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

Ying Ying Liu, Parimala Thulasiraman
Correspondence: umliu369@myumanitoba.ca

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Presenters' Bios

Ying Ying Liu is a PhD student from the InterDisciplinary Evolving Algorithmic Sicence (IDEAS) lab of the University of Manitoba, Canada. She joined the IDEAS lab as an undergraduate honors student in 2013. Her strengths are in Computational Intelligence, Internet of Things, High Performance Computing, and Distributed Algorithms.

Dr. Parimala Thulasiraman is a Professor with the Department of Computer Science at the University of Manitoba. Parimala's research interests are in the intersection of high performance computing and graph analytics for real world applications in Network Science. Her IDEAS lab applies innovative soft computing techniques to solve challenging issues in complex network systems and data scientific problems.

Agenda

- Problem Statement
- Related Work
- Solution Methodology
- Evaluation and Analysis of Results
- Conclusion and Future Work

Agenda

Problem Statement

- Safety: avoid traffic collisions
- Green: choose a less congested path to reduce emission
- Fast: choose the fastest path
- Distance: choose the shortest path
- These objectives are sometimes contradictory

The Multi-objective Optimization Problem

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 $x = (x_1, x_2, ...x_n)^T$.

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 Path Planning as an Optimization Problem

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 and $v_j \in V$ is shown by $e_{ij} \in E$. The three objectives are minimization of distance (f_1), time (f_2), and the inverse of Road Congestion Index (f_3).

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

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

$$f_3(R^{-1}) = \frac{\sum_e L_e}{\sum_e R_e L_e} \forall e \tag{3}$$

- Road Congestion Index (R) is calculated from average vehicle speed, speed limit, length of road segment, and rule-of-thumb traffic state thresholds.
- f_2 and f_3 dependent on real-time traffic.

Multi-objective Path Planning as an Optimization Problem

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

$$e \in G, \forall e \in P \tag{4}$$

$$count(v) = 1, \forall v \in P \tag{5}$$

$$g_(e) = \sum_{e} CollisionCount_e = 0, \forall e \in P \tag{6}$$

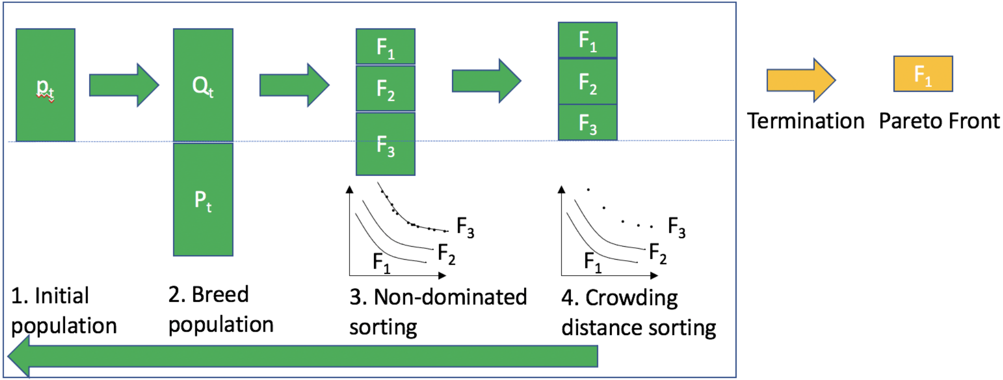
- (4) ensures that a path P is valid
- (5) ensures that a path P is loop free
- (6) ensures that the collision count on the entire path is zero. This constraint is also dependent on real-time traffic.

Agenda

Related Work

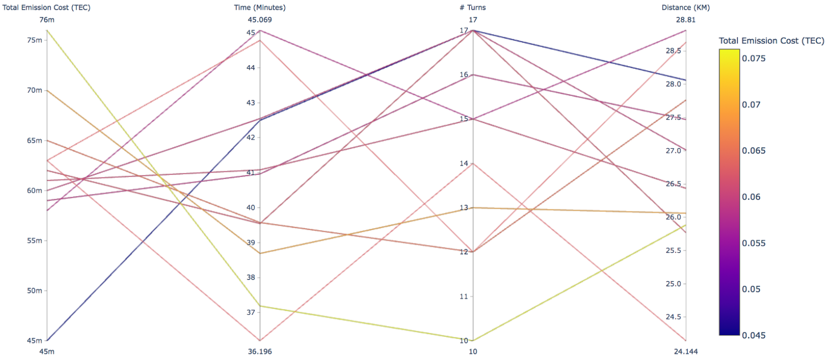
Genetic Algorithms

- 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.



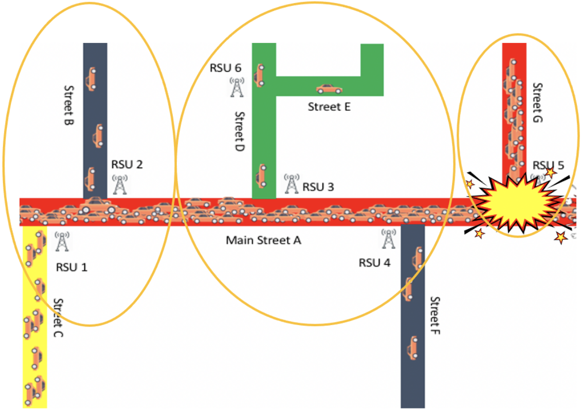
This general framework of NSGA-II has been applied to solve multi-objective optimization problems in real world.

Many-objective Path Finding Using NSGA-II [Liu et al. 2019]



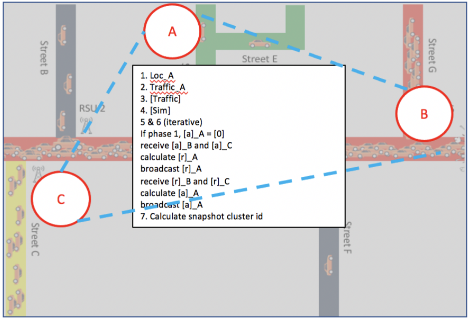
Drawback: Few work in many-objective path finding has extended the consideration of node-node relationship that exists naturally on a dynamic road network, that is, the temporal and spatial domino effects of traffic congestion.

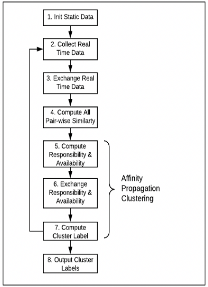
The Domino Effect of Congestion [Wang et al. 2019]



How are street G, E, F, B, C affected by an accident at the end of street A? One approach of understanding this relationship is through traffic clustering.

Affinity Propagation Clustering for Traffic Understanding [Wang et al. 2019]





Road points are clustered based on the traffic flow similarity between each pair. Affinity Propagation [Frey and Dueck, 2007] is a distributed, message-passing clustering algorithm and does not require k to be given.

Solution Methodology

Improve Flow based Clustering with Speed Performance Index

Speed Performance Index [He et al. 2016], R_v, is an intermediate index for road segments in the calculation of Road Congestion Index (f_3). 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, and R_v is in the range of $[0, 100]$.

$$R_v = \begin{cases} \frac{min(v, V_{max})}{V_{max}} \times 100 & \text{if vehicle count} > 0 \\ 100 & \text{otherwise} \end{cases} \tag{7}$$

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 $R_v \in (75, 100]$

Improve Flow based Clustering with Speed Performance Index

First, we generate a node based SPI.

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
$SPI_i = \text{average}(\frac{ineSPI}{len(ine)}, \frac{outeSPI}{len(oute)})$

Second, we generate pair-wise SPI based similarity.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.

Algorithm 2 Pairwise SPI Similarity

Require: road graph G, origin i, target j, time step t, SPI Matrix S
Ensure: $Sim(i,j)$

1: Calculate SPI_j
2: $p =$ G.ShortestPath(i,j)
3: $minSPI$ is the smallest SPI on p
{Distance in km}
4: $dist = len(p)$
5: $Sim(i,j) = \frac{minSPI}{SPI_j * max(dist,1)}$

Improve Flow based Clustering with Speed Performance Index

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.

Algorithm 3 Message Passing Affinity Propagation Traffic Clustering at Node i

Require: road graph G, time step t
Ensure: cluster id k

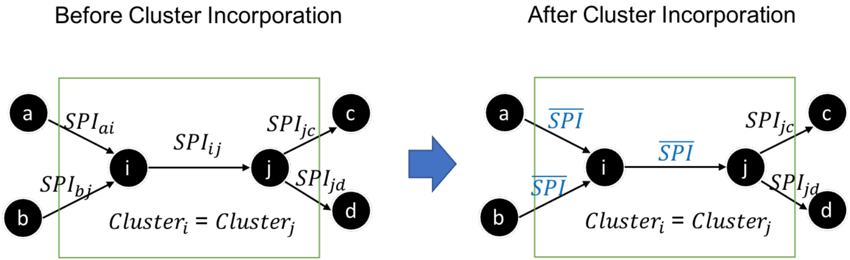
```
Initialize availability a_i = [0]
while not terminated do
    Compute pair-wise similarity s
    Collect a from adjacent nodes
    Calculate r_i
    Broadcast r_i
    Receive r from adjacent nodes
    Calculate a_i
    Broadcast a_i
    Compute local cluster id k at time t
end while
```

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 [Branke et al. 2008]:

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

Many-objective Path Finding Cluster Incorporation

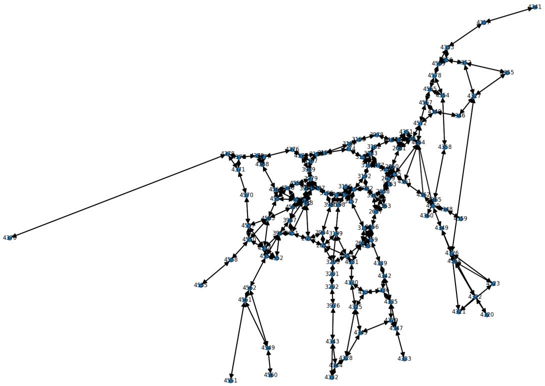
Assumption: if start node i and j of a directed edge $\bar{e} = i \rightarrow j$ are in the same traffic cluster at time t, then all the incoming edges of i are affected by $\bar{e}$ in terms of traffic. Based on this assumption, we take the average of all SPI values of the incoming edges of i and $\bar{e}$, and assign the average value back to these edges.



