o_{sr} + v_r (r \in S(s))$ following Eq. (1). Note that all the intermediate or relays nodes are chosen from super nodes residing at the edge network.

$$J = \arg \min_{r \in S(s)} \{D^o_{sr} + v_r\} \tag{1}$$

III. Evaluation

To evaluate the performance of the proposed measurement-driven overlay routing algorithm, we conducted a simulation study with the Internet delay data set [5]. First, we extracted the available connected nodes from the data set, then generated a number of network topologies with random 500 nodes consisting of 400 pairs of edge nodes and 100 super nodes for alternative path discovery simulations, as shown in Fig. 3. Finally, we compare the K-th Stochastic Shortest Path (KSSP) routing algorithm with two traditional algorithms: the Deterministic Shortest Path (DSP) and the Minimal Hop (MHP) in terms of the average delay performance.

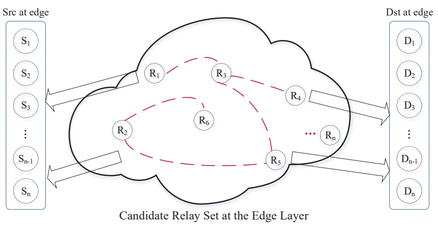


Fig. 3. Network simulation scenarios with 100 edge nodes.

As shown in Fig. 4, the cumulative distribution function curve of KSSP converges much faster than the other two algorithms. The results demonstrate that the delay performance of KSSP is more centralized with various network topologies and different path value K. Table I shows that the proposed KSSP algorithm achieves a low delay variance, which means the alternative path delay performance by KSSP is quite stable under dynamic network conditions. Note that the delay performance of the multi alternative shortest path is slightly worse than the single shortest path. It is because the proposed algorithm selects different shortest paths, and the selected paths would be excluded from the candidate shortest paths.

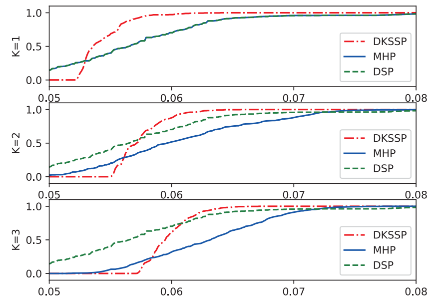


Fig. 4. CDF of the edge-to-edge delay (seconds)

TABLE I
Delay mean and variance (seconds) with different K values

Algorithms	K=1		K=2		K=3	
	Mean	Variance	Mean	Variance	Mean	Variance
KSSP	5.43e-2	3.82e-6	5.74e-2	3.80e-6	5.98e-2	3.33e-6
DSP	5.69e-2	5.37e-5	5.69e-2	5.37e-5	5.69e-2	5.37e-5
MHP	5.69e-2	5.37e-5	6.07e-2	4.24e-5	6.30e-2	6.33e-5

IV. Conclusion

Our simulation results demonstrate the proposed multi-path routing algorithm is applicable for edge networking. The default edge-to-edge path may be unavailable or experience degraded performance; detour is beneficial to achieve ultimate edge-to-edge delivery by employing the intermediate nodes. This indicates that the traditional dynamic routing algorithms may not achieve a desired performance in edge networking. The proposed stochastic routing is constructed only based on the statistical information of overlay links between edge nodes; thus, it is resilient to inaccurate link state information. It brings forth potential applications of stochastic routing in edge-based applications.

Acknowledgment

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References

[1] P. Garcia Lopez, A. Montresor, D. Epema, A. Datta, T. Higashino, A. Iamnitchi, M. Barcellos, P. Felber, and E. Riviere, "Edge-centric computing: Vision and challenges," SIGCOMM Comput. Commun. Rev., vol. 45, no. 5, pp. 37–42, Sept. 2015.

[2] E. Zeydan, E. Bastug, M. Bennis, M. Kader, I. Karatepe, A. Er, and M. Debbah, "Big data caching for networking: moving from cloud to edge," IEEE Communications Magazine, vol. 54, no. 9, pp. 36 – 42, 2016.

[3] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, Oct 2016.

[4] M. Chiang, S. Ha, C.-L. I, F. Risso, and T. Zhang, "Clarifying fog computing and networking: 10 questions and answers," IEEE Communications Magazine, vol. 55, no. 4, pp. 18 – 20, 2017.

[5] C. Zhang, A. Y. Wang, and X. Hei, "Relay discovery and selection for large-scale P2P streaming," PLOS ONE, vol. 12, no. 4, 2017.