Integrating Traffic Network Clustering with Multi-objective Route Planning: a Heuristic Approach

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***Abstract*—We model the autonomous path planning problem as a three-objective minimization problem with the constraint of collision free. We optimize the three objectives of distance, time, and traffic congestion, measured by the inverse of road network congestion index, with Non-dominated Sorting Genetic Algorithm II (NSGA-II) using real time traffic information on the road. In order to reduce the domino effect of congestion, we propose a novel technique to improve our optimization algorithm with road point clustering using Speed Performance Index (SPI) based similarity measurement. Our experiment shows that NSGA-II with clustering produces more congestion smart solutions than NSGA-II without clustering.**

***Keywords*–Internet of Things. Autonomous Path Planning. Collision Free. Multi-Objective Optimization. NSGA-II. Traffic Clustering. Affinity Propagation.**

I. INTRODUCTION

Long Term Path planning for an autonomous vehicle is a complex task. Autonomous planning algorithms should be efficient and, most importantly, avoid traffic collisions. The efficiency of the algorithm is usually measured by the travel time and/or travel distance [1] under dynamic real time traffic conditions on the road network. With the importance of reducing greenhouse emission, being traffic aware and choosing less congested paths have become important objectives as well [2]. The traffic on the road adds some constrains in route planning. *Depending on the real time traffic condition, the shortest path may not be the fastest route, or the "greenest" route (least congestion), or the safest route (collision-free).* While this paper does not consider the steps for an autonomous vehicle after the initial long term path planning, such as short term maneuvers and decision making, we argue that it is important to generate more than one path at the path planning stage to provide the decision making process with alternative paths for different preferences of the sometimes conflicting objectives. Therefore, we model our autonomous path planning task as a multi-objective optimization problem [3]. The multi-objective optimization problem is to solve the minimization or maximization of N conflicting objective functions $f_i(x)$ for $i \in [1, N]$, simultaneously, subject to equality constraint function $g_j(x) = 0$ for $j \in [1, M]$ and inequality constraint function $h_k(x) \leq 0$ for $l \in [1, K]$, where the decision vectors $x = (x_1, x_2, ...x_n)^T$ belongs to the nonempty feasible region $S \subset R^n$ [4] [5]. Solution x_1 dominates x_2 if two conditions are satisfied: 1) $\forall i \in [1, N]$: $f_i(x_1) \leq f_i(x_2)$, and 2) $\exists j \in [1, N]$: $f_i(x_1) < f_i(x_2)$. Solution x_1 is also called the *non-dominated* solution. The goal of the multi-objective optimization problem can also be modeled as finding the *Pareto front* that has the set of all non-dominated solutions. Multi-objective optimization problems are often NP-hard [5]. Therefore, exact or deterministic algorithms are infeasible.

A road network can be modeled as a planar graph, where the nodes represent road points, and edges represent road segments. This graph may be considered as static or dynamic (time-dependent), and as deterministic or stochastic with respect to different aspects of the network. We consider our road network as dynamic and stochastic taking into consideration the effect of real-time traffic that changes over time. Evolutionary algorithms, based on natural and biological systems, have been adapted to solve dynamic optimization problems. Genetic algorithms is one such common evolutionary algorithm. Evolutionary meta-heuristics have applications in difficult real-world optimization problems that possess non-linearity, discreteness, large data sizes, uncertainties in computation of objectives and constraints, and so on [5] [6] .

We model the autonomous path planning problem as a three-objective minimization problem: that is, minimization of distance, time, and traffic congestion, with collision avoidance as the constraint. We consider one of the most applicable evolutionary algorithms, Non-dominated Sorting Genetic Algorithm II (NSGA-II) [7] in this paper. We further improve our optimization algorithm using real time traffic information on the road. The road network exhibits both spatial and temporal locality. Spatial because a congested road affects other roads within its neighbourhood and temporal because the traffic spreads over a period of time. This creates a domino effect on the road network. We propose an innovative technique to solve the route planning problem on this traffic network. We propose to cluster road points based on traffic conditions and integrate the clusters with the multi-objective optimization algorithm to reduce the domino effect of congestion. The paper is organized as follows. Section II discusses the related work in multi-objective path planning using NSGA-II and traffic clustering. Section III provides the formal problem statement, objectives and assumptions. Section IV explains the workings of our algorithm. Section V shows our experiment result and analysis, including visualization of the pareto front and alternative routes. Finally, Section VI concludes the paper with a summary and thoughts for future work.