$\overline{SPI}$ = Avg(SPI_{ij}, SPI_{ai}, SPI_{bj})

Evaluation and Analysis of Results

Road Network and Traffic Data



The road network of Aarhus, Denmark [Open Data Aarhus] is represented as a graph composed of 136 nodes and 443 edges. The traffic data includes sensor data recorded on each edge from February to June 2014.

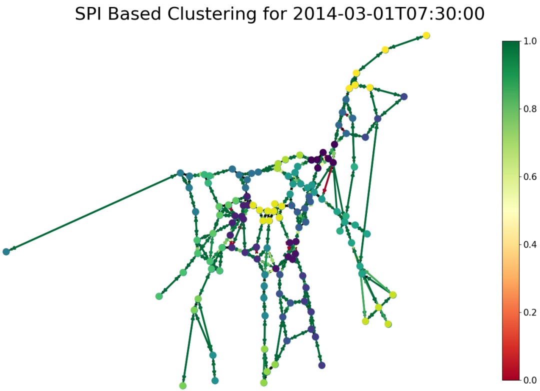
Improvement of Traffic Clustering using SPI Based Similarity

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

SPI based clustering creates much higher values of Silhouette coefficient and mean similarity consistently.

Improvement of Traffic Clustering using SPI Based Similarity



The nodes are marked and color coded with their cluster ID's, 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 $R_i = 1$.

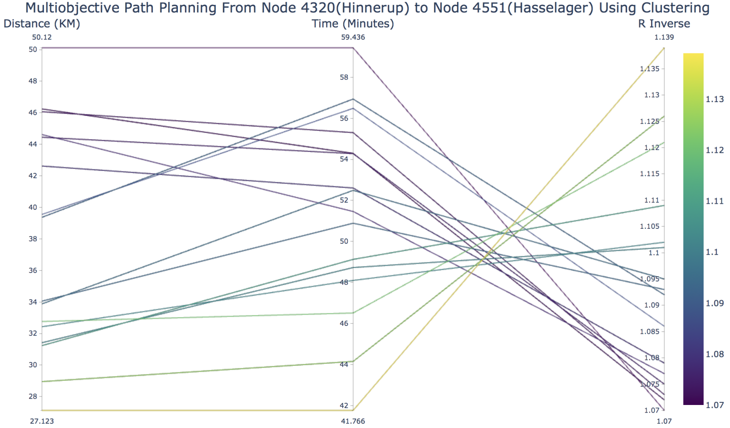
Improvement of Multi-objective Path Planning with Clustering

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

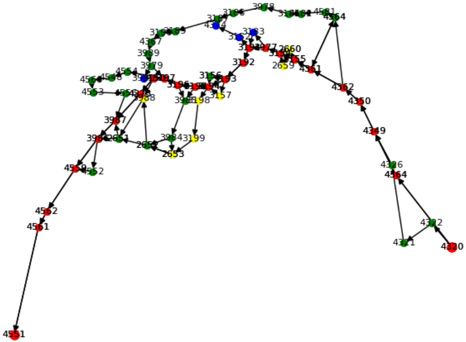
Although the clustering based approach generates longer paths in average, the travel time and congestion are both more optimized than the basic approach. The lower average value of Total Emission Cost (TEC) also indicates that these solutions are more traffic smart.

Improvement of Multi-objective Path Planning with Clustering



The clustering assisted multi-objective path planning produces a diverse variety of solutions for the decision making process to choose from.

Improvement of Multi-objective Path Planning with Clustering



- Blue: the multi-objective path with minimum distance
- Yellow: the multi-objective path with minimum time
- Green: the multi-objective path with minimum congestion
- Red: the single-objective A* shortest path
- Nodes belonging to multiple paths have overlapping colors.

Conclusion and Future Work

Conclusion

Our contributions:

1. We improve the multi-objective dynamic path planning algorithm in [Liu et al. 2019] with a new objective for traffic congestion minimization and collision free constraint.
2. We improve the traffic clustering in [Wang et al. 2019] with SPI [He et al. 2016] 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.

Future Work

1. Explore other multi-objective evolutionary algorithms for the dynamic path planning problem, such as multi-objective Ant Colony Optimization (ACO) [Ke et al. 2013] and multiobjective evolutionary algorithm based on decomposition (MOEA/D) [Zhang and Li, 2007].
2. Explore traffic prediction techniques such as the emerging Graph Neural Networks [Cui et al. 2019].
3. Simulate the traffic flow and collision in the Simulation of Urban MObility (SUMO)

Thank You!