Modeling indirect interaction
for evolving adaptive multi-agent systems in dynamic persistent environments

Doctoral thesis proposal
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Three research communities

- Multi-agent systems (MAS)
- Evolutionary computation (EC)
- Models of computation

Subcommunities:

- Theory and Practice of Open Computational Systems (TAPOCS)
- Environments for Multi-Agent Systems (E4MAS)
- Foundations of Interactive Computation (FInCo)
- EC in dynamic environments
- Coordination

Common trends in EC and MAS research

- Trend toward addressing environments that are *dynamic and persistent* (to be defined)
- Trend toward using agents in MASs that communicate via their environments
- We call this communication via the environment *indirect interaction*
- The theory of these fields is emerging

A gap between practice and theory in MAS and EC research

- Whereas *in practice*, agents in MASs and EC often interact indirectly via their environments…
- …*theory of concurrency* models all interaction as direct *message passing*
- *Gap:* Indirect interaction in practice, direct interaction in theory
- *Q*: Is indirect interaction *necessary* to solve certain classes of problems?
- *A* (our central hypothesis): *Yes.* Hence new, more expressive models are needed to close the gap

Outline

1. **Relevant definitions**
   - **Algorithmic computation**
   - **Interactive computation**
   - **Multi-stream interaction**
   - **Direct vs. indirect interaction**
2. Indirect interaction in MAS research
3. Indirect interaction and adaptation in EC
4. Formal models of interaction
5. Our research goals

Algorithms

Algorithmic computation* (Knuth)*:
The effective transformation of a finite, pre-specified input, to a finite output, in a finite number of steps.

- Algorithms *compute functions*
- A system that executes an algorithm is *closed*
- Algorithms are equivalent to Turing-machine computation

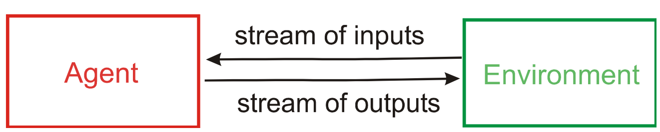
Interactive computation

***Interactive computation* (Wegner):** The ongoing exchange of data among the participants (agents or their environment) such that the output of each participant may causally influence its later inputs.

- Interaction involves *feedback from environment* during the computation
- Interaction is assumed to be unending
- *Example:* An automatic car driving from point *A* to point *B*

Sequential interaction

Sequential interactive computation: Interaction involving two participants, at least one of which is a finite computing agent (machine, device).

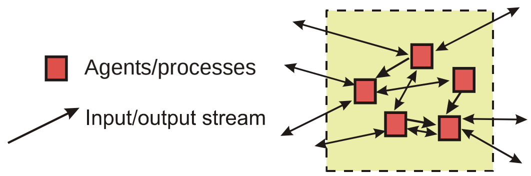


- Characterized by a single interaction stream of input/output; input alternates with output
- If one participant is an agent, the other is its *environment*
- Interaction may involve changes of state

Multi-stream interaction

Multi-stream interaction: Interactive computation involving *more* than two entities; the entities may be *asynchronous*.

In contrast to sequential interaction, multi-stream interaction may include:



- Nondeterminism when attempts to write collide
- Dynamic linking and unlinking, creation/destruction
- *Indirect* interaction via a shared environment

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Direct and indirect interaction

Direct interaction: interaction via *messages*, where the identifier of the recipient is specified in a message.

Indirect interaction: interaction via persistent, observable changes to a *common environment*; recipients are any agents that will *observe* these changes.

- Sequential interaction is direct
- Preconditions for indirect interaction:
  - Agents share access to parts of the environment
  - Persistence of environment
- *Example of indirect interaction:* use of semaphores in process synchronization (critical section problem)

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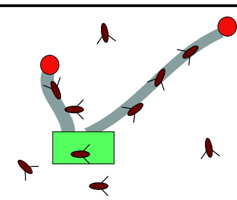
Stigmergy in nature



1. Ants foraging for food: Ants leave pheromone trail, prefer existing trails, blaze shorter and shorter trails to and from food

2. Termites gathering chips into pile: Move at random, pick up chip when encountered, put down when another chip found; the pile structure is used to coordinate creation of pile (*StarLogo*)

3. Slime mold dividing and aggregating: These amoeba may aggregate by emitting a chemical, migrating toward its greatest concentration

Q: Is stigmergy essential for some tasks?

