Sensitivity and Stigmergy in Agent-Based Systems

Camelia Chira
Computational Intelligence Research Group
Babes-Bolyai University
Kogalniceanu 1
Cluj-Napoca 400084, Romania

cchira@cs.ubbcluj.ro

Camelia-M. Pintea
Computational Intelligence Research Group
Babes-Bolyai University
Kogalniceanu 1
Cluj-Napoca 400084, Romania

cmpintea@cs.ubbcluj.ro

D. Dumitrescu
Computational Intelligence Research Group
Babes-Bolyai University
Kogalniceanu 1
Cluj-Napoca 400084, Romania

ddumitr@cs.ubbcluj.ro

Abstract

A computational metaheuristic combining stigmergic behavior and gradual pheromone sensitivity of agents is proposed. Resulting multi-agent models can potentially address complex real-world problems particularly combinatorial optimization NP-hard problems. The new model employs agents able to communicate both directly and in a stigmergic manner. Stigmergic communication is based on different reactions to virtual pheromone trails produced by agents. Each stigmergic agent is endowed with a certain level of sensitivity to the pheromone allowing various types of reactions to the environment. The introduced model can be viewed as a multi-agent system composed of several sensitive stigmergic agents that can cooperate to solve complex problems. The proposed system is tested for solving the NP-hard Generalized Traveling Salesman Problem. Numerical experiments indicate the robustness and potential of the new metaheuristic.

Keywords: agent communication, stigmergy, sensitivity, multi-agent system, ant colony optimization

1 Introduction

Many optimization problems are NP-hard and cannot be solved within polynomial computation times. NP-hard problems arise in many and diverse domains including network design, scheduling, mathematical programming, algebra, games, language theory and program optimization. Metaheuristics are powerful strategies to efficiently find high-quality near optimal solutions within reasonable running time for problems of realistic size and complexity.

The aim of this paper is to design a metaheuristic technique combining multi-agent systems, stigmergic behavior (inspired by Ant Colony Systems) and the new concept of
gradual pheromone sensitivity of agents. The proposed technique is called Sensitive Stigmergic Agent (SSA) model. Agents are able to communicate both directly and in a stigmergic manner using pheromone trails produced by agents. The idea of stigmergic agents was introduced in [1] where a system composed of stigmergic agents is outlined and illustrated by an example. Proposed SSA is a new model that explores stigmergy in agents, furthermore endowing them with sensitivity characteristics. Sensitivity allows agents to react either autonomously or in a purely stigmergic manner to changes of the environment. Intelligent problem solutions naturally emerge due to agent communication, autonomy and different levels of sensitivity to pheromone trails.

The SSA method can be viewed as an approach to use multi-agent systems for solving NP-hard combinatorial optimization problems. The main advantage is that agents with sensitive stigmergy become very suitable to address real-world problems which may be non-stationary. Agents adopt a stigmergic behavior to identify problem solutions and can share information concerning dynamic changes in the environment (e.g. node or edge removing in a dynamic graph, cost modification of an edge, introduction of new nodes or new edges) improving the quality of the search process. The SSA approach can be useful for addressing large problems concerning vehicle routing, communication in mobile systems, dynamic location, etc.

The SSA model is tested for solving a NP-hard problem – a generalized version of the Traveling Salesman Problem. Numerical results indicate the potential of the proposed system.

2 Stigmergic Agents

Metaheuristics inspired from nature represent a powerful and robust approach to solve NP-difficult problems. Biology studies emphasize the remarkable solutions that many species managed to develop after millions of years of evolution. Self-organization [2] and indirect interactions between individuals make possible the identification of intelligent solutions to complex problems. These indirect interactions occur when one individual modifies the environment and other individuals respond to the change at a later time. This process refers to the idea of stigmergy [3] which is engaged by the proposed model.

The bio-inspired Ant Colony Optimization (ACO) metaheuristic [4, 5] simulates real ant behavior to find the minimum length path – associated to a problem solution – between the ant nest and the food source. Each ant deposits a substance called pheromone on the followed path. The decisions of the ants regarding the path to follow when arriving at an intersection are influenced by the amount of pheromone on the path. Stronger pheromone trails are preferred and the most promising paths receive a greater pheromone trail after some time. This stigmergic communication among ants is engaged in the proposed agent model.

Furthermore, the introduced model inherits agent properties such as autonomy, communication, reactivity, learning, mobility and pro-activeness used in multi-agent systems [6, 7, 8]. The agents that form the system have the ability to operate without human intervention, can cooperate to exchange information and can learn while acting and reacting in their environment.

The proposed SSA model engages a system composed of several interacting agents able to produce complex problem solutions by interoperating at the two levels as follows [1]:
• *Direct communication*: agents are able to exchange different types of messages in order to share knowledge and support direct interoperation

• *Stigmergic communication*: agents are endowed with the ability to produce pheromone trails that will influence future decisions of other agents within the system.

Hybridization of Ant Colony and Multi-Agent Systems occurs at the system conceptual level. This approach can be easily extended for solving problems that involve very complex search spaces. Agents incrementally build a problem solution. The search space can be a graph, a tree or a complex network.

3 **Sensitive Stigmergic Agents**

The proposed SSA model enables the identification of complex problem solutions using the hybridization mechanism described in the previous section. Furthermore, the SSA agents are endowed with sensitivity characteristics. A robust and flexible system can be obtained by considering that not all agents react in the same way to pheromone trails. Within the proposed model each agent is characterized by a *pheromone sensitivity level* denoted by PSL which is expressed by a real number in the unit interval [0, 1]. Extreme situations are:

- If PSL = 0 the agent completely ignores stigmergic information (the agent is ‘pheromone blind’);
- If PSL = 1 the agent has maximum pheromone sensitivity.

Small PSL values indicate that the agent will normally choose very high pheromone levels moves (as the agent has reduced pheromone sensitivity). These agents are more independent and can be considered environment explorers. They have the potential to autonomously discover new promising regions of the solution space. Therefore, search diversification can be sustained.

Agents with high PSL values will choose any pheromone marked move. Agents of this category are able to intensively exploit the promising search regions already identified. In this case the agent’s behavior emphasizes search intensification.

During their lifetime agents may improve their performance by learning. This process translates to modifications of the pheromone sensitivity. The PSL value can increase or decrease according to the search space topology encoded in the agent’s experience. The current implementation of the proposed SSA model generates PSL levels uniformly distributed over the interval [0, 1] and these levels are constant during the search process.

4 **SSA Model**

The SSA model is initialized with a population of agents that have no knowledge of the environment characteristics. Each path followed by an agent is associated with a possible solution for a given problem. Each agent deposits pheromone on the followed path and is able to communicate to the other agents in the system the knowledge it has about the environment after a full path is created or an intermediary solution is built.

The infrastructure evolves as the current agent that has to determine the shortest path is able to make decisions about which route to take at each point in a sensitive stigmergic manner. Agents with small PSL values will normally choose only paths with
very high pheromone intensity or alternatively use the knowledge base of the system to make a decision. These agents can easily take into account Agent Communication Language (ACL) messages received from other agents. The information contained in the ACL message refers to environment characteristics and is specific to the problem that is being solved. On the other hand, agents with high PSL values are more sensitive to pheromone trails and easily influenced by stronger pheromone trails. However, this does not exclude the possibility of additionally using the information about the environment received from other agents.

Not all agents have to take into account the knowledge propagated in the system by other agents. One of the major properties of an agent is autonomy and this allows agents to take the initiative and choose a certain path regardless of communicated information. Agents can lead the way to the shortest path in a proactive way ensuring that the entire solution space is explored. However, agents can demonstrate reactivity and respond to changes that occur in the environment by choosing the path to follow based on both pheromone trails (influenced by the PSL value) and communicated information.

The proposed SSA model is exemplified in Figure 1 for a small number of agents showing how agents interact with the environment (stigmergic communication), interact with each other (direct agent communication) and with the knowledge base.

![Figure 1. The Sensitive Stigmergic Agent model](image)

After a set of agents determines a set of problem solutions, the proposed model allows the activation of another set of agents with the same objective but having some knowledge about the environment. The initial knowledge base of each agent refers to the information about the path previously discovered by each agent.

## 5 Computational Experiments

The SSA model is illustrated for solving the Generalized Traveling Salesman Problem (GTSP). GTSP is one of the possible generalizations of the well-known NP-hard problem TSP. Within GTSP the nodes of a complete undirected graph are partitioned into clusters. The objective is to find a minimum-cost tour passing through exactly one node from each cluster.
The SSA system is implemented using two sets of sensitive stigmergic agents. Agents of the first set have small PSL values indicating that they normally choose very high pheromone level moves. These sensitive-explorer agents are called small PSL agents (sPSL agents). They autonomously discover new promising regions of the solution space to sustain search diversification. Agents of the second set have high PSL values. These sensitive-exploiter agents called high PSL agents (hPSL agents) potentially choose any pheromone marked move. They intensively exploit the promising search regions already identified by the sPSL agents.

Agents deposit pheromone on the followed path. Unit evaporation takes place each cycle. This prevents unbounded intensity trail increasing. In order to stop agents visiting the same node in the same tour a tabu list is maintained.

The SSA model for solving GTSP works as follows:

**Step 1.** Initially the agents are placed randomly in the nodes of the graph.

**Step 2.** Each hPSL-agent moves to a new node with a probability based on the distance to that node and the amount of trail intensity on the connecting edge. The agent can send an ACL message to the other agents containing the latter edge formed and its cost.

