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EMERGENCE OF POPULATION STRUCTURE IN SOCIO-COGNITIVELY INSPIRED ANT COLONY OPTIMIZATION

Abstract *A metaheuristic proposed by us recently, Ant Colony Optimization (ACO) hybridized with socio-cognitive inspirations, turned out to generate interesting results when compared to classic ACO. Even though it does not always find better solutions to the considered problems, it usually finds sub-optimal solutions. Moreover, instead of a trial-and-error approach to configure the parameters of the ant species in the population, the actual structure of the population emerges from a predefined species-to-species ant migration strategies in our approach. Experimental results of our approach are compared to classic ACO and selected socio-cognitive versions of this algorithm.*

Keywords ant colony optimization, socio-cognitive systems, discrete optimization, emergence

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1. Introduction

We recently proposed a socio-cognitive computing paradigm [5] that incorporates some socio-psychological mechanisms – in particular, mechanisms of taking the perspective of and inspiration from another agent – into classic ACO systems. We have conducted a number of experiments with the application of this socio-cognitive ACO approach for solving the TSP (Traveling Salesman Problem) and adapting PSO (Particle Swarm Optimization) algorithms in a similar way (thus, creating socio-cognitive PSO). PSO was applied to the problem of global optimization in the continuous domain [1].

During our earlier experiments, we used an ad-hoc approach in setting the parameters of socio-cognitive populations: either by looking for an optimal configuration manually (e.g., checking the performances of different compositions by trial and error) or by basing it on the data from the human population [4]. One of the best configurations found was a population of socio-cognitive ants that contain mostly so-called egocentric ants but omit the totally random-working ants. This might have been a good choice, but in order to verify this or search for other good configurations of our metaheuristic, we had to either do some data-farming experiments (using the Scalarm data-farming system[1], for example) or employing some kind of meta-algorithm (in order to evolve these parameters). There is also a third possibility: allowing the system to find these parameters by means of emergence. This is the approach tried in this paper: to seek an optimal composition of the population for a given problem instead of following a trial-and-error approach.

Emergent behavior is defined in [16] as a phenomenon occurring suddenly in a complex system consisting of a sum of simpler entities. The behavior of the whole system can be more-sophisticated that the behavior of the particular entities. Another definition can be found in [19], where the emergent behavior is described as a phenomenon that cannot be explained in a simple way based on an observation of the system as a sum of its simpler entities. One should also refer to a classic cellular automata system here, such as Conway's Game of Life, where the emergent behavior of the system can also be clearly observed by complex structures emerging from very simple rules [12].

Following these guidelines, we have proposed several strategies for the automatic adaptation of the population of the socio-cognitive entities (ants) to evolve towards an optimal composition of the computing population. We describe these strategies and the outcomes of the evaluation experiments here, which achieve a similar efficiency as those obtained in our previous research using an exhaustive search for the best configuration of the whole system. In the approach presented here, the optimal population composition arises emergently, so the search is not as tedious as in the earlier approach. Thus, the main contribution of this paper does not consist of exceeding the up-to-date attainments in the search for the optimal parameters of a socio-cognitive system but rather proposing ways to do this more easily and quickly. It must be noted that, similar to other metaheuristics, socio-cognitive ACO is configured by a number of different

[1] `www.scalarm.com`

parameters, and our approach relieves the user from the necessity of tuning them by trial and error.

After this introduction, we give a brief ACO background, then summarize the most-important information about the socio-cognitive ACO. Next, the emergent migration strategies are defined, and the evaluation results are presented. The conclusions are presented in the final section.

2. From classic to socio-cognitive ACO

The Ant System, introduced in 1991 by Marco Dorigo to solve graph problems, is a progenitor of all ant colony optimization (ACO) techniques [8]. The classic ACO algorithm is an iterative process during which a certain number of agents (ants) create a solution step-by-step [9, 10]. The main goal of the ants is to traverse a graph and find the path with the lowest cost (usually the shortest distance, but it can also be the lowest fuel consumption, and so on). The socio-cognitive ACO proposed by us follows the results shown in [20] and the inspirations presented by Nowé et al. [18] as well as Chira et al. [6]. We have introduced a different ant species and vary their sensitivity to the pheromones of other ant species.

