Improving HBM Affordability: A High-Level Language for Cognitive Architectures

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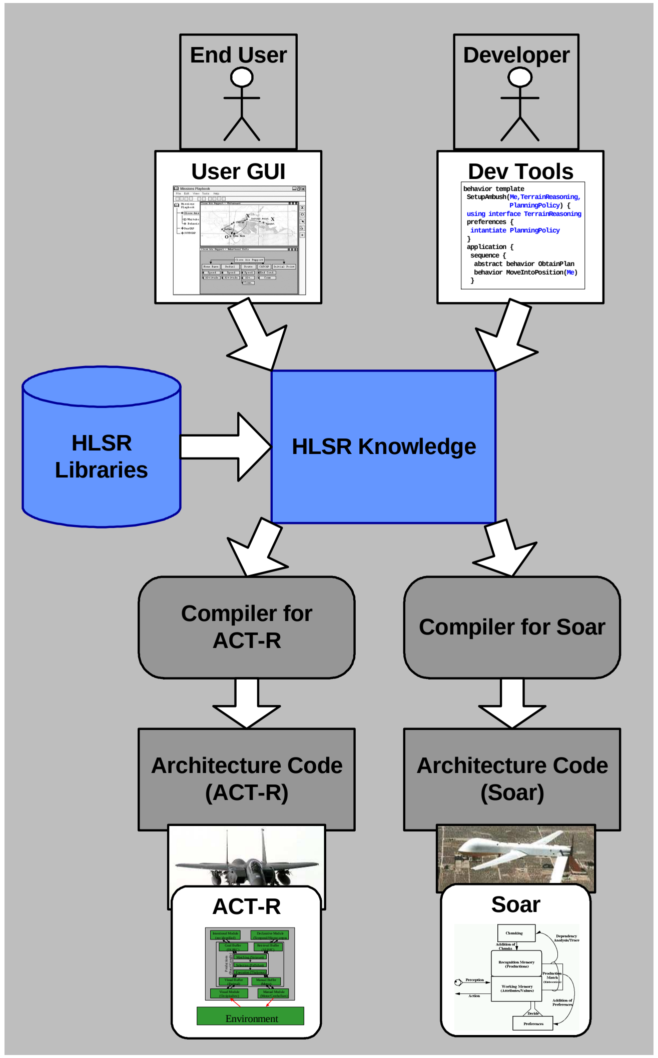
What is HLSR?

- **H**igh **L**evel **S**ymbolic **R**epresentation
- A language for knowledge encoding
- The language is:
  - Architecture independent
  - Domain independent
  - High-level
  - Designed to support reuse
- Target users:
  - Behavior developers
  - End user tool developers



Primary accomplishments prior to 2007

- Review of cognitive/intelligent agent architectures
- Design of initial HLSR "virtual machine" and language
- Implementation of compiler parser and code generation
- Full implementation of code generation for Soar
- Partial implementation of code generation for ACT-R
- Initial comparative study of ACT-R, Soar, and HLSR programming
- *Internal Funding*: Developed an IDE and debugger for HLSR

Primary activities in 2007

- Finished implementation of code generation for ACT-R (for 2006 HLSR definition)
- Completed design and implementation of code-based metrics tools for HLSR, Soar, and ACT-R
- Designed I/O language elements in HLSR
- Designed and partially completed implementation of ACT-R and Soar code generation for new language elements
- Created TankHLSR models using the Tank Soar framework – DEMO will show this working
    - Evaluated these models using HLSR's metrics
- HLSR evaluation
    - Designed and executed user study to evaluate HLSR
    - Created algorithms for automated evaluation metrics
    - Improved understanding of HLSR strengths and weaknesses
    - Improved understanding of Soar and ACT-R architectural differences

Primary activities in 2008

- Final report for current ONR funding
- Outline and draft sections of potential journal paper

Comparative user study

- Goal: To evaluate potential advantages of HLSR over Soar and ACT-R for novice programmers
- Subjects:
  - Junior and senior computer science majors from Carnegie Mellon University plus a couple of graduate students
  - Cognitive modeling and AI programming experience not required
  - Volunteers randomly assigned to groups (ACT-R, Soar, HLSR)
- Design
  - 2 hour interactive tutorial (with exercises) in language followed by 1 hour exam
  - Each group learned only one language
  - ACT-R N=8; Soar N=6; HLSR N=9

Tutorials, exercises and exam problems

- Developed separate tutorials with interactive exercises for each language
  - All tutorials covered the same basic concepts
  - Exercise were the same across languages
- Kept exam problems simple
  - Subjects were novices
  - Not much time to learn or practice language before exam
- Designed exam problems to gauge:
  - Ability to understand existing code, including how it will behave dynamically (when executing)
  - Ability to make changes to existing code
  - Ability to design behavior using specific language constructs