**Step 3.** The trail intensity is updated.

**Step 4.** Step 2 is reconsidered for the sPSL-agents. Information received from the hPSL agents or available in the knowledge base can be considered (for example, if a sPSL agent is currently in node \( i \) and is notified by another agent that the last visited edge is \((i, j)\) then the sPSL agent decides to choose a different node than \( j \) to better explore the search space).

**Step 5.** Only agents that generate the best tour are allowed to globally update the virtual pheromone and the knowledge base. The global update rule is applied to the edges belonging to the best tour.

A run of the algorithm returns the shortest tour found.

The proposed SSA model is compared to the results of classical Ant Colony System (ACS) technique [9], the Nearest Neighbor (NN) algorithm, the GI\(^3\) composite heuristic [10] and Random Key Genetic Algorithm [11].

Several problems from TSP library [12] are considered for numerical experiments. TSPLIB provides the optimal objective values (representing the length of the tour) for each problem. Comparative results obtained are presented in Table 1.

<table>
<thead>
<tr>
<th>No.</th>
<th>Problem</th>
<th>Optimum Value</th>
<th>NN</th>
<th>GI(^3)</th>
<th>ACS</th>
<th>Random Key GA</th>
<th>SSA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11EIL51</td>
<td>174</td>
<td>174</td>
<td>174</td>
<td>174</td>
<td>174</td>
<td>174</td>
</tr>
<tr>
<td>2</td>
<td>14ST70</td>
<td>316</td>
<td>316</td>
<td>316</td>
<td>316</td>
<td>316</td>
<td>316</td>
</tr>
<tr>
<td>3</td>
<td>21EIL101</td>
<td>249</td>
<td>250</td>
<td>250</td>
<td>249</td>
<td>249</td>
<td>249</td>
</tr>
<tr>
<td>4</td>
<td>53GIL262</td>
<td>1013</td>
<td>1152</td>
<td>1064</td>
<td>1015.8</td>
<td>1021</td>
<td>1016.6</td>
</tr>
<tr>
<td>5</td>
<td>64LIN318</td>
<td>20765</td>
<td>24626</td>
<td>21719</td>
<td>21738.8</td>
<td>20894</td>
<td>20834</td>
</tr>
<tr>
<td>6</td>
<td>80RD400</td>
<td>6361</td>
<td>7996</td>
<td>6439</td>
<td>6559.4</td>
<td>6436</td>
<td>6380.4</td>
</tr>
<tr>
<td>7</td>
<td>84FL417</td>
<td>9651</td>
<td>9754</td>
<td>9697</td>
<td>9706.4</td>
<td>9656</td>
<td>9654.2</td>
</tr>
<tr>
<td>8</td>
<td>88PR439</td>
<td>60099</td>
<td>67428</td>
<td>62215</td>
<td>64017.6</td>
<td>60258</td>
<td>60142</td>
</tr>
<tr>
<td>9</td>
<td>89PCB442</td>
<td>21657</td>
<td>21704</td>
<td>22936</td>
<td>21806.4</td>
<td>22026</td>
<td>21668.2</td>
</tr>
</tbody>
</table>
Table 1. Numerical results: solving GTSP using NN, GI³, ACS, Random Key GA and SSA

The test results emphasize that the proposed SSA technique gives better results than the standard ACS model and the NN algorithm. Furthermore, the results of SSA are comparable and – for some of the considered problems better – than the GI³ algorithm and the Random Key Genetic Algorithm.

The running times for these algorithms (using equivalent processing power) are given in Figure 2. The proposed SSA technique and the Random Key Genetic Algorithm report comparable results, significantly better than the rest of the considered methods.

![Figure 2. Running time in seconds for the compared methods applied to the nine problems from Table 1](image)

The use of stigmergic communication in agent-based environments coupled with sensitive agent reactions to different levels of pheromone offer promising results for the exploitation of multi-agent systems in solving combinatorial optimization problems.

6 Conclusions and Future Work

A sensitive stigmergic agent model is proposed to address complex real-world problems. The proposed SSA model combines stigmergic and direct agent communication in a powerful and robust optimizer. Within non-stationary problems solutions are incrementally built based on individual reactions to a changing environment. Therefore, this approach opens the possibility to combine metaheuristics and multi-agent systems in solving combinatorial problems in dynamic environments.

Future work focuses on the improvement of the proposed SSA model by quantifying the specific roles of stigmergic and direct communication in order to ensure a good balance in the search process. Agents with variable PSL level have to be investigated in conjunction with learning capabilities. Further numerical experiments refer to the application of the proposed method for other NP-hard problems particularly those in dynamic environments for which the importance of message exchange between agents can become critical in the search process.
References

12. http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/