2.1. Socio-cognitive inspirations

Our socio-cognitive approach is rooted in cognitive psychology, where the character traits of egocentrism (taking one's own perspective) and altercentrism (taking another person's perspective into consideration) have long been recognized as playing a key role in interpersonal relationships (see, for instance, [11, 17]). Moreover, brain-imaging studies have shown that altercentricity and the strategy of perspective-taking develop in parallel with brain maturation and psychosocial development during adolescence [3, 7]. Perhaps mirroring this psychological development, artificial intelligence researchers have started to incorporate altercentricity into robots and autonomous systems in recent years [15]. We also continue with the utilization of the notions of egocentrism and altercentrism, adapting them appropriately for use in our computing system.

It has been shown that the less a person focuses on his/her own perspective, the more that person will be motivated to engage in perspective-taking [2]. Experimental research has suggested that these two dimensions (conflict handling and perspective priority) might be independent; also, factors such as guilt or shame affect each of these dimensions individually [4]. This two-dimensional approach to perspective-taking inspired us to follow the definitions of four types of individuals:

- Egocentric individuals, focusing on their own perspectives and becoming creative thanks to finding their own new solutions to given tasks. These individuals do not pay attention to others and do not get inspired by the actions of others (or these inspirations do not become a main factor of their work).
- Altercentric individuals, focusing on the perspective of others and, thus, following the masses. Such individuals become less creative, but they can still end up supporting good solutions by simply following others.

- Good-at-conflict-handling individuals, getting inspired in a complex way by the actions of other individuals, considering different perspectives, and choosing the one considered as the best for them.
- Bad-at-conflict-handling individuals, acting purely randomly, sometimes following one perspective, sometimes another without any inner logic.

Such assumptions along with the findings of Samson and Bukowski presented in [4] lead us to propose the following types of populations with arbitrarily chosen parameters, reflecting the real-world human populations driven by such feelings as guilt and anger:

- Control Sample (baseline proportions of different types of perspective takers found in a typical human population), where good conflict handlers form a major proportion with a roughly similar proportion of the three other types of perspective takers. It is to note that this is also the sample with the highest proportion of egocentric individuals.
- Increased Good Conflict Handling Sample (proportions based on a population of humans that has been induced to feel anger), where the proportion of good conflict handlers is further increased as compared to the control sample while reducing the fraction of the altercentric and egocentric individuals.
- Increased Altercentricity Sample (proportions based on a population of humans that has been induced to feel guilt), where the proportion of good conflict handlers and egocentric individuals is significantly decreased and is compensated by a higher proportion of altercentric individuals and, to a lesser extent, a higher proportion of bad conflict handlers.

The outcomes of our research presented in previous papers [5, 20] are based on the above-mentioned ideas.

3. Socio-cognitive ACO

In this section, an outline of the socio-cognitive ACO is presented (for details, please refer to [5], for example). In the classical ACO algorithm, the individuals (ants) are deployed in a graph in which each edge is associated with a distance. Each ant gets a randomly chosen starting graph node and searches for a cycle by moving between the nodes (always choosing the next one, never returning to a previous node). While choosing which node to visit next, the ant has to evaluate the attractiveness factor for all possible edges that can be followed from the present node. The attractiveness is proportional to the amount of pheromone placed on the edge and inversely proportional to the distance that the ant must travel. After visiting all of the nodes exactly once, the ant finishes its trip and returns the found cycle as a proposed solution and then retreats, depositing a certain amount of pheromone on the path of its current cycle. The pheromone is not only deposited, but it also slowly evaporates from the edges in order to avoid getting caught in a local extremum of the goal function.

In the proposed socio-cognitive ACO, the idea of having many pheromones instead of only one is implemented by introducing different "species" of ants and enabling their interactions (similar to the approach taken in [18]). The interaction is considered a partial inspiration (similar to perspective-taking in the real world) realized by a particular ant reacting to the decisions taken by ants belonging to other species. This is made possible by having ants of different species leave different "smells" (see Fig. 1).

