The Problem of Spatio-temporally Constrained Motion Planning for Cooperative Vehicles

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Abstract. We describe the spatio-temporally constrained motion planning problem (STCMP) using the example of harvesting crop with multiple cooperative vehicles. The vehicles have to meet at rendezvous points observing time, location, orientation and velocities to interact. Due to vehicle constraints, the STCMP involves two combinatorial optimization problems that are restricting each other in space and time.

1 Introduction

Agricultural vehicles are getting more and more autonomous. Modern combine harvesters can follow a given path automatically using DGPS and drive-by-wire technology. However, there is a practical problem of unloading harvesters in full operation into service vehicles, which, in themselves, might work autonomously.

Fig. 1 shows a scenario with two such combine harvesters and one service vehicle. The latter is needed to unload the harvesters and transfer the crops to a resource point at the field border, which is assumed here to have infinite capacity. The harvester is unloaded while both vehicles drive parallel to each other. Harvesters are only able to unload to a vehicle driving left of them.

The vehicles may only move on tracks that are defined by the geometry of the field and the furrows. Thus, motion planning for the harvesters can be considered as sequencing of tracks and connecting them to a feasible path. Optimally, no harvester should ever have to stop and waste process time. To achieve this, all harvesters need to empty their grain tanks into a service vehicle before reaching their filling capacity limits. Thus, motion planning for the service vehicle has to use the planned paths, the capacity, the filling level and the harvesting performance for the harvesters and the average yield of the field to estimate optimal rendezvous points for overloading. It may be necessary to change a harvester's path to get a valid set of rendezvous points. Another constraint to the motion planning for a service vehicle is that it may only move across harvested area.

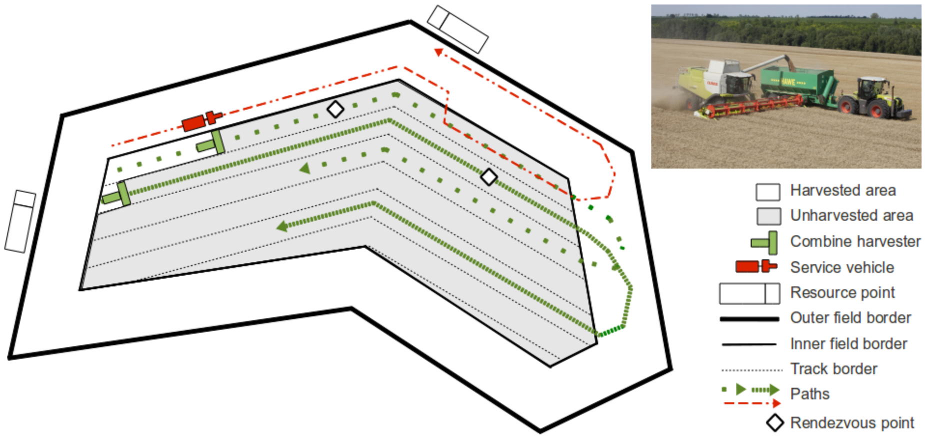

Fig. 1. The scenario of harvesting crop with multiple cooperative vehicles. The area between the outer and inner field border, the *headlands,* is considered to be harvested before the planning starts. The combine harvesters have to move parallel to the tracks; the service vehicle may additionally cross tracks at low speed.

The harvesters drive as fast as their harvesting performance and the effective yields at their locations allow. Due to non predictable local deviation of the yield, their speed is varying, and time and location of rendezvous points are likely to differ from the plan. Consequently, the execution of the plans has to be monitored, and replanning is needed when a tolerance limit is exceeded.

The emerging *spatio-temporally constrained motion planning problem* (STCMP) can be considered as the problem of optimizing the routing of tracks and the sequencing of resulting rendezvous points, given the constraints mentioned. However, the STCMP does not solely apply to the crop harvesting scenario. The planning of in-flight refuelling for a set of unmanned aerial vehicles can be considered a STCMP as well as a logistics scenario, in which forklifts have to pick pallets and load them on the trailor of a tractor at a given time and location.

In the remainder of this paper, we will give a more abstract specification of the harvesting problem, and we will argue why STCMP is a challenge for AI methods.

2 The STCMP Problem

A set of tracks covering a polygonal area has to be processed by several harvesters requiring a service after a varying distance and time. A collision free plan has to be created for the motions of the involved vehicles regarding that none of the harvesters should stop before the overall process is finished. This procedure contains two mutually dependent planning problems.

The first is the motion planning for the harvesters. All tracks have to be processed by a set of paths with minimal length or working duration, considering kinematic and dynamic constraints of the vehicles. When selecting a track sequence for a harvester, its range must be observed. When servicing is needed, the track left of the path has to be used, because the service vehicle may only pass harvested area. The result is a path for every harvester, each containing a sequence of tracks, combined with valid motions to connect them.

