Interval Programming: A Multiple Criteria Decision Making Model for Autonomous Vehicle Control

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The Problem: We want to create a new model for capturing and optimizing over multiple competing objectives that characterize autonomous vehicle control in complex, dynamic, and unpredictable environments. In particular we want from our model:

- No restrictions in underlying objective function form: restrictions or assumptions of linearity, convexity etc. are unrealistic in the applications of interest.
- The ability to simultaneously optimize over objective functions reflecting long-term, high-level plans, as well as short-term reactive needs *in each decision*.
- Globally optimal solutions.
- Solutions in real-time, i.e., satisfying control loop requirements.

Motivation: The two motivating applications are autonomous control of unmanned underwater vehicles and a maneuver decision aid for manned underwater vehicles (US nuclear submarines). The first is challenging due to the complete lack of a man-in-the-loop, and the second is challenging since the decision recommendations potentially affect the lives of the crew and generated decisions must compete with a domain expert (a submarine commander). Both applications are complicated by the presence of a multitude of competing objectives, extremely large state and action spaces, and an unpredictable and rapidly changing environment.

Previous Work: In recent years, the notion of Multiple Criteria Decision Making (MCDM), [4], has been explicitly linked to the problem of action selection in autonomous vehicle control, [5, 6, 7]. The separation of objectives reflects the influence of the behavior-based control architecture, [1, 2, 3], and is an effective means for dealing with what would otherwise be an extremely large state space.

The problem is that the MCDM approach to action selection requires that each behavior produce an objective function defined over the action space, which is typically the Cartesian product of each control variable's domain and can be quite large. To deal with this, action selection can be broken up into separate decisions for each variable [7] or restricted to a small number of control variables with small domains [5, 6]. The former approach can lead to unacceptable errors, while the latter restricts applications to but a few simple control variables.

Approach: The key idea in the interval programming (IvP) model is the use of piecewise defined objective functions, where each piece is given by an *interval* over decision variables and contains an interior function. Collectively the pieces approximate some other underlying function, as depicted in figure 1. Solving an IvP problem with several such objective functions, involves a search through the space of piece combinations, one from each function. The search through this space, rather than the decision / action space is what makes the claims of *global* optimization possible.

In making vehicle motion decisions, an IvP problem is created and solved in each pass through the control loop. Weights are assigned to different objective functions based on situation context, as in Figure 2, where the two paths ownship takes to its destination differ primarily in the importance of keeping a good distance from the contact shown. The use of piecewise defined functions allows for a healthy mix of *flexibility* which traditional analytical methods lack, *speed* which exhaustive voting methods lack [5, 6], and *accuracy* which a variety of simplification techniques (e.g. [7]) lack. The distribution of pieces is not typically uniform, allowing more pieces to be dedicated

$$f(x,y) =$$

$$((1 - \frac{(\sqrt{(x-81)^2+(y-146)^2}-200)}{1000})^2 * 200)+$$

$$((1 - \frac{(\sqrt{(x-266)^2+(y-278)^2}-353)}{1000})^{12} * 200)$$

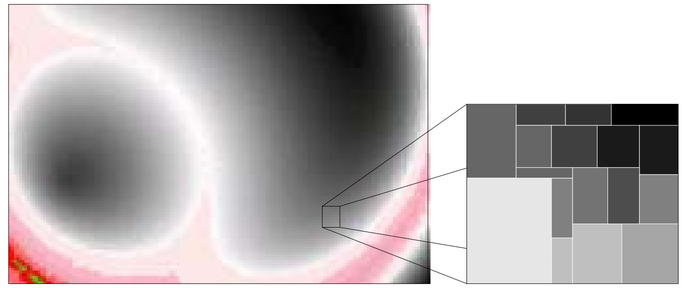

Figure 1: The analytical function (left) approximated with 15,000 pieces (right) with linear interiors.

Figure 2: Ownship maneuvers to destination while reacting to a moving contact. Each position marker reflects one iteration in the control loop.

to more interesting areas of the function. Furthermore, a powerful feature is that the intervals that define the piece shapes, may also be intervals over *functions* on the decision variables. This is key in merging functions describing long-term plans with those describing short-term reactive needs.

Impact: The IvP model will be robust and powerful enough to bring a new level of multi-objective vehicle control not yet available, but absolutely necessary in the applications of interest (see Motivation above). It also makes viable an alternative to the predominant single state-policy approach to modeling mobile physical agents. Furthermore, a large portion of research support is aimed at using the IvP model in Multi-disciplinary Design Optimization (MDO) in large-scale engineering projects (e.g. vehicle design), where different design objectives compete / conflict in a large design space.

Future Work: Ongoing work is primarily aimed at pushing the speed envelope on larger, more expressive problems. While current IvP performance has reached a level sufficient for vehicle control in our simulators, the interest in progressively higher dimension problems motivates the work for improved performance. A key to future performance gains is the improved use of pieces with nonlinear edges.

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