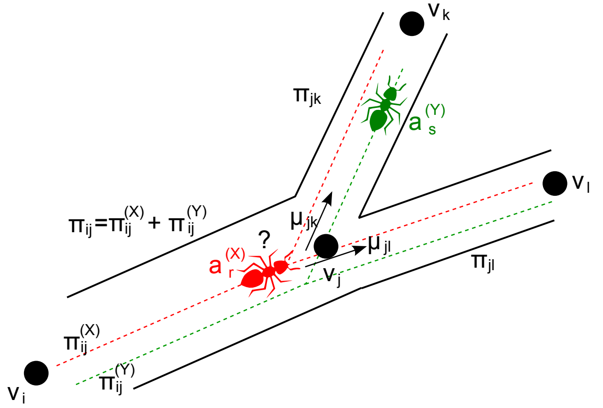

Figure 1. Multi-pheromone ACO setting: different species of ants leave different pheromones; however, the ants may make decisions based not only on the pheromone of its species but also by combining information about the other ones. In this case, the red ant decides to take the path based on pheromones from the red and green species.

Different ants follow different rules (i.e., they consider different properties of the path) of computing the attractiveness factor. They utilize the smells of pheromones left by other species in a predefined way.

Different ant species leave pheromones that 'smell' different, and ants may react to different combinations of these pheromones. Of course, more species and more pheromones may be introduced into the system if necessary. Based on this framework, details of the actions undertaken by various ant species are described below. It is to note that the chosen species (namely, Egocentric, Altercentric, Good-, and Bad-at-conflict handling) were chosen based on the real-world features of the human population (based on the suggestions of one of the co-authors).

- Egocentric ants (EC). These ants are supposed to be creative in trying to find a new solution. They care less about other ants and different pheromone trails. Instead, they focus mostly on the distance of traveling the path as a way to determine their subsequent directions.
- Altercentric ants (AC). These ants follow the majority of the others, focusing on pheromones without caring about the distance.

- Good-at-conflict-handling ants (GC). These ants observe the others, caring about all existing pheromones, applying different weights to different levels of pheromones.
- Bad-at-conflict-handling ants (BC). These ants behave randomly, irrespective of pheromone or distance.

4. Emergence in socio-cognitive ACO

Following the definition of emergence [16] as a phenomenon occurring suddenly in a complex system consisting of a sum of simpler entities and being inspired by the behavior observed in cellular automata, for example (as in Conway's Game of Life, for one) and at the same time perceiving the whole computing system proposed here as a simulation of "living beings," we try to leverage the emergence phenomenon in order to properly configure the computing system without the need for doing data-farming-related experiments, checking thousands of different configurations of the system parameters. Even if we found an optimal one, it would not be equally best for all of the considered problems (cf. no free lunch theorem [22]). Thus, we try to define the simple actions of individuals that affect the structure of the population, eventually hoping for stabilization and the attainment of good quality in the produced solution.

To sum up, the emergence in multi-species socio-cognitive ACO is based on the dynamic exchange of the types of individuals when a certain condition is true (e.g., regarding the best solution observed in both species). Because the population consists of several species, all of the emergence strategies are based on the concept of the migration of the ant between them, changing its species.

It is worth noting that, in [14], a very sound mathematical notation for social positions in agent-based systems is introduced that is based on assigning number-based positions to the agents and introducing a certain order into the agent sets. A similar notation could be used in the presented paper; however, it would only be useful in the case of stepwise migration – the other approaches presented do not assume any order introduced by the positions of agents (there are no "better" or "worse" agents).

Migration between the species is realized when a certain condition (usually related to quality) is true; the ants are then chosen and moved to other species. Below, a summary of all proposed emergent migration settings is given.

Migration from worst to best species

In this strategy, one ant belonging to the current worst species (including the ant with the worst solution during one iteration) changes its species to the one where the current best ant belongs. The condition for starting this strategy is decreasing the global result (the best solution of the ants belonging to all species) down by a certain percentage.

Stepwise migration of one ant

In this strategy, the migration is carried out in a more-fluent way; because of this, the ants are "promoted" gradually. The species are sorted according to the best solutions belonging to them, and a certain ant is migrated from its current species to the species located one step above in the mentioned order. The condition for starting this migration is the same as in the case of the first migration strategy: the worsening of the best solution in the whole population by a certain percentage.

Stepwise migration of many ants

In this strategy, many ants are migrated in a "stepwise" manner in a similar way as described in the case of one ant. The number of migrated ants depends on the percentage of the worsening of the global result as compared to the previous iteration (e.g., for a 3% worsening, 3 ants will be migrated, while for 0.5%, only one will move). The condition for starting the migration is similar to the previous case.

Competition-based migