Comparison of Selection Methods in On-line Distributed Evolutionary Robotics

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Outline

1 Problem and approaches
   - Evolutionary Robotics
   - On-line Distributed ER
   - Selection pressure in ER

2 Methodology
   - The algorithm
   - Experiments

3 Results
   - Median fitness during evolution
   - Proposed measures for on-line distrib. ER

4 Conclusion
Evolutionary Robotics (ER) [Nolfi and Floreano, 2000]
Exploit behavior while learning

Variation

Selection

Environment

On-line distributed ER

[Watson et al., 2002]
Selection pressure in evolutionary robotics

**Off-line ER**
- Selection over the whole population
- Important to explicitly keep diversity
  - Novelty search [Lehman and Stanley, 2011]
  - Behavioral diversity [Mouret and Doncieux, 2009]
  - ...

**On-line distributed ER**
- Local populations: selection at the agent level
- Agents physically scattered + local communication
  - Disjoint populations → slow chromosome propagation
Selection Methods in on-line distributed ER

- **mEDEA** (minimal Environ.-driven Distr. EA) [Bredeche and Montanier, 2010]
  - Always transmit and receive
  - Randomly select

- **MONEE** (MO aNd open-Ended Evo.) [Noskov et al., 2013]
  - mEDEA + task-driven fitness and market mechanism
  - Rank-based selection

- **PGTA** (Prob. Gene Transfer Alg.) [Watson et al., 2002]
  - Fit individuals transmit with high probability
  - Unfit individuals accept with high probability

- **odNEAT** (On-line Distrib. NEAT) [Silva et al., 2012]
  - Group individuals in niches
  - Fit individuals transmit with high probability
  - Select a niche based on fitness → select individual (binary tourn.)

- **EDEA** (Embodied Distrib. EA) [Karafotias et al., 2011]
  - Always transmit and receive
  - Select individuals (binary tourn.) → x-over with probability
Question

- Selection operators → one way of exploring search spaces (of maintaining diversity)
- The choice of the selection pressure level allows to better explore the search space (reduce stagnation in local optima)
- Does selection have the same function in on-line distributed ER?
  - How does the intensity of selection pressure influence on-line distributed evolution?
Selection operators → one way of exploring search spaces (of maintaining diversity)

The choice of the selection pressure level allows to better explore the search space (reduce stagnation in local optima)

Does selection have the same function in on-line distributed ER?
  - How does the intensity of selection pressure influence on-line distributed evolution?
Distributed ER Algorithm: mEDEA variant

mEDEA with selection

\[ g_a := \text{random()} \]

\textbf{while} true \textbf{do}
\begin{align*}
l & := \emptyset \\
& // \text{Evaluation phase} \\
& \text{for } t = 1 \text{ to } T_e \text{ do} \\
& \quad \text{exec}(g_a) \\
& \quad \text{broadcast}(g_a) \\
& \text{end for} \\
& // \text{Listening phase} \\
& \text{for } t = 1 \text{ to } T_1 \text{ do} \\
& \quad l := l \cup \text{listen()} \\
& \text{end for} \\
& l := l \cup \{g_a\} \\
& \text{selected} := \text{select}(l) \\
& g_a := \text{mutate}(\text{selected})
\end{align*}

\textbf{end while}
Distributed ER Algorithm: mEDEA variant

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  \hspace{1cm} // Evaluation phase 
  \hspace{1cm} for \( t = 1 \) to \( T_e \) do 
  \hspace{2cm} exec\((g_a)\) 
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  \hspace{1cm} end for 
  \hspace{1cm} // Listening phase 
  \hspace{1cm} for \( t = 1 \) to \( T_l \) do 
  \hspace{2cm} \( l := l \cup \text{listen}() \) 
  \hspace{1cm} end for 
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- Best
- Rank-based
- Binary Tournament
- Random
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- Best
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Navigation with obstacle avoidance
[Nolfi and Floreano, 2000]

Maximize

\[
\sum_{t=1}^{T_e} v_t(t) \cdot (1 - |v_r(t)|) \cdot \min(a_s(t))
\]

- Max. translational velocity
- Min. rotational velocity
- Max. distance to obstacles

Collective foraging

Maximize

# Collected items

RoboRobo [Bredeche et al., 2013]
### Experimental protocol

![Diagram of experimental protocol]

<table>
<thead>
<tr>
<th>Settings</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swarm size</td>
<td>50 agents</td>
</tr>
<tr>
<td>Comm. radius</td>
<td>$\approx 5$ agent radius</td>
</tr>
<tr>
<td># food items</td>
<td>150</td>
</tr>
<tr>
<td>Experiment length</td>
<td>$5 \times 10^5$ sim. steps ($\approx 250$ gen.)</td>
</tr>
<tr>
<td># runs</td>
<td>30</td>
</tr>
<tr>
<td>Search space</td>
<td>$\mathbb{R}^n$, ($n = 22$, $n = 38$)</td>
</tr>
<tr>
<td>Mutation</td>
<td>$x^t = select(list) + \mathcal{N}(0, \sigma^2)$, $\sigma = 0.5$</td>
</tr>
</tbody>
</table>
Results: median fitness during evolution

**Swarm fitness**

\[ F_s(g) = \sum_{r \in \text{swarm}} f_r^g \]

**Navigation**

**Foraging**
Analysis of the results

Impact of selection pressure

- With selection pressure → better fitness values
- Stronger selection pressure → higher performance
  - Best > Rank-based > Binary tournament > Random
- Without selection pressure → lower fitness values
  - Adaptation to survival, as in mEDEA. Navigation to maximize mating opportunities
  - In foraging, item gathering → byproduct of max. mating opportunities
- In foraging without selection pressure agents are not attracted by the food items

Performance measures over time

- Motivation:
  - Learning during operation
  - Constantly adapting
  - Open-ended, . . .
- Measures with information on several generations
Analysis of the results

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Performance measures over time

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Proposed measures for on-line distrib. ER

Avg. accumulated swarm fitness

Fixed budget swarm fitness

Time to reach target

Accumulated fitness above target
Proposed measures for on-line distrib. ER

- Median fitness during evolution
- Proposed measures for on-line distrib. ER

Graphs showing:
- Avg. accumulated swarm fitness
- Fixed budget swarm fitness
- Time to reach target
- Accumulated fitness above target
Proposed measures for on-line distrib. ER

Median fitness during evolution

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Time to reach target

Accumulated fitness above target
Result: proposed measures (navigation)

Pairwise Mann-Whitney tests (99%)

Analysis
- With selection pressure
  - High performances
  - Rapidly reach target level
- Without selection pressure (Random)
  - Worse results on all four measures

With selection pressure:
- High performances
- Rapidly reach target level
- That are maintained and surpass it (especially with Best)
Result: proposed measures (foraging)

Pairwise Mann-Whitney tests (99%)

Analysis

- **High selection pressure (Best and Rank-based)**
  - High performances (especially with Best) that are maintained
  - Rapidly reach target level and surpass it (especially with Best)

- **Low selection pressure (Binary tournament and Random)**
  - Worse results on all four measures and the *target* level was not achieved
We are interested in the effect of selection pressure in on-line distrib. ER.
We compared four selection methods on two collective tasks.
Upon analysis of the fitness during evolution, selection pressure leads to better results than random selection.
We introduced four measures that, taken together, integrate information about the performance over time.
On these measures, statistical tests yield a clear correlation between intensity of selection pressure and performances.
Generally, in AE we do not aim to be extremely selective
  Maintain diversity in order to explore the search space
  Recall novelty search, diversity search, . . .

Is it the same case in distributed evolutionary robotics?
. . . or is diversity is naturally maintained by the disjoint sub-populations?
  Selection at agent level and agents physically scattered
  This work suggests that diversity is naturally maintained, but this should be investigated

Maybe links to spatially structured EA’s and island models can give further insights
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