II. RELATED WORK

Chitra and Subbaraj [8] use NSGA to minimize cost and delay of the dynamic shortest path routing problem in computer networks. The authors show that the pareto approach generates more diverse pareto optimal solutions than the single objective weighting factor method based on Genetic Algorithm (GA). NSGA-II is an improvement of the NSGA algorithm in terms of diversity preservation and speed. In [9], timeliness reliability and travel expense are considered as the two objectives in path planning on a stochastic time-dependent transportation network. A route between an origin-destination pair is encoded as a variable-length chromosome in the NSGA-II to find the pareto-optimal routes. A road network, consisting of main streets in Beijing is considered as the case study. The selection of the route from the resulting pareto-front is said to be dependent to the travelers' decision based on their risk-sensitivity and cost-sensitivity.

Rauniyar et al. [10] formulate the pollution-routing problem with two objectives, minimization of fuel consumption (CO2 emissions), and minimization of total distance to be traversed by multiple vehicles. The authors incorporate a new paradigm of evolutionary algorithm, called multi-factorial optimization, into NSGA-II and show better performance and faster convergence than the traditional NSGA-II framework. In [11], we study 4-objective dynamic path planning using NSGA-II based on real road network and real traffic data from Aarhus, Denmark. Our 4 objectives include Total vehicular Emission Cost (TEC), travel time, number of turns, and distance. Our experiments produced a diverse set of solutions for this problem and provided the user the flexibility of selecting a path based on their preferences of the four objectives. However, this framework does not consider the collision avoidance constraint. It also does not include clustering the traffic network first before searching for the routes in the network.

We further notice that in the literature of multi-objective path planning on dynamic and stochastic road networks, the focus has been on the total cost of individual road segments that are part of the paths. Few works have extended the consideration of node-node relationship that exists naturally on a dynamic road network, that is, the temporal and spatial domino effects of traffic congestion. One approach of understanding this node-node relationship is through traffic clustering. Wang et al. [12] developed a distributed traffic clustering system based on affinity propagation algorithm [13] using Internet of Things (IoT) technologies and sensors around road points, that dynamically collects and analyzes the traffic flow data using concepts from network theory, in particular maximum flow and shortest path algorithms.

In this paper, we will first improve the traffic clustering in [12] with Speed Performance Index (SPI) [14] based similarity instead of flow based similarity. Then, we will integrate the traffic clustering into the multi-objective path planning to improve the overall solution quality of the path planning algorithm. To our best knowledge, there are few works in improving the accuracy of multi-objective dynamic path planning with clustering. In the literature, clustering has been employed to reduce the complexity of multi-objective problems. In [15], clustering of objectives is used to reduce the dimension of the optimization problem. In [16], density based clustering is used to classify regions into clusters to improve the efficiency and reliability of coverage path planning method for autonomous heterogeneous Unmanned Aerial Vehicles (UAVs). The contributions of this paper are as follows:

1) We improve the multi-objective dynamic path planning algorithm in [11] with a new objective for traffic congestion minimization and collision free constraint.
2) We improve the traffic clustering in [12] with SPI [14] based similarity instead of flow based similarity.
3) We propose an innovative technique to integrate the clusters with the multi-objective optimization algorithm to improve route planning.

III. Objectives

A road network is modeled as a directed graph $G = (V, E)$, where V is the set of nodes, and E is the set of edges. A link from node $v_i \in V$ to node $v_j \in V$ is shown by $e_{ij} \in E$. A loop-free path is represented as a linked list of nodes, with the source node S as the head and the destination node T as the tail of the linked list, with no node appearing more than once. The constrained multi-objective path planning problem is a minimization problem that finds a set of solutions with the minimum travel time, minimum distance and minimum traffic congestion, with the constraint of avoiding collisions based on real-time sensor data.

A. Objective 1: Distance

The distance of a path is calculated using (1)

$$f_1(Distance) = \sum_e l_e, \forall e \tag{1}$$

where l_e is the length of edge e on a path. l_e is calculated based on the static road network once a path is determined.

B. Objective 2: Time

The total time on a path is given by (2)

$$f_2(Time) = \sum_e t_e \forall e \tag{2}$$

where e is an edge on a path, and t_e is the total time the vehicle travels on the edge. t_e is recorded by the simulator based on real-time vehicle dynamics.

C. Objective 3: Inverse of Road Congestion Index

Road Segment Congestion Index is a measure introduced by He et al. [14]. In [14], the *SPI* R_v is expressed in (3), where v represents average vehicle speed in km/h, and V_{max} represents speed limit on the road segment in km/h. To normalize SPI, speeding is not considered in this equation, and R_v is in the range of $[0, 100]$.

$$R_v = \begin{cases} \frac{min(v, V_{max})}{V_{max}} \times 100 & \text{if vehicle count} > 0 \\ 100 & \text{otherwise} \end{cases} \tag{3}$$

The traffic state level is considered

- heavy congestion if $R_v \in [0, 25]$
- mild congestion if $R_v \in (25, 50]$
- smooth if $R_v \in (50, 75]$
- very smooth if $R_v \in (75, 100]$

The Road Segment Congestion Index, R_i, is calculated in (4) and (5), where $\overline{R_v}$ represents the average of SPI, R_{NC} denotes the proportion of non-congestion state, i.e., when the SPI is in the range of $(50, 100]$, t_{NC} denotes the duration of non-congestion state in minutes, and T_t denotes the length of the observation period in minutes. The value of R_i is in the range of $[0, 1]$. The smaller the value of R_i, the more congested a road segment is.

$$R_i = \frac{\overline{R_v}}{100} \times R_{NC} \tag{4}$$

$$R_{NC} = \frac{t_{NC}}{T_t} \tag{5}$$

The road network congestion index, R is then expressed in (6), where L_i is the length of road segment in km. Similarity, $R \in [0, 1]$, and the smaller the value of R, the more congested a road network is. For our minimization problem, we want to find the minimal values of R^{-1} for the least congested paths using (7). Theoretically, it is possible for R to be 0, meaning that every road segment on a path is congested. However, this scenario rarely happens in reality. As shown in Figure 1, at the rush hour of 7:30 a.m., only a few disconnected road segments were color coded as red, representing high congestion status. Even if a path has R as 0 and therefore infinite value for R^{-1}, this path will be deemed a bad solution and abandoned by the optimization algorithm.

$$R = \frac{\sum_i R_i L_i}{\sum_i L_i} \tag{6}$$

$$f_3(R^{-1}) = \frac{\sum_e L_e}{\sum_e R_e L_e} \forall e \tag{7}$$

D. Constraints

The minimization optimization of the three objectives is subject to the following constraints:

$$e \in G, \forall e \in P \tag{8}$$

$$count(v) = 1, \forall v \in P \tag{9}$$

$$g_(e) = \sum_e CollisionCount_e = 0, \forall e \in P \tag{10}$$

where the first constraint (8) ensures that a path P is valid, that is, all its edges belong to the road network G, the second constraint (9) ensures that a path P is loop free by making sure any node in P appears exactly once, and the third constraint (10) ensures that the collision count on the entire path is zero.

IV. Solution Methodology

A. Affinity Propagation Clustering

Clustering is a preprocessing step for the multi-objective path finding. Our clustering algorithm is based on the distributed, message-passing Affinity Propagation clustering proposed by [12]. We further improve the clustering algorithm with SPI based similarity instead of flow based similarity.

First, we generate a node based SPI using algorithm 1.

Then we calculate pairwise similarity based on SPI at nodes using algorithm 2. The similarity is based on the assumption that if the target node j is congested, then the similarity between source node i and j is related to the most congested node on the shortest path from i to j. In addition, the closer i and j are spatially, the more likely they are similar.

