

Planning Robot Control Parameter Values with Qualitative Reasoning*

Stephen F. Peters+, Shigeoki Hirai‡, Toru Ornata‡, and Tomomasa Sato‡

+Jet Propulsion Laboratory
California Institute of Technology
4800 Oak Grove Drive
Pasadena, California 91109, USA

‡Electrotechnical Laboratory
1-1-4 Umezono, Tsukuba
Ibaraki 305, JAPAN

Abstract

A qualitative reasoning planner for determining robot control parameters to drive manipulation actions has been developed, integrated into a telerobot system, and demonstrated for a match striking task. The planner consists of a qualitative reasoner and a numerical execution history which interact to jointly direct and narrow the search for reliable numerical control parameter values. The planner algorithm, implementation, and an execution example are described. The relationship to previous qualitative reasoning work is also discussed.

1 Introduction

Model-based intelligent robotic systems typically make use of numerical—especially geometric—representations of the robot and the workspace when planning robot motions in detail. Such plans, even after successful computer simulation with the model, frequently fail to achieve the intended results when actually executed by the robot. Approaches to overcoming this problem include precise calibration, more detailed modeling, error recovery, and human intervention.

The qualitative reasoning paradigm can help overcome some of the difficulties associated with error and uncertainty by reasoning about the behavior of the physical equations describing a system, thereby providing the system with intelligence about its own behavior and how to achieve desirable states.

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A considerable amount of theoretical work has been done on qualitative reasoning [De Kleer and Brown, 1984, Forbus, 1984, Kuipers, 1984, Kuipers, 1986, Sacks, 1990], but much of this work has focussed on simulation and has not specifically addressed planning issues. A topic currently receiving attention as real applications are attempted is the coordination of qualitative and numerical elements [Kuipers and Berleant, 1988] to achieve a complete reasoning system.

This paper describes a qualitative reasoning planner which has been developed and integrated into the MEISTER (Model Enhanced Intelligent and Skillful TELEoperational Robot) system [Hirai and Sato, 1988, Hirai *et al.*, 1990] and has been demonstrated for a match striking task. A qualitative reasoner and a numerical execution history work together to search for effective control parameter values. The present work makes use of earlier studies on the application of qualitative reasoning to manipulation planning and the relevant physical equations [Ornata *et al.*, 1987, Hirai *et al.*, 1989J.

In the following sections we describe a match striking network and the qualitative math used. Then the planning algorithm is presented. Descriptions of the telerobot, workspace, and an execution example follow. Finally, this work is placed in context with the qualitative reasoning literature.

2 A Network for Match Striking

A qualitative reasoning network was proposed [Hirai *et al.*, 1989] to represent a single match striking motion. The network represents the physical equations describing bending moment on the match stick and the total accumulated heat at the contact point of the match head with the striking surface. The physical parameters considered were the force perpendicular to the striking surface, the velocity along the striking surface, and the angle from perpendicular that the match is inclined in the direction of motion (figure 1). The possible outcomes were match

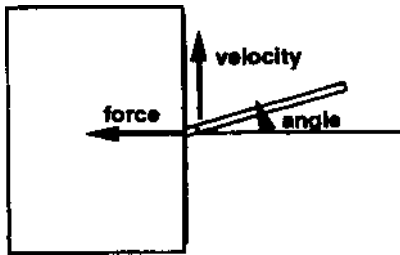


Figure 1: Physical Parameters for Match Striking

breakage and match ignition, represented as the absolute value of bending moment on the match and the amount of accumulated heat respectively.

The proposed network has been extended here (figure 2) to include an additional preliminary motion to the starting position and force. Representations of the parameters actually used for controlling the ETA2 robot and the results of actual trial execution—match breakage and match ignition—were also added. Note that the match can break as a result of either motion. Both actions are in the same network because they share control parameters related to angle and force.

In the figure, nodes with wide shaded arrows indicate the interface with the external system; other nodes are entirely internal to the qualitative reasoning network itself. The robot control system does not support servoing to force and velocity during the brief match striking action so the corresponding monotonically increasing digging depth (distance of position control trajectory into the match box) and jumping gap (distance between servo samples) robot control parameters are used. Angle, digging depth, and jumping gap are all parameters controlled by—and therefore known to—the robot system. Match ignition and breakage are results observed by the human operator or an appropriate sensing system.

3 Qualitative Math with "Likelihoods"

Eight network node types are defined: sum, product, M+, negative, absolute-value, constant, control, and threshold. Each node logically consists of two parts: (1) a value for a parameter and (2) the relationship between the parameter itself and its cause nodes. This relationship provides for reasoning in both directions through the network. Relationships with effect nodes are contained in those effect nodes as relationships with causes. Ultimate cause nodes, control and constant, have a relationship part of nil.

Four qualitative values are defined: +, 0, -, and ? for unknown. All nodes in the network have qualitative values, and the externally visible control and threshold nodes have additional actual values. The qualitative value of each control node is the sign of the actual numerical value. The qualitative value of each threshold node is + when its actual logical value is true, indicating that an unknown real number has exceeded an unknown positive threshold, and - when the actual value is false.

Relation-tables (figure 3) have been constructed to represent the qualitative function for each node type. Reasoning functions use these tables both to propagate

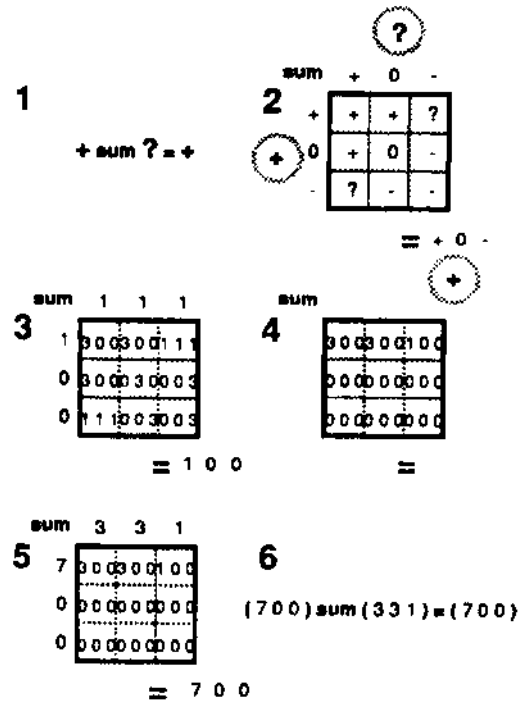


Figure 4: Example of the Computation of likely-potentials

current qualitative values through the network and for planning changes to control values for subsequent trials. Values in shaded triangles in the figure are qualitative values of the parameters; other values are qualitative values of numerical change consistent with the associated shaded values.

The heart of the qualitative math engine is the likely-potentials function, described through an example below. This function is used both for propagating qualitative values through the network and as an aid in selecting among alternatives during the planning process. The analogous likely-change-potentials function is used for propagating and planning change.

Figure 4 illustrates the computation performed by the likely-potentials function for the example of the sum relation, given inputs + and ? and a result of +. A triple of potentials is assigned to each entry in the table, representing the relative likelihoods that a result of +, 0, and - will occur when inputs match the table entry. These triples always add up to 3, embodying an assumption that each combination of inputs is equally likely. Triples defined for results +, 0, -, and ? all appear in step 3 of the example. Three possibility factors are assigned to each of the input and result arguments, with 1 representing the possibility of a match with the values +, 0, and -, and 0 representing a mismatch. For inputs, these factors are multiplied into all three triplet values of the table entries of corresponding rows and columns; for the result, the factors are multiplied into the corresponding triplet values of each table entry. The resulting table is shown in step 4 of the example. The final likelihood potentials returned by the function are, for the inputs, the sums of all triplet values in the rows and columns and, for

8. Control nodes (ultimate causes) which are at physical or contextual limits are marked with the at-maximum and at-minimum properties as appropriate. These properties are propagated toward effects and depend upon the actual relations in the network.

Plan qualitative change, propagating through the network from all must-change results toward ultimate cause nodes.

- 9a. Planning for this trial is complete if all nodes marked must-change are changed and at least one change to an ultimate cause node has been made.
 - 9b. Propagation of this thread is complete if a change has already been planned for one of the causes of this node.
 - 9c. Select an immediate cause of this node to propagate change through according to the following selection preferences:
 - highest nodes marked must-change
 - intermediate nodes not marked
 - low nodes marked resist-change
 - very low nodes for which a change of 0 has the highest likelihood potential
 - lowest nodes for which no change is possible consistent with the current known values, changes, and at-maximum and at-minimum limit constraints
 - lowest nodes marked cycle-back
 - 9d. For the selected cause, choose the change (+ or -) which has the higher likelihood potential.
 - 9e. Make the change to the selected node and propagate.
- Record, choose numerical value, and execute.
10. Put the last trial and this plan (goals, numerical control values, results, and qualitative plan) on the history.
 11. Choose a numerical value to use in the next trial (within the contextual numerical range) for the control parameter selected for change.
 12. Execute the newly planned trial.

5 Utilization of Numerical Experience

The most important feature of the planner is the mechanism of coordination of qualitative and numerical information for planning.

Qualitative information is embedded within the numerical execution history in the form of a qualitative vector at a point in the numerical search space which indicates the qualitative direction of the goal region from that point. Numerical information influences qualitative search by asserting constraints on qualitative motion when numerical limits are exceeded.

