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Qualitative reasoning about physical systems: a return to roots

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1. What qualitative reasoning is

Seven years ago the Journal *Artificial Intelligence* published a special volume entitled "Qualitative Reasoning about Physical Systems" [3]—qualitative reasoning for short. This special volume proved to be a watershed for qualitative reasoning research, which inspired a decade of ferment and innovative exploration. Now qualitative reasoning has reached another watershed, by returning to its original roots of coping with fundamental engineering tasks. [1] As both editors feel that addressing real tasks is crucial to the success of the qualitative reasoning enterprise, we decided that now would be a judicious time to recognize and explicitly encourage this focus—through this special volume.

This introduction conveys our personal perspective on what qualitative reasoning is about, what are some of the common misconceptions, and where we would like to see the research headed. The motivation for qualitative reasoning arose predominantly from research on engineering problem solving, which sought techniques for automating engineering practice for a variety of important tasks—circuit analysis and parameter selection [15,42,41], the diagnosis and teleological description of bipolar amplifiers [11], tutoring systems for steam plant operation [19], the design of MOS memory buffers [48], and the interpretation of geological structures [38].

It quickly became clear that, if we want to capture the skills of an engineer or technician we must do far more than build bigger simulators (such as Spice [44]) or equation solvers (such as Macsyma [28])—the

[1] This direction was particularly evident at the most recent Qualitative Reasoning Workshop [24].

computer must somehow embody the common sense of these experts.[2] While these traditional tools are crucial, much of an engineer's energy is devoted to problem formulation—deciding when and how these tools are applied—and interpretation—identifying the significant features of the analysis results and evaluating their impact with respect to the task being performed (e.g., identifying faulty components during diagnosis or critical paths during design).

Thus *the heart of the qualitative reasoning enterprise is to develop computational theories of the core skills underlying engineers, scientists, and just plain folk's ability to hypothesize, test, predict, create, optimize, diagnose and debug physical mechanisms.* This perspective both gives us the means to evaluate new theories (do they address significant components or yield significant improvements on these tasks?) and places to look for new ideas (e.g., engineering practice).

From the start the ability to explain how a device works was perceived as a core skill—due to its value in pinpointing responsibility (e.g., during diagnosis [7,30,37]). Early papers concentrated primarily on the qualitative, causal explanation of instantaneous change [10,21,30,31]. A watershed of the first special volume was the ability to generate causal explanations for time-evolved behavior [11,14,19,48].

Progress since the first special volume has been extraordinary (see [47] for examples). The community has become substantially more sophisticated mathematically—formalizing many aspects of qualitative representations and reasoning techniques. Research has forged a link between qualitative reasoning and traditional numeric and analytic techniques. And work has branched into a wide variety of new forms of reasoning and ontologies.

There have been growing pains—at times the link to tasks and explanations seems all but lost. While many new reasoning techniques have been proposed, only a few have used tasks to explicitly establish their importance or to evaluate their successes and shortcomings. The early work has been reinterpreted by some as being about event-driven simulation with qualitative landmarks—not explanation—and a subset of the community has pursued this direction without providing a compelling motivation or performing an evaluation with respect to tasks.

The papers in this special volume demonstrate a shift in focus away from direct extensions of qualitative simulation and envisionment, towards the explicit treatment of tasks that elucidate important new reasoning techniques.

Several of the papers are directly about tasks: Two are concerned with aspects of diagnosis—one proposes the use of temporally abstract behaviors

[2]See the introduction to [47] for a longer discussion of this.

to avoid costly reasoning about temporal details (Hamscher), and a second applies qualitative envisionment to data interpretation (DeCoste). A third focuses on encoding the numerical exploration process of an expert dynamicist, allowing the expert to be pulled out of the loop (Yip).

Two papers formalize new reasoning techniques that arose out of explicit research on tasks. The paper on order of magnitude reasoning (Raiman) arose from the difficulty of dealing with tolerances in analog diagnosis, and the intuition that symptoms are significant deviations from normal behavior [5]. The work on hybrid symbolic algebra (Williams) arose from the task of verification during conceptual design [50], and the inability to show that predicted behaviors will occur, using purely qualitative techniques.