Once the similarity is defined, the Affinity Propagation clustering algorithm works as follows. First, a node i considers itself as a cluster k, then it calculates two local variables responsibility $r(i, k)$ using (11), and availability $a(i, k)$ using (12) based on a, r values from other nodes of its communication range, as well as pair-wise similarity s it calculates based on the traffic information received from the other nodes. To compute responsibility $r(i, k)$, the algorithm finds another data point $k^{'}$ that has the highest (maximum) availability and similarity, and computes the difference in the similarity. In addition, responsibility $r(i, k)$ represents how well k is the center of i, so it does not only consider how similar i and k are, but also considers which one of i and k is more suitable be the center. Self responsibility $r(k, k)$ could be negative or positive. If it is negative, it implies that the node is more likely to be a member of some cluster rather than the center of a cluster. Finally, node i belongs to the center k that gives maximum $a(i, k) + r(i, k)$. The message passing Affinity Propagation clustering algorithm has no central control, does not require the number of clusters to be given, and runs dynamically unless terminated deliberately.

$$r(i, k) = s(i, k) - \max_{k' \neq k}(a(i, k') + s(i, k')) \tag{11}$$

$$a(i, k) = \begin{cases} \min(0, r(k, k)) - \sum_{i' \neq i,k} \max(0, r(i', k)) & \text{if } i \neq k \\ \sum_{i' \neq i,k} \max(0, r(i', k) & \text{if } i = k \end{cases} \tag{12}$$

Algorithm 1 Node Speed Performance Index

Require: road graph G, node i, time step t, SPI Matrix S
Ensure: SPI_i
ine = G.in_edges(i)
oute = G.out_edges(i)
ineSPI, outeSPI = 0
for i, j, d in ine **do**
  $ineSPI = ineSPI + S[i, j][t]$
end for
for i, j, d in oute **do**
  $outeSPI = outSPI + S[i, j][t]$
end for
$SPI_i =$ average$(\frac{ineSPI}{len(ine)}, \frac{outeSPI}{len(oute)})$

Algorithm 2 Pairwise SPI Similarity

Require: road graph G, origin i, target j, time step t, SPI Matrix S
Ensure: $Sim(i, j)$
Calculate SPI_j
$p =$ G.ShortestPath(i, j)
$minSPI$ is the smallest SPI on p
{Distance in km}
$dist = len(p)$
$Sim(i, j) = \frac{minSPI}{SPI_j * max(dist, 1)}$

B. Multi-objective Path Finding

Once we have cluster ids of each node at time step t, the NSGA-II multi-objective path finding process in (4) [11] is executed.

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Algorithm 3 Message Passing Affinity Propagation Traffic Clustering at Node i

Require: road graph G, time step t
Ensure: cluster id k
Initialize availability $a_i = [0]$
while not terminated **do**
  Compute pair-wise similarity s
  Collect a from adjacent nodes
  Calculate r_i
  Broadcast r_i
  Receive r from adjacent nodes
  Calculate a_i
  Broadcast a_i
  Compute local cluster id k at time t
end while

Algorithm 4 NSGAII for Traffic Aware Many-Objective Dynamic Route Planning

Require: road graph G, start node s, end node t, $initPopulationSize$, $generations$, $crossoverPoints$, $tournamentSize$, $mutationProb$
Ensure: $paretoFront$
{Initialization}
$population$ = randomLoopFreePath (s, t, $initPopulationSize$)
{Main loop}
for $generation \leftarrow 1, generations$ **do**
  $population$ = breedPopulation($population$, $crossoverPoints$, $tournamentSize$, $mutationProb$)
  $scores$ = scorePopulation($population$)
  $population$ = buildParetoPopulation($population$, $scores$)
end for
{Final Pareto Front}
$scores$ = scorePopulation($population$)
$paretoFront$ = identifyPareto($population$,$scores$)

1) Collision Avoidance: The constraint of collision avoidance is added to the solution selection process of the main algorithm. Solution x_1 constrained-dominate x_2 in the following three situations [5]:

- solution x_1 is feasible and x_2 is not.
- x_1 and x_2 are both infeasible, but x_1 has a smaller constraint violation.
- x_1 and x_2 are both feasible and solution x_1 dominates solution x_2 in the usual sense.