Ubiquity of indirect interaction

- **Social biology**: Social insects interact by modifying common structures or through pheromones
- **Operating systems**: Processes communicate via *semaphores* in shared memory
- **Coordination languages**: Shared *tuple spaces* enable coordination in Linda
- **Anatomy**: Cells exchange information via *hormones* in the blood stream
- **Economics**: A *market* is an environment for buyers and sellers that serves as a medium for indirect interaction

Properties of indirect interaction

- **Time decoupling (asynchrony):** State changes persist
- **Anonymity:** Recipient ID not used in access
- **Space decoupling:** Agents need not meet
- **Non-intentionality:** Agents need not have goal of communicating
- **Hybrid nature:** Physical environment may play role
- **Late binding** of recipient

What is an environment?

An ***environment*** of a system of computing entities is a *physical* or *virtual* setting that acts as the producer of the system's inputs and consumer of its outputs.

- The environment is a participant and a memory, not just a medium for message transport
- This creates a need to elevate the MAS environment to first-class status
- EU conferences (e.g., E4MAS) have called attention to role of environments

Environments for multi-agent systems

E4MAS 2005 Proceedings cited as examples the environments of:

- visitors to a web site;
- a system of autonomous guided vehicles;
- a system of manufacturing control;
- a PDA-based system of agents to help support activities of museum visitors.

All involve indirect interaction

A taxonomy of environments

Amnesic vs.	Static vs.	Virtual vs.
Persistent	**Dynamic**	**Physical**

- An environment is ***amnesic*** if its outputs depend only on its *immediately preceding* inputs
- An environment *E* is ***static*** with respect to an agent or MAS *A* if its outputs to *A* are *strictly dependent* on its previous inputs from *A*
- A ***virtual*** environment is accessed digitally; a *physical* environment is observable only by analog sensors.

Adaptation in difficult environments

- The most difficult problem environments are *persistent*, *dynamic*, and *physical*
- MASs can offer powerful *adaptive*, *flexible* solutions in such environments
- *Conjecture:* Indirect interaction provides added power in MAS solutions because of anonymity, asynchrony, space decoupling, non-intentionality

Adaptation and multi-agent systems

- MASs enable *distributed AI* (Ferber)
- *Behavior:* action to change the environment
- *Adaptation:* learning that changes behavior – occurs in dynamic persistent environments
- MASs are often flexible enough to adapt well
- Three ways to view adaptation:
  - Ontogenetic (adaptive agent)
  - Sociogenetic (adaptive population)
  - Phylogenetic (adaptation by species)
- *Sociogenetic adaptation* = adaptation by multi-agent systems

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Decentralized, self-organizing systems

- Decentralized and self-organizing systems lend themselves to flexibility and adaptiveness
- *Where required*: in environments that are dynamic, persistent, multi-agent, decentralized, and self-organizing.

Decentralized system: a multi-agent system whose components do not respond to commands from an active director or manager component, and do not execute prespecified synchronized roles under a design or plan.

Self-organizing system: a multi-agent system with a coherent global structure or pattern shaped by local interactions among components, rather than by external forces.

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The evolutionary algorithm

- A *population-based* approach to function optimization
- Solutions are evolved, using *selection*, *mutation*, *crossover*
- Traditional EC uses *objective (fitness) function* to evaluate an element of a population

```
t ← 0                        // time
initialize (P_0)             // evolving population
y ← evaluate (P_0)           // fitnesses of population members
while not terminate (y, t) do
    t ← t + 1
    P_t ← select (P_t-1, y)  // choose a good new generation
    P_t ← alter (P_t)        // involves mutation, crossover
    y ← evaluate (P_t)       // generates a vector of fitnesses
```

Based on (Michalewicz, 1996)

- The evolution occurs *offline*, not embedded in environment

Example: checkers heuristics

- A set of checkers-playing heuristics (weights of attributes of a board layout), is evolved (Samuels ’59)
- Fitness: rate of wins that a set of heuristics obtains
- Population *P* consists of sets of weights (values) of different attributes of a *checkers board configuration*
- E.g., opportunity to jump is of weight 5, opportunity to king is 3, etc.
- EC here refines heuristics that help compute a function from board configurations to (good) moves
- Fitness function is applied by putting heuristics in competition with other heuristics

EC has addressed *static* environments

- Environment is *static* in the checkers example because the game rules don’t change during evolution
- *Static environment* =
  single (unchanging) fitness function
- In a *dynamic* environment, fitness or reward will *change* as the environment changes
- An interactive agent in a changing environment must adapt its response as environment changes
- Single fitness function in EC ⇒
  Environment cannot be dynamic

Policy in a dynamic environment

- When environment changes *policy* must evolve; *policy search* is a reinforcement-learning concept
- A rational policy: one that maximizes reward

The *policy* of agent *M*, with respect to environment *E*, is a computable function from possible perceptions, or models, of *E*, to *M*'s set of outputs.

The *fitness of a policy in environment E*, is the expected long-term reward in *E* of an agent with that policy.

- In dynamic environment, reward function evolves
- Policy must change as the environment's responses to agent change; policy search is online

Dynamic-environment example

- Suppose we play *cat-and-mouse* on a grid
- *Agent* is mouse; *Environment* is cat and grid
- Goals of mouse policy: escape by fleeing or hiding
- Assume mouse policy is to be evolved; fitness function is survival rate of a policy
- If cat speeds up over time, then mouse policy must switch from *flee* to *hide*
- Traditional evolutionary algorithm *fails* here because it assumes static environment

The evolutionary algorithm revisited

- When environment E is dynamic, EA must be parameterized with it

```
t ← 0
initialize (P0 , E0)
y ← evaluate (P0, E0)
while not terminate (y, t) do
    t ← t + 1
    Et ← update-environment (Et-1, y)
    Pt ← select (Pt-1, y)
    Pt ← alter (Pt)
    y ← evaluate (Pt, Et)
```

- Goal is to evolve solution population P to better fitness relative to changing environment
- If *update-environment* is autonomous, then evolution of the population is not an algorithm!

No Free Lunch theorem (1996)

- No algorithmic procedure can optimize cost functions better than any other algorithmic procedure, averaged over all cost functions.

$$\sum_f P(\vec{c} \mid f, m, a_1) = \sum_f P(\vec{c} \mid f, m, a_2)$$

- c = histogram of cost function f;
  a_1, a_2: arbitrary function-optimization algorithms
  P = probability of histogram
  m = a sample size
- *NFLT corollary:* If a given optimizing algorithm does well on one problem, it will do poorly on another one
- *Result:* Human domain knowledge is needed for most evolutionary computation

Resolving the NFLT paradox

- *Paradox:* Whereas by NFLT good general-purpose problem-solving *algorithms* can't exist…
- …still, such *processes* are known *to* exist, such as natural evolution of life, and the scientific method
- *Solution:* NFLT applies to *algorithms* in *static* environments; does not apply to interactive learning processes occurring in dynamic persistent environments
- *Adaptation* to environments (learning of policies) is interactive, not algorithmic

Multi-agent interaction in EC research

The two research areas (MAS and EC) intersect in research on:

- *Swarm or ant computing*
- *Coevolution:* Evolution of species whose instances interact in multi-agent systems
- *Particle swarm optimization:* Particles are candidate solutions to a problem in *n*-dimensional space, particles are accelerated through this space in relation to each other and to objective function

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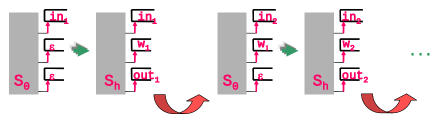
Contributions to the theory of interactive computing