The key is the use of limits. For the 2-dimensional example in figure 6, the limits visible from a most recent trial are the physical limits above, below, and to the right, but to the left, an earlier trial asserts a tighter

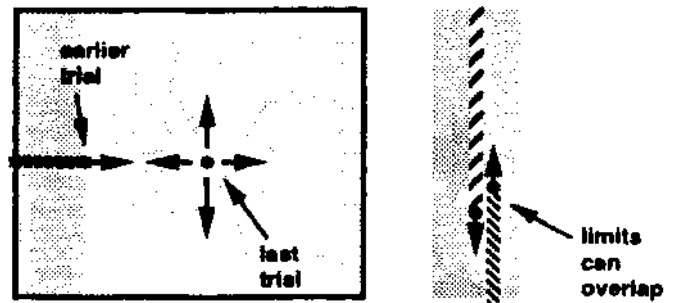


Figure 6: Control Limits Visible from a Point and Overlap

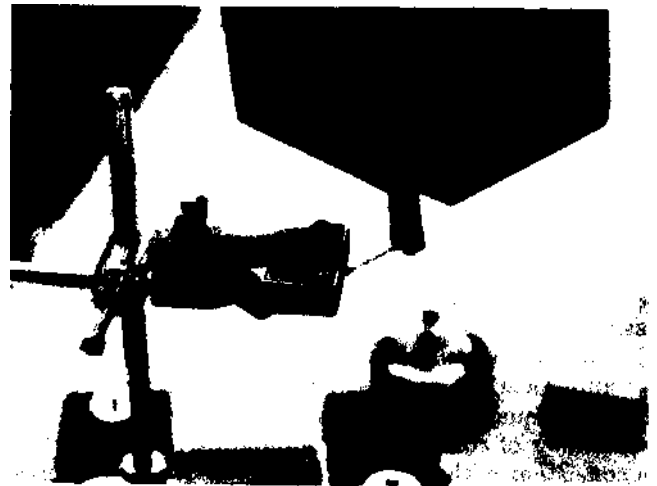


Figure 7: Just Before the Strike Motion

limit. Only the region in white is considered for the next trial. When limits overlap, the planner must consider another direction. The qualitative reasoning engine easily handles limits by zeroing out the likelihood potentials for changes in nodes which would attempt to exceed limits.

6 The MEISTER Telerobot and Experiment Workspace

The qualitative reasoning planner and match-striking network described have been integrated into the MEISTER (Model Enhanced Intelligent and Skillful Teleoperational Robot) telerobot system [Hirai and Sato, 1988, Hirai *et al.*, 1990].

MEISTER hardware includes the 6-DOF ETA2 slave manipulator, a Lord gripper with force/torque sensors at the base of each finger, a 6-DOF master manipulator, several cameras, some on pan-tilt heads, and several monitors including a Sun workstation and a custom Multi-Media Display, which supports real-time stereo graphics overlay.

MEISTER high-level software is written in object-oriented EusLisp [Matsui and Inaba, 1990]. The match-striking network was added into the match-box object.

Among a variety of objects in the workspace for a flame-test chemical experiment is a match box in a clamp on a stand and several matches lined up for easy grasp-

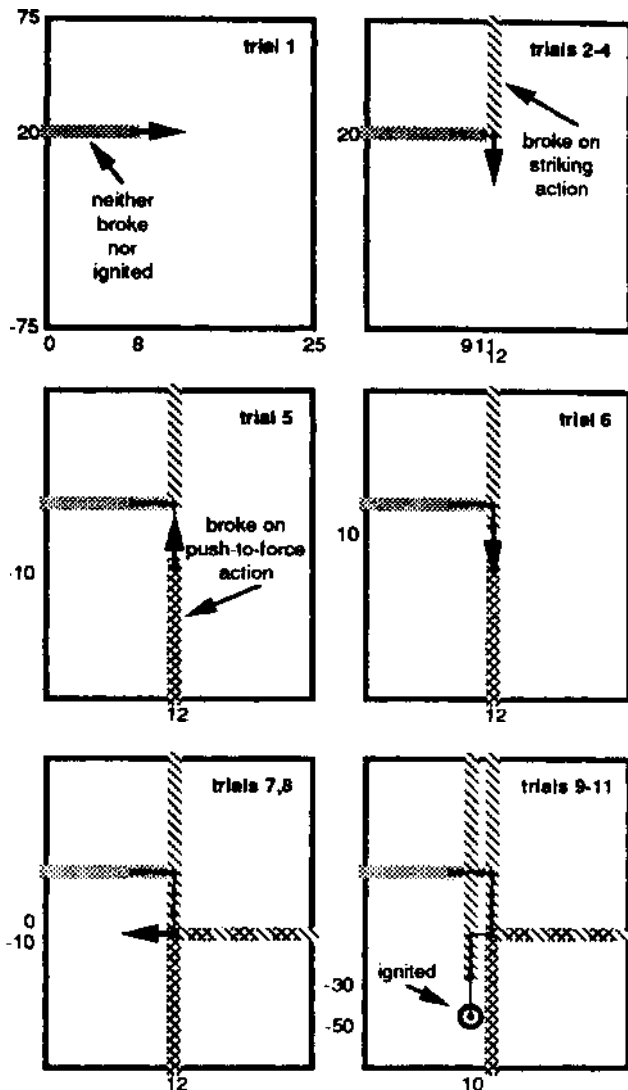


Figure 8: Match Striking Example

ing by the manipulator. Figure 7 shows the robot just before executing a striking motion.

With EusLisp running on a Spare station equipped with 24Mb of memory and evaluating uncompiled qualitative planner lisp code, it took less than 3 seconds to plan each trial. The qualitative reasoning software consists of approximately 2000 lines of general-purpose qualitative reasoning code, 200 lines of match-striking network definition, and roughly 200 lines of MEISTER interface code.

7 A Match Striking Example

Figure 8 presents the data and the search performed during actual execution of the qualitative reasoning planner while directing the robot for the match-striking task. The vertical dimension in each frame is the angle in degrees and the horizontal dimension is the digging depth in millimeters. All frames represent the plane where the jumping gap is at the maximum physical limit of 20mm.

The match neither ignited nor broke upon a first trial

at a digging depth of 8mm and angle of 20deg. The qualitative reasoning planner determined that the digging depth should be increased. This trial is represented by a point and an arrow. The half-tone bar indicates a limit due to non-ignition/non-breakage visible along the angle=20deg line. The 2nd and 3rd trials were similar, successively increasing the digging depth. The match broke upon the striking action of the 4th trial. At this point, the planner decided to decrease the angle, asserting a limit (striped bar) along the digging depth=12mm line. A new match, on the 5th trial, broke on the move to the starting force and position, at an angle of -10deg. Again the planner asserted a limit (cross-hatched bar) visible from the 12mm line, but in the opposite direction. The angle at this digging depth must now lie between 20deg and -10deg. Breakage on the striking action in the 6th and 7th trials further narrowed the angle range until on the 8th trial the angle was fixed at -10deg. Notice that there were two trials at this precise location in the control space with different results. Now the qualitative reasoner was constrained from changing the angle and decided to reduce the digging depth instead. The 9th and 10th trials both resulted in breakage on the striking action and an 11th trial was successful at an angle of -50deg and a digging depth of 10mm.

This example illustrates the narrowing of numerical search and the need for contextual limits to achieve success. Overlapping of failure regions is also evident.

8 Relationship to Other Qualitative Reasoning Work

Sacks [1990] characterized qualitative simulation as a trajectory through phase space. Here, we view planning similarly as a search for a path through the space of control parameters.

De Kleer and Brown [1984] mentioned the use of additional network nodes to represent landmarks. The constant node (figure 2) is just such a landmark corresponding to the angle where, during the striking motion, the force is directed along the match stick and the bending moment is zero.

Forbus [1984] uses the term "quantity space" to represent a relative ordering of comparable values. A single representation is used to express qualitative values of multiple physical parameters. In the present work, the state of the entire system is represented in terms of ranges of control parameters, ranges whose values vary with position in the control space.

Kuipers [1984, 1986] uses a network to describe the physical equations governing the system, and defines a set of network node types. We do the same here, adding, in the same spirit, absolute-value and threshold node types. Our approach is similar to Kuipers', with differences deriving from the use for planning rather than simulation. We use only the values +, 0, and - instead of a system of general intervals, and so do not generate landmarks during simulation. Indeed, we are concerned only with where the goal region is relative to any "current" region, and are not interested in the topologies of paths through the various regions as embodied in the series of

intervals of Kuipers' simulation. Also, the development of qualitative math functions which return "likelihood potentials" in place of simple Boolean values is a direct consequence of their application to planning.

Kuipers and Berleant [1988] propagate constraints on the numerical value each node in the network can take. We do not attempt to imbue network nodes whose numerical values are not externally visible with numerical information beyond the constraints of the qualitative representation.

9 Conclusions

A simple planner utilizing qualitative reasoning and numerical experience has been developed and integrated into the MEISTER telerobot system and demonstrated for a match striking task. The primary contribution of this work is the identification of a mechanism utilizing limits for coordinating numerical and qualitative information to direct search. Qualitative math functions which return "likelihood possibilities" facilitate the use of qualitative constraints in the planning process.

Directions for the future include work on more robust search algorithms, exploring expanded use of likelihoods for planning, and more extensive testing of applications to a variety of tasks.

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