This relaxed selection process allows infeasible but less constrained parents to be included in the breed process, and allows for better diversity in the end. At the selection of the final pareto front, all the infeasible solutions are removed from the solution set.

2) Clustering Incorporation: In order to incorporate the clustering result into the process, we make an important assumption: if start node i and j of a directed edge $e = i- > j$ are in the same traffic cluster at time t, then all the incoming edges of i are affected by e in terms of traffic, because the traffic flows in this order: the incoming edges of $i- > i- > j$. Based on this assumption, we take the average of all SPI values of the incoming edges of i and e, and assign the average value back to these edges. This process is described in the following algorithm 5.

Algorithm 5 Cluster Average SPI

Require: road graph G, begin node i, end node j, time step t, SPI matrix S, Cluster matrix C
Ensure: Cluster Average SPI matrix S'
if C[i][t] == C[j][t] **then**
  ine = G.in_edges(i)
  eid = G.edges.index((i,j))
  sumSPI = S[eid][t]
  for a, b, d in ine **do**
    eid = G.edges.index((a,b))
    sumSPI += S[eid][t]
  end for
  avgSPI = $\frac{sumSPI}{(1+len(ine))}$
  for a, b, d in ine **do**
    eid = G.edges.index((a,b))
    S[eid][t] = avgSPI
  end for
end if

V. Evaluation and Analysis of Results

A. Road Network and Traffic Data

The road network of Aarhus, Denmark [17] is represented as a graph composed of 136 nodes and 443 edges. In addition to the topology, the metadata also includes the latitude and longitude of the nodes, the street name of a node, and the speed limit and length of an edge. The traffic data includes sensor data recorded on each edge from February to June 2014, such as vehicle counts and average speed. The sensor data is collected every five minutes. Because there is no collision data available at the data set, we simulated random collision points using the roulette wheel selection, that is, if a random number is smaller than the probability calculated using a small constant p and the road segment congestion index R_e, then there is a collision on the road. In this paper, $p = 5$. Since $R_e \in [0, 1]$, the selection probability is in the range of $[5\%, 10\%]$. The more congested a road segment is, the more likely there is a collision. In the future work, we will simulate the traffic flow and collision in the road network simulator SUMO (Simulation of Urban MObility) [18].

B. Implementation and Parameters

The code of the paper is written in Python 3, with references to code snippets from [19]–[21].The experiments are run on a MacBook Pro with 2.3 GHz Intel Core i5 and 8 GB 2133 MHz LPDDR3.

For our experiments, we consider multi-objective dynamic path planning from $startNode$ 4320 (city of Hinnerup) to $endNode$ 4551 (city of Hasselager). We determine experimentally the parameters for NSGA-II as $initPopulationSize = 100$, $generations = 100$, $crossoverPoints = 5$, $tournamentSize = 2$, $mutationProb = 0.8$. For traffic data, we treat the beginning timestamp 2014-03-01T07:30:00 as $timeIdx = 0$.

C. Improvement of Traffic Clustering using SPI Based Similarity

We evaluate the cluster quality using the same metrics used by [12], including Silhouette coefficient [22] and the mean

TABLE I. RESULT COMPARISON OF FLOW BASED AND SPI BASED AFFINITY PROPAGATION CLUSTERING

Time Stamp	Flow Based Clustering			SPI Based Clustering		
	Number of Clusters	Silhouette coefficient	Mean Similarity	Number of Clusters	Silhouette coefficient	Mean Similarity
2014-03-01 T07:30:00	0	0	0.041	25	0.481	0.710
2014-03-01 T07:35:00	26	0.207	0.313	25	0.480	0.713
2014-03-01 T07:40:00	21	0.174	0.266	25	0.480	0.712
2014-03-01 T07:45:00	22	0.206	0.296	25	0.475	0.710