- *c*-machine (Turing), finite transducer (Moore)
- Cybernetics: models of feedback systems (Wiener)
- Information theory/communication theory (Shannon)
- Concurrency with message passing: CSP (Hoare), CCS (Milner), π calculus (Milner)
- Recent models of sequential interaction:
  I/O Automata (Lynch), Abstract State Machines (Gurevich), Site Machines (van Leeuwen, Wiedermann)
- Interaction Machines and Persistent Turing Machine (Wegner, Goldin)
- *Emerging intuition:* Interaction is part of computation

Persistent Turing Machines

- A minimal extension of TMs expressing *sequential* interactive behavior (Goldin, *I&C*)
- A *PTM* is a 3-tape TM with
  - I/O as dynamically generated *streams of interleaved inputs and outputs*
  - TM executions (*macrosteps*) iterated
  - A persistent worktape, called a *memory*, preserved between macrosteps



- *Example:* automatic car

Stream behavior of PTMs

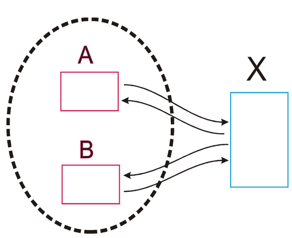
- The *persistent stream language* (PSL) of a PTM is the set of streams $L \subseteq (\Sigma^* \times \Sigma^*)^\infty$ observable on it
- The set of all I/O streams over alphabet Σ: $(\Sigma^* \times \Sigma^*)^\infty = \{ (a, x) \mid a \in (\Sigma^* \times \Sigma^*), x \in (\Sigma^* \times \Sigma^*)^\infty \}$
- $\mathcal{PSL}$ is the set of all persistent stream languages
- *Amnesic* PTMs do not make use of their memory, i.e., are equivalent to TMs in that sense
- $\mathcal{ASL}$: The set of *amnesic* stream languages
- *Theorem:* $\mathcal{ASL} \subset \mathcal{PSL}$ (Goldin, Smolka, et al, *I&C*, 2004), hence PTMs are more expressive than TMs

The message-passing model of concurrency

- Due to Robin Milner: CCS, π Calculus; associated with theory of concurrency and with process algebra
- These models capture the notion of *direct interaction* by *message passing*
- Axiom of concurrency theory:
  interaction = message passing
  i.e., atomic communication of a *message* from one *process* to another (targeted send/receive)
- Shared variables are deemed *processes*

Limitations of the message-passing model

- Message passing does not support properties of indirect interaction: anonymity, asynchrony, space decoupling, non-intentionality, and late binding
- Embedded and situated systems aren't supported
- Suppose agents *A* and *B* communicate via shared variable *X*
  - The message-passing model accounts for *direct* *A* ↔*X* and *B* ↔ *X* interaction .
  - …but not between *A* and *B* via *X*



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Research goals

- We propose to obtain formal results to establish some limitations of the message-passing model
- We seek an *expressiveness result* analogous to the one for sequential interaction by Goldin-Smolka et al
- Setting: A large system of simple agents
- We propose to use three proof approaches:
  – Formal behavioral specifications
  – Unscalability
  – Simulation asymmetry

Goal: formal specification of problems that entail indirect interaction

- We propose to find a class of useful *missions or tasks* that would require indirect interaction
- *Setting:* A large system of simple agents
- *Initial idea:* to look at insect stigmergy examples – would tasks be impossible without stigmergy?
- If indirect interaction is *needed* to meet these specs, then an adequate model must represent that interaction explicitly
- *A tool:* specification languages and notations

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Goal: to show unscalability of message passing

- *Motivation:* As unscalable architectures in AI are *brittle* and will fail in realistic settings (R. Brooks), so for unscalable MAS architectures and models
- *Hypothesis:* As the number of agents rises asymptotically, either number of connections grows too fast, or else paths between agents become too long
- Other dimensions to show unscalability:
  - Synchronization vs. asynchrony
  - Centralized vs. decentralized storage

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Goal: to show an asymmetric simulation relation

- … between message-passing-based models and models based on indirect interaction
- *Motivation:* Simulation asymmetry would imply that current models are inadequate
- *Hypothesis:* Direct interaction *cannot* simulate indirect interaction in setting of large system of simple agents
- One possible simulation of direct interaction by indirect:
  - An agent puts a tuple into the shared environment
  - Tuple contains the both message and addresses
  - Recipient reads tuples that contain its ID

Summary

1. Common trends in EC and MAS research
2. A *gap* separates the practice and the theory of these fields
3. NFL Theorem does not apply in dynamic environments
4. *Properties* enabled by indirect interaction: *anonymity, asynchrony, non-intentionality* – models must support them
5. *Goal:* Expressiveness results showing the need for explicit models of indirect interaction;
6. *Approaches:*
   - show *behavioral specifications* that entail indir. inter.
   - show *unscalability* of message-passing models
   - show an *asymmetric simulation relation* between models of message-passing and indirect interaction.

References

Dina Goldin and David Keil. Evolution, Interaction, and Intelligence. In *Proc., Congress on Evolutionary Computation (CEC-2001), Seoul, Korea*, 2001.

Dina Goldin and David Keil. Toward Domain-Independent Formalization of Indirect Interaction. *TAPOCS Workshop, Proc. WET ICE 04*, 2004.

David Keil and Dina Goldin. Modeling Indirect Interaction in Open Computational Systems. *TAPOCS Workshop, Proc. WET ICE 03*, 2003.

David Keil and Dina Goldin. Indirect Interaction and Decentralized Coordination. *Extended draft*, 2004, *http://www.cse.uconn.edu/ dqg/papers/indirect.pdf*.

David Keil and Dina Goldin. Adaptation and Evolution in Dynamic Persistent Environments. In *Proc. FInCo2005, Edinburgh*, 2005.

David Keil and Dina Goldin. Modeling Indirect Interaction in Environments for Multi-Agent Systems In *Proc. E4MAS*, 2005.

References (cont'd)

Rodney A. Brooks. Intelligence without reason. *MIT A.I. Memo. www.ai.mit.edu/people/brooks*, 1991.

Jacques Ferber. *Multi-Agent Systems: An Introduction to Distributed Artificial Intelligence.* Addison Wesley, 1999.

Dina Goldin. Persistent Turing Machines as a Model of Interactive Computation. *In: K-D. Schewe and B. Thalheim (Eds.),* Foundations of information and knowledge systems, First Int'l Symposium (FoIKS'2000), *LNCS 1762*, pages 116-135, 2000.

Dina Goldin, Scott A. Smolka, Paul Attie, and Elaine Sonderegger. Turing Machines, Transition Systems, and Interaction. *Information and Computation Journal* 194(2): 101-128, Nov. 2004.

Dina Goldin and Peter Wegner. The Church-Turing Thesis: Breaking the Myth. Presented at CiE 2005, Amsterdam, June 2005. LNCS 3526, Springer 2005, pp. 152-168

Zbigniew Michalewicz. Genetic algorithms + data structures = evolution programs, 3rd Ed. Springer, 1996.

Arthur Samuel. Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of Research & Development*, (3):211–229, 1959.

Starlogo site at MIT Media Lab. *http://starlogo.www.media.mit.edu/people/starlogo*.

David H. Wolpert and William G. Macready. No free lunch theorems for search. *Santa Fe Institute technical report SFI-TR-0*, 10, 1996.

Evolution and distributed AI

Old	Find a computational path	**New**	Learn a policy
AI/EC	Reasoning in a closed world	**AI/EC**	Rational reactive behavior
	Human intervention		Autonomy
	Heuristics		Emergent behavior
	Toy environment		Real-world environment
	Brittle solutions		Scalable solutions

- AI has moved away from systems that reason in a closed algorithmic world, toward rational-agent behavior
- The same can happen with EC and MAS as they converge
- AI is more and more associated with distributed and MASs
- A hierarchy of difficulties of interactive problems: