On two speeding-up techniques for the computation of multi-objective shortest paths with a label setting algorithm

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Exact Efficient Solution of Mixed Integer Programming Problems with Multiple Objective Functions (ANR/DFG-14-CE35-0034-01)

1. Introduction

- On the problem:
 - G(N, A, C), a static, connected, directed and valued graph
 - $p \sum$, i.e. p linear objectives with $p \ge 2$
 - Compute 1-to-all (source s to other nodes) shortest paths
- On the instance:
 - No specific topology for G
 - p positive costs on arcs
- On the solutions:
 - No preference on shortest paths
 - $s \in N$ given:

efficient paths over p objectives from s to all $t \in N \setminus \{s\}$

 X_E , a complete set of efficient paths,

- On the algorithm:
 - Label setting principle
 - Martins' algorithm (1984)

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- Temporary and permanent labels
- Lexicographic selection of a temporary label
- Propagation principle over outgoing arcs
- All permanent labels correspond to efficient paths
- Pruning temporary labels on nodes by dominance



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Motivation and Questions

- Motivations: good base
 - to investigate the influence of an instance on the algorithm
 - to measure the impact of additional components on the algorithm
 - to develop an implementation to be integrated into vOptSolver
- Questions:
 - Concerning the maintenance of non-dominated temporary labels (operations of comparison, insertion, deletion) on nodes:

What is the added value of an advanced data structure for maintaining on nodes during the iterations of the algorithm?

Concerning the generation of temporary labels on nodes:

What is the added value of a two-directional strategy on the total number of temporary labels generated by the algorithm?

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 Concerning the generation of temporary labels on nodes:
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Observation

▶ Maximal number of labels (temporary and permanents) on 1 node:



- Maintaining non-dominated labels on nodes requires operations of comparison, insertion, deletion.
- ▶ A multi-dimensional data structure is then required for storing the information and facilitating these operations during the iterations of the algorithm.
- ▶ The data structures found in specialized literature in MOO are:
 - a linear structure
 - list, sorted or not
 - \rightarrow simple vs cost of the pairwise comparison
 - a tree structure

AVL-Tree (p = 2), Quad-Tree ($p \ge 2$), ND-Tree ($p \ge 2$)

 \rightarrow fast vs complexity for maintaining the structure

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ND-Tree

Andrzej Jaszkiewicz and Thibaut Lust, "ND-Tree-Based Update: A Fast Algorithm for the Dynamic Nondominance Problem". *IEEE Transactions on Evolutionary Computation*, vol. 22, no. 5, pp. 778-791, Oct. 2018.



Principle:

- to divide the objective space into hyperrectangles
- if a hyperrectangle contains too many points then it is divided

Parameters:

- $\sigma:$ maximal number of points per hyperrectangle
- $\delta:$ number of sub-hyperrectangles created when a hyperrectangle is divided

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ND-Tree: numerical experiments

▶ One ND-Tree on each node of the graph:



Linear list vs ND-tree for a grid graph. Cost values are in U[1; 100]

X axis: Number of nodes (gridSize × gridsize) — Y axis: CPUt (in seconds) in logarithmic scale — Results in average on 50 runs

 \Rightarrow ND-tree appears competitive against the linear list when the number of objectives and the number of nodes are high

▶▶ goto next section

Execution time for MOSP with 2 objectives





Execution time for MOSP with 5 objectives



3. On the strategy of label propagation

Observation

New assumption:

1-to-1 (source s to destination t) efficient paths



A random graph with clusters (200 nodes randomly generated, each node is connected with its 4 closest neighbors according to the e Euclidean distance) and 3 linear objectives. Cost values are randomly selected in the range U[1;300]

All efficient shortest paths (in red) between - the origin node (square in the south-west) and - the destination node (square in the north-east)

The triangles represent the maximum number of labels on a node

▶ Number of labels may grow significantly near the termination node *t*.

Alternative: a bi-directional strategy

- Well-known in single objective case (Nicholson 1966; Pohl 1969)
- Use two separated procedures:
 - a forward search from the origin node and
 - a backward search starting from the destination node
 - \rightarrow two search trees,

potentially expanding fewer labels than a single search

- Existing literature in MOP:
 - Demeyer et al., 2013 (4OR journal)
 p ≥ 2
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Main ideas:

- a forward and backward search (similar to the unidirectional algorithm)
- a stopping condition is based on the use of a vector of minimal values of objectives for temporary labels

Numerical experiments:

- up to 20 time faster for transportation graphs with 2 and 3 objectives (instances: sparse graphs representing transportation problems with hundreds of thousands nodes and links, average node degree between 2 and 3)
- mitigated for random graphs
- not pertinent for complete graphs and square grid graphs
- ⇒ performance of the strategy is dependant on the graph configuration and predicting the average speedup is difficult.

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Our ongoing attempt on the general case

- ▹ Observation: good results appear with a specific graph topology or when not considering a subset of X_E.
- Question: can we find a way to improve the computation time using a bi-directional strategy considering:
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- ▶ Proposals :
 - a separation of the graph in two sub-graphs in preprocessing
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Main ideas:

• compute a separation of the graph in two parts such that the source is in one sub-graph and the destination node is in the other one



- apply Martins' algorithm on each sub-graph
- merge the permanent labels existing at the frontier of the two sub-graphs



Difficulties :

- cost of merging of the paths
- are we sure to compute Y_N ?

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- Question: is it possible to find a way to separate the graph such that there is no paths crossing each sub-graph twice or more?
 - no in general in an undirected graph
 - maybe in a directed graph
 - *yes* in a "well-oriented" graph

- an example of "well-oriented" graph
- Remaining questions:
 - efficiency of a separation strategy in "well-oriented" graph?
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4. Summary

Conclusion and ongoing works

- $\rightarrow\,$ A novel context of using ND-tree for maintaining temporary labels
- $\rightarrow\,$ A learning on the bi-directional strategy
- $\rightarrow\,$ A (coming) open-source package dealing with several MOSP

PROS:

- ND-tree: interesting even with few objectives
- bi-directional strategy: interesting for transportation graphs

CONS:

- ND-tree: parameters to tune
- bi-directional strategy: predicting the average speedup is difficult

NOW:

- ND-tree: measuring the impact of σ and δ
- Bi-directional strategy: dealing with stated questions
- Label setting algorithm: working on others pending questions
- vOptSolver: releasing the MOSP.jl package

MOSP.jl awaited to be integrated to vOptSolver

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ூ https://vopt-ANR-DFG.univ-n	518 contributions in the last year		
	Oct Nov Dec Jan Feb Mar Apr May Jun Jul Aug Sep Oct		

http://voptsolver.github.io/vOptSolver/

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> Homepage of vOptSolver: http://voptsolver.github.io/vOptSolver/

> > Repository of vOptSolver: http://github.com/vOptSolver

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