The papers by Addanki et al. and Falkenhainer/Forbus are two examples of a large body of research breaking ground into the area of modeling—including model selection [46], composition [29], abstraction [51] and compilation [4,12,17]—an area essential to progress in tasks like diagnosis [8]. And of the three papers concerned directly with envisionment and qualitative simulation, (Kuipers et al., Forbus et al., Joskowicz/Sacks), the first is a clear formulation that builds upon earlier work on higher-order derivatives [13,48], and the last two branch into the exciting new subarea of kinematics and spatial reasoning.

2. What qualitative reasoning is not

Like any exciting new field of study, qualitative reasoning is in constant ferment, with rapidly changing and often inconsistent goals and perspectives. This has made the field very exciting, but it can leave an observer (and even participants) confused about the current progress, predominant beliefs and aspirations of the field. In this section we hope to shed light by examining some of the more common misconceptions (e.g., as raised in [18,34]).

Note that several of these misconceptions were introduced by early writings in the field (including our own), which were groping with "What is an appropriate focus for qualitative reasoning research", given a broad, and sometimes incompatible set of possibilities. It is not our intent here to defend any early writing, but to convey our current thoughts on the topic, and to convey what we believe to be the predominant directions of the research community:

Misconception 1. *Qualitative reasoning eschews quantitative information.* Some researchers outside the community take the term "qualitative reasoning" to be an implicit exclusion of quantitative information—numeric or symbolic [18]. This is by no means the case. The first application of qualitative reasoning was its use to guide the appropriate application of

quantitative analysis [9], and the coupling of qualitative and quantitative information has been a continuous topic ever since.

The papers in this special volume demonstrate the importance given to coupling qualitative and quantitative. Raiman strengthens the qualitative calculus with an order of magnitude algebra, while Williams argues that a qualitative/quantitative algebra coupled with symbolic manipulation is the key to overcoming certain well-known problems with purely qualitative formalisms [23,40]. Both Forbus et al. and Joskowicz/Sacks argue for the necessity of quantitative metric spaces during geometric prediction, and the approaches in these two papers, along with those by Yip and DeCoste, extract qualitative features from quantitative data. Furthermore, Yip's use of qualitative knowledge to guide numerical simulation is directly in the spirit of [9], mentioned above. Finally, the two approaches to model selection, by Addanki et al. and Falkenhainer/Forbus, are explicitly applied to both qualitative and quantitative models. There is an even larger body of work on incorporating quantitative information not represented. This includes interval arithmetic reasoning [33,39], its application to temporal prediction [25,38,49], the integration of numeric simulation [2,20], and the use of piecewise linear [32], and order of magnitude reasoning [6,26,27,45].

Misconception 2. *Qualitative reasoning eschews sophisticated mathematics.* This is a refinement of the above claim. It suggests that, while qualitative reasoning does admit quantitative techniques, it is concerned only with the general, common sense techniques used by layman (e.g., arithmetic) [34]. It is true that qualitative reasoning has focused primarily on general, "common sense" techniques. However, it has not been the intent to segregate or exclude more sophisticated mathematical tools. We would like to encourage the use of whatever tools are the most appropriate for the task. And we view work in recent years to incorporate results in traditional symbolic algebra, interval arithmetic and algebra, numeric simulation and dynamics as an important trend.

But an important caveat is that a mathematical tool should not be judged better simply because it provides more information. In the late 1970s the attempts to apply Macsyma—a moderately sophisticated technique—to circuit analysis and synthesis [15,42] showed that advanced techniques can carry with them an extreme computational cost, which prevents them from being used indiscriminantly. This experience taught us three lessons, first that an expert is not the one with the more sophisticated mathematical tools, but the one who knows which tool—a scalpel or axe—is most appropriate for the task at hand. Second, that for many tasks or portions of tasks one can get away with suprisingly little information and extremely weak inferences; thus the cost in acquiring much more precise information is sometimes avoidable. Third, like curare in medicine, the more computationally advanced

techniques can be extremely valuable, but are best used with moderation.

These three lessons have had a significant impact on both of our research. We believe that through qualitative reasoning, an engineer identifies where the appropriate tool is required. For example, ambiguities during qualitative analysis indicate places where more quantitative techniques are required [48]. Likewise the research methodology that we and others have pursued is to push the use of weak, qualitative information as far as it can go, and to use its failure (both in terms of expressivity and computational cost) to better understand both what additional knowledge is required and how it is best applied. Its suprising that what we perceive as progress—identifying where a set of techniques fail, and thus require additional knowledge—is taken by some as the failure of the qualitative reasoning endeavor [34].

Misconception 3. *Qualitative reasoning is a theory of naivism.* This is a different slant on the no advanced mathematics misconception, where "naivism", carries with it the connotation of endorsing faulty reasoning and abandoning existing scientific and mathematical theories.

It is true that work in cognitive psychology on mental models [22] has tried to model, for example, how school children learn physics in the context of developing better educational tools. And of course there is Pat Hayes's "naive physics manifesto," which is a reaction against the study of blocks world micro-theories, and argues that research in automated theorem proving should instead be driven by real domain theories. However, while we believe both to be worthy endeavors, the majority of the research has been driven by engineering problem solving or some other form of expert reasoning (e.g., medical diagnosis).

Misconception 4. *Qualitative reasoning is inventing a new physics.* This often goes along with the naivism claim. While some researchers early on used principles or representations inconsistent with traditional formalisms [1,19], many have paid careful attention to tying qualitative reasoning formalisms to existing theories of physics—circuit theory and physical system dynamics [14,48], kinematics (Joskowicz/Sacks, Forbus et al.) and thermodynamics [36]—and mathematics—calculus and analysis [14,48], differential equations [23,45], algebra [17,43] and (Williams), interval algebra [33,40] and dynamics [32] as well (Yip).

Misconception 5. *Qualitative reasoning is just event driven simulation.* Some argue that qualitative reasoning is just event-driven simulation using finite landmarks [34]. While this might be an adequate characterization of the work on QSIM [23] and some of its successors, it should not be equated or confused with the goals of the larger community. First, the heart of qualitative reasoning is capturing the core skills to perform a variety of tasks.

Simulation is just a small fraction of a broad set of skills currently being pursued, including order of magnitude reasoning, qualitative symbolic algebra, model selection/composition/abstraction/compilation, sensitivity and comparative analysis, guided numerical exploration, and limited forms of propositional and terminological reasoning.

Second, even if we concentrate just on qualitative envisionment/simulation, describing them as event-driven simulation with qualitative landmarks fails to capture the essential characteristics of techniques like QUAL [11,14], qualitative process theory [19], temporal qualitative analysis [48] and temporal constraint propagation [49]. These techniques were developed with the belief that explanation of time-varying behavior is a core skill. While traditional simulation and analysis tools tell us *what* behavior occurs, what most distinguishes these four qualitative reasoning techniques is the ability to explain *how* the interesting aspects of the behavior came about. This is important to tasks such as diagnosis and design which require reasoning about the connection between internal mechanisms and behavior. Given these points, event-driven simulation with landmarks captures only a fraction of what qualitative reasoning is really about.

3. Wither qualitative reasoning?

In the early 1980s the community made a bet—that qualitative reasoning is at the core of an engineer, scientist or just plain folk's ability to perform a wide variety of tasks. While there is no one best way to identify and explore new core skills, it is money lost unless we take tasks seriously. This does not mean simply adding boiler plate to the beginning of our papers about the wonders of qualitative reasoning with respect to diagnosis, design or automated tutoring; rather:

- ... *we need to perform task analyses of reasoning techniques.* We must be careful not to assert without justification that a new qualitative representation highlights interesting features, nor should we argue the superiority and sophistication of our techniques because they are more precise. Rather, we need to carefully analyze the tasks we are serving—both to argue that our reasoning techniques address significant, unsolved problems with respect to the state of the art in those task areas, and to argue why our qualitative representations and techniques produce the right information.
- ... *we need to explicitly perform research on tasks.* It is very difficult to assess what types of reasoning are truly important for a task without simultaneously developing a computational theory of that task. Likewise, it is difficult to assess the hypothesized importance of

a reasoning technique without explicitly applying it to the intended task. In the editors' recent experience with tasks, what was most crucial (e.g., minimum entropy and probabilistic, best-first search for diagnosis [16], and qualitative algebraic and terminological reasoning for design [50]) turned out to be very different from what we anticipated. Thus, explicit research on tasks also provides fuel for identifying important new forms of reasoning.

- ... *we need to participate in task oriented communities.* A community, like qualitative reasoning or knowledge representation, concerned with an agent's core reasoning skills is certainly crucial to the AI pursuit. Nevertheless qualitative reasoning cannot exist as an insular community. The community's interests are simply too diverse to provide any task proper attention. Nor are the techniques of qualitative reasoning sufficient in themselves to perform any one task. Instead, the critical attention and diversity of techniques can only be achieved by participating in task oriented communities (e.g., model-based diagnosis, design, intelligent tutoring).

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