The second problem is, given the harvesters' paths, generate paths for the service vehicles with rendezvous points that ensure that the harvesters can always be served in time to avoid idle time. A rendezvous point is described by time, position, orientation and velocity. These parameters are constrained by the path of the harvester that gets served at the point, because the servicing is done while driving in parallel to each other, where the service vehicle has to drive on the left track next to the serviced harvester. If no valid path can be found because these points are badly selected, some of them must be changed. A rendezvous point can be shifted in time to keep its location on the path, or its location can be moved on the path to keep the rendezvous time. Another possibility to keep the time is to adjust the paths by changing the track order. The latter approach would affect the motion plan of the corresponding harvester.

For an accurate formalization different STCMP problems have to be further investigated. The following list summarizes the structure of the harvesting problem. A problem instance with the required data listed above is available at [5].

Given parameters ...
- geometrically / fixed:
  - outer field border *[polygon]*
  - inner field border and fixed obstacles*[polygon with holes]*
  - headlands (area between outer and inner field border) *[polygon with inner ring]*
  - parallel tracks *[polylines]* with fixed width (working width) covering the area enclosed by the inner field border
  - resource points *[points]* at the field border
- vehicle specific
  - kinematic and dynamic constraints (max. turn radius, ac-/deceleration, speed)
  - capacity *[kg]*
  - unloading performance *[kg/s]*
  - max. harvesting performance (*for harvesters only*) *[kg/s]*
  - working width (*for harvesters only*) *[m]*

... and additional constraints ...
- harvester should not stop during the harvesting process
- harvester can only unload to the left side
- unloading must be finished inside inner field border
- inside the inner field area harvesters may only move along tracks
- service vehicles may additionally cross tracks at a low speed
- service vehicles may only move on harvested area
- complete field has to be harvested

... and non predictable parameters
- real yield map of the field *[kg/m^2]* – planning is based on an estimation

Find
- rendezvous points *[points with time, position, orientation and velocities]*
- paths *[set of points with position, orientation and desired time]* consisting of a

series of tracks connected by turning manoeuvres in the headlands and representing a valid sequence of motions for all vehicles

3 Why the STCMP Problem is a Challenge

The STCMP problem is characterized by the tight interleaving of spatial constraints (tracks, field borders, asymmetry of harvesters, (non-)harvested area, etc.) and temporal constraints (speeds, capacity limits, expected yields, unload rates, etc.) plus the fact that the plan needs to be adapted on-line, depending on effective yields and vehicle performances.

Solutions for the *individual* aspects of this are available. [3] covers motion planning of single vehicles with different constraints. When multiple vehicles are involved, decentralized approaches are often used in which every vehicle's path is planned separately. Bhattacharya et al. [1] proposed an algorithm to optimize the planned paths of multiple robots to fulfil pairwise constraints. Their algorithm does generate rendezvous points for mobile robots at given times by adapting their paths. As the time of rendezvous points is not fixed but has to be optimized in the described problem, this algorithm can not be applied to the STCMP.

In agricultural planning, Bochtis et al. [2] proposed a hierarchical decomposition of fieldwork operations to break down the complexity into smaller, independent, well known problems from operations research. The resulting problems are assignment of machines to fields, field area coverage, the machines' motion generation, and the routing of service vehicles. An STCMP only covers the later two points, which we described as spatio-temporally constrained motion planning for cooperative vehicles. When creating the motion plan for the service vehicles, [2] do not allow the paths of the working machines to be changed, but use the resulting fixed time windows and locations as static inputs. The drawback is that only the locally optimal subplans for the disconnected subproblems are calculated assuming a fixed result for the other subplans. But due to their interdependency, the resulting global plan is in general suboptimal.

There is currently some research about *interpreting* spatio-temporal data. One example is the project Co-Friend [4], in which heterogeneous sensor data is used to track objects in space and time to learn and recognize activities. However, combining planning and scheduling of actions is not a focus in this research area.

Scheduling and motion planning alone are solvable with state-of-the-art methods. The STCMP problem can be modeled and solved in principle using any of the standard general methods of AI or OR, such as (T)CSP or LP/LIP. However, problems with tight interleaving of temporal and spatial constraints seem to be scarcely investigated. Moreover, the online re-planning requirements from unexpected yields and by possible failure to act as planned would make very efficient algorithms desirable. We are not aware that such efficient algorithms exist for the problem. We therefore propose it as a challenge problem to the AI community.

Acknowledgments. This paper was created within the project marion. This research and development project is funded by the German Federal Ministry of Economics and Technology (BMWi) and supervised by the project management agency for multimedia, German Aerospace Center (DLR), Cologne, grant no. 01MA10027.

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