Data Collection and Analysis

- Subjects self-recorded time spent on each exam problem (and sub-problem)
- Subject submitted all written work and solutions
- Experimenters coded various aspects of solutions
  - Quality, correctness, and format of program design
  - Quality and correctness of program code
  - Evidence of understanding of language concepts
  - Correct use of language-specific constructs
- Exams coded by language experts
  - ACT-R: Lebiere; Soar: Jones; HLSR: Crossman
  - Initial coding followed by group discussions and analysis for consistency

Hypotheses

- Major differences between groups were not expected
  - The problems were very simple
  - Hopefully some trends would still be visible
  - The problems were built from a Soar tutorial, and may have been biased toward "Soar-like thinking"
- Expectations
  - Tasks dealing with complex logic, sequences/loops, and declarative structures should be easier in HLSR (fewer mistakes, shorter time) **[not confirmed]**
  - Because they are at a higher level of abstraction, HLSR constructs should be used more often in design than ACT-R and Soar constructs **[positive trend, n too small for χ^2]**
  - Time taken to complete some tasks should be reduced in HLSR **[confirmed significant difference]**

HLSR I/O

- Why I/O over Other Language Features?
  - I/O is critical for almost any useful model
  - Practical: I/O can be implemented in the limited time remaining
- **Observation**: Both Soar and ACT-R
  - Treat I/O structure the same as declarative memory
  - Have I/O modules that run in parallel to decision cycle
- **Approach**: HLSR I/O leverages the relation – relations can be "sensed" (input) or "externalized" (output)
  - Conceptually input relations form an input pool
  - Input relations are "sensed" when the model sensors detect instance of what the relation represents
  - Output relations are visible to motor system
  - Output relations exist in declarative memory so output processes can be queried (meta reasoning over motor process)

Metrics – Results for Tank Model

	Metric	HLSR	ACT-R	Soar
Volume	LOC	134	780 (5.8x)	337 (2.5x)
	Tokens	516	1417 (2.75x)	892 (1.73x)
Encaps.	Objects per construct	2.9 objects/construct (construct = relation w. cond., transform, AT)	5.8 chunk types/goal 2.3 chunk types/rule	4.3 objs/operator 4.13 objs/production
	Attributes per construct	2.4 attr/construct	14.2 attributes/goal 4.8 attributes/rule	7.3 attr/operator 7.7 attr/production
Complexity	# Procedural Constructs	19 constructs 36 statements	6 goals 54 rules	9 operators 45 productions (36 are elaborations)
	# Tests	90 tests total 4.74 tests/construct	210 tests total 34.8 attr tests/goal 3.9 attr tests/rule	100 logical tests total 1.89 tests/operator 2.22 tests/production
	Average Fanning	4 fanning/act. table 3 fanning/transform 2.15 fanning/statement	1.67 fanning/goal 9.2 fanning/rule	0.67 fanning/operator 6.6 fanning/production

- Note we started with Soar model (optimal Soar model)

HLSR lessons learned in 2007

- HLSR's "activation table" construct appears to be quite powerful (especially in terms of saving lines of code), and was of particular interest in the user study
- HLSR's relation/goal/fact constructs withstand formalization and compilation in ACT-R and Soar, and work will in a variety of implemented models
  - Difficult implementation issues sometimes, but appears to be at a good level of abstraction
  - Provides a uniform construct that encompasses various ACT-R and Soar modeling patterns (Soar i-support, ACT-R retrieve-best, goal/belief maintenance)
- Demonstrated 2-3x code reduction in small problem domains
  - Reductions increased with move to more complex problems (using I/O)
  - More reduction should be possible with language features that have been partially designed but not implemented
- User study was not conclusive in all respects, but
  - HLSR subjects spent less time on some problems (with comparable correctness) than ACT-R and Soar subjects
  - Differences between design and code appear to be smaller for HLSR
- There are interesting low-level modeling differences that Soar and ACT-R languages constrain modelers to use.
  - HLSR provides a method for formalizing these differences and encouraging consistent modeling solutions.
  - Should allow improved consistency and comparison of models within and across architectures.

HLSR issues identified in 2007

- The transform language construct is too limited
  - Does not cover some of the more flexible modeling patterns in Soar and ACT-R
  - Does not really make difficult procedures much easier to write
  - RESPONSE: Divide transform into two separate constructs. One for simple sequences of actions, others to support conditions, looping, parallelism, and aspect-oriented programming
- The relation language construct should have slightly different semantics
  - Current implementation makes asserted facts immutable (ala ACT-R), which leads to programming at an unnecessary level of detail
  - Needs an inheritance system for richer declarative knowledge specifications
- Design and implementation of parallelism needs to be enhanced and improved