TABLE II. RESULT COMPARISON OF A*, NSGA-II, AND NSGA-II WITH CLUSTERING

Path Finding Algorithm	Number of Solutions	Objectives			Constraint	Other Metric
		Average Distance (KM)	*Average Time (Minutes)*	*Average R Inverse*	*Average Collision*	*Average TEC*
A*	1	22.825	33.031	1.201	1	0.069
NSGA-II	100	29.769	57.828	1.132	0	0.075
NSGA-II with Clustering	100	31.072	45.457	1.089	0	0.068

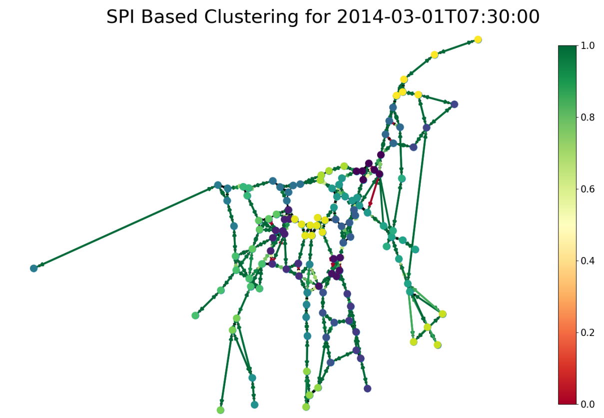

Figure 1. Traffic Clustering of the road network of Aarhus, Denmark

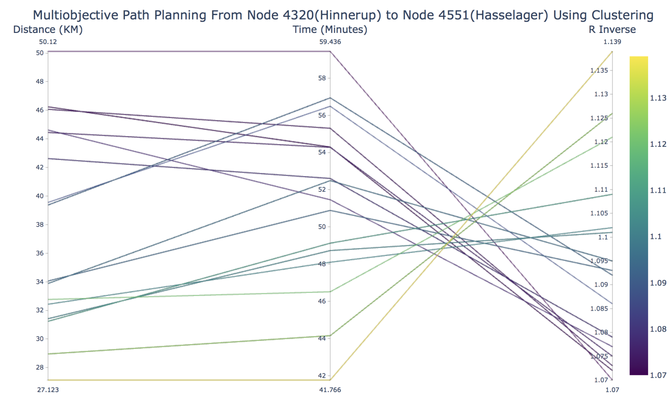

Figure 2. MOO with Clustering Pareto Front Visualization

similarity within all clusters. Silhouette coefficient evaluates item similarities of inter and intra clusters. Mean similarity is the average of all pairs of intra-cluster similarity. For both metrics, higher values indicate higher cluster quality. As shown in table I, the use of SPI based similarity is very effective in improving the clustering of the road points. In these four time stamps, SPI based clustering creates much higher values of Silhouette coefficient and mean similarity consistently. Figure 1 is a visualization of the road map of Aarhus, Denmark at 7:30 a.m. on 2014-03-01, where the nodes are marked and color coded with their cluster ids, and the edges are color coded with road segment congestion index R_i. The color red means heavy congestion with $R_i = 0$, and green means very smooth with $R_i = 1$. The visualization shows that adjacently connected road points usually belong to the same cluster, and these road segments have similar traffic conditions. This is because the SPI based similarity considers both congestion conditions and spatial adjacency between two road points.

D. Improvement of Multi-objective Path Planning with Clustering

For the multi-objective path planning, we compare our NSGA-II with clustering with the same algorithm without incorporation of clustering. Table II shows the comparison of A* [23] shortest path, NSGA-II and NSGA-II with clustering in terms of the three objectives, one constraint, and an additional metric called total vehicular emission cost (TEC) [24]. This metric is used in our previous paper [11] as one objective of monetized value for vehicular emission. For the convenience of comparison, we take average of each object for all the pareto front solutions in three independent executions of the programs. The single objective A* path has the shortest distance, but it does not guarantee collision free. It also has higher than average R^{-1} compared to the multi-objective approaches. In comparison, the multi-objective approaches produce a diverse variety of solutions for the decision making process to choose from. Between the two multi-objective approaches, we observe that although the clustering based approach generates longer paths in average, the travel time and congestion are both more optimized than the other approach. The lower average value of TEC also indicates that these solutions are more traffic smart. Figure 2 is the parallel coordinate visualizations of pareto front.

Finally, Figure 3 shows three alternative paths found by the clustering based approach: the path with minimum distance (blue nodes), the one with minimum time (yellow nodes), the one with least congestion (green nodes). For comparison, A* shortest path is also highlighted (red nodes). This visualization has a limitation that a node belonging to multiple paths only carries the color of one path following the coloring sequence mentioned in the previous sentences. For example, if a node is on both the MOO path of least congestion and the A* path, it is colored as red. Despite of this limitation, this figure shows different possibilities of path planning depending on the preference of the decision making system.

VI. CONCLUSION AND FUTURE WORK

In this paper, we model the autonomous path planning problem as a three-objective minimization problem with the constraint of collision free. We show that our NSGA-II based framework finds a diverse set of alternative solutions for the decision making system to choose from based on the

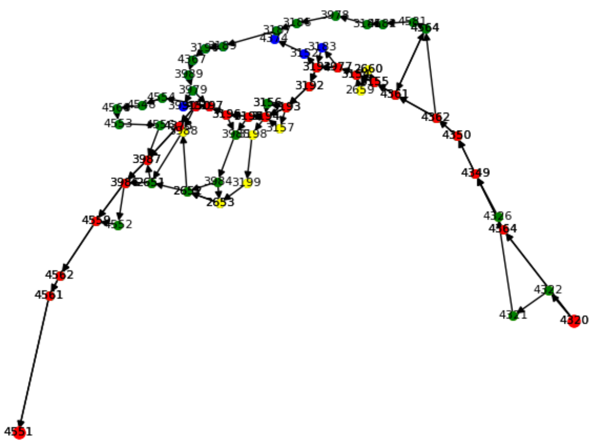

Figure 3. MOO with Clustering Path Examples Visualization

preference of the three objectives: distance, time, and traffic congestion, instead of one single solution from the A* shortest path algorithm. We propose a novel approach to integrate SPI based road point clustering into the multi-objective optimization considering the domino effect of congestion. Our experiment shows that NSGA-II with clustering produces more congestion smart solutions than NSGA-II without clustering.

As a future work, we would like to extend our work in three directions:

1) Explore other multi-objective evolutionary algorithms, such as multi-objective Ant Colony Optimization (ACO) [25] and MultiObjective Evolutionary Algorithm based on Decomposition (MOEA/D) [26].
2) Explore traffic prediction techniques such as the emerging Graph Neural Networks [27].
3) Simulate the traffic flow and collision in the road network simulator SUMO (Simulation of Urban MObility).

References

[1] S. Aggarwal and N. Kumar, "Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges," Computer Communications, vol. 149, 2020, pp. 270–299.

[2] V. Roberge and M. Tarbouchi, "Fast path planning for unmanned aerial vehicle using embedded gpu system," in 2017 14th International Multi-Conference on Systems, Signals & Devices (SSD). IEEE, 2017, pp. 145–150.

[3] H. W. Kuhn and A. W. Tucker, "Nonlinear programming," in Traces and emergence of nonlinear programming. Springer, 2014, pp. 247–258.

[4] M. Abido, "A novel multiobjective evolutionary algorithm for environmental/economic power dispatch," Electric power systems research, vol. 65, no. 1, 2003, pp. 71–81.

[5] J. Branke, J. Branke, K. Deb, K. Miettinen, and R. Slowiński, Multiobjective optimization: Interactive and evolutionary approaches. Springer Science & Business Media, 2008, vol. 5252.

[6] J. Del Ser, E. Osaba, J. J. Sanchez-Medina, and I. Fister, "Bioinspired computational intelligence and transportation systems: a long road ahead," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 2, 2019, pp. 466–495.

[7] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," IEEE transactions on evolutionary computation, vol. 6, no. 2, 2002, pp. 182–197.

[8] C. Chitra and P. Subbaraj, "A nondominated sorting genetic algorithm for shortest path routing problem," International journal of computer engineering, vol. 5, no. 1, 2010, pp. 55–63.

[9] Y. Li and L. Guo, "Multi-objective optimal path finding in stochastic time-dependent transportation networks considering timeliness reliability and travel expense," in 2016 Prognostics and System Health Management Conference (PHM-Chengdu). IEEE, 2016, pp. 1–6.

[10] A. Rauniyar, R. Nath, and P. K. Muhuri, "Multi-factorial evolutionary algorithm based novel solution approach for multi-objective pollution-routing problem," Computers & Industrial Engineering, vol. 130, 2019, pp. 757–771.

[11] Y. Y. Liu, F. Enayatollahi, and P. Thulasiraman, "Traffic aware many-objective dynamic route planning," in 2019 IEEE Symposium Series on Computational Intelligence (SSCI). IEEE, 2019, pp. 1241–1248.

[12] Z. Wang, P. Thulasiraman, and R. Thulasiram, "A dynamic traffic awareness system for urban driving," in 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). IEEE, 2019, pp. 945–952.

[13] B. J. Frey and D. Dueck, "Clustering by passing messages between data points," science, vol. 315, no. 5814, 2007, pp. 972–976.

[14] F. He, X. Yan, Y. Liu, and L. Ma, "A traffic congestion assessment method for urban road networks based on speed performance index," Procedia engineering, vol. 137, 2016, pp. 425–433.

[15] X. Guo, Y. Wang, and X. Wang, "Using objective clustering for solving many-objective optimization problems," Mathematical Problems in Engineering, vol. 2013, 2013.

[16] J. Chen, C. Du, Y. Zhang, P. Han, and W. Wei, "A clustering-based coverage path planning method for autonomous heterogeneous uavs," IEEE Transactions on Intelligent Transportation Systems, 2021, pp. 1–11.

[17] "Road traffic data of Aarhus, Denmark," http://iot.ee.surrey.ac.uk:8080/datasets.html, accessed: 2021-04-20.

[18] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. WieBner, "Microscopic traffic simulation using SUMO," in 2018 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2018, pp. 2575–2582.

[19] "Python for healthcare modelling and data science," https://pythonhealthcare.org/2019/01/17/117-genetic-algorithms-2-a-multiple-objective-genetic-algorithm-nsga-ii/, accessed: 2021-04-20.

[20] "Platypus - multiobjective optimization in python," https://platypus.readthedocs.io/en/latest/, accessed: 2021-04-20.

[21] "scikit-learn - machine learning in python," https://scikit-learn.org/stable/, accessed: 2021-04-20.

[22] P. J. Rousseeuw, "Silhouettes: a graphical aid to the interpretation and validation of cluster analysis," Journal of computational and applied mathematics, vol. 20, 1987, pp. 53–65.

[23] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," IEEE transactions on Systems Science and Cybernetics, vol. 4, no. 2, 1968, pp. 100–107.

[24] Y. Wang and W. Y. Szeto, "Multiobjective environmentally sustainable road network design using pareto optimization," Computer-Aided Civil and Infrastructure Engineering, vol. 32, no. 11, 2017, pp. 964–987.

[25] L. Ke, Q. Zhang, and R. Battiti, "Moea/d-aco: A multiobjective evolutionary algorithm using decomposition and antcolony," IEEE transactions on cybernetics, vol. 43, no. 6, 2013, pp. 1845–1859.

[26] Q. Zhang and H. Li, "Moea/d: A multiobjective evolutionary algorithm based on decomposition," IEEE Transactions on evolutionary computation, vol. 11, no. 6, 2007, pp. 712–731.

[27] Z. Cui, K. Henrickson, R. Ke, and Y. Wang, "Traffic graph convolutional recurrent neural network: A deep learning framework for network-scale traffic learning and forecasting," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 11, 2019, pp. 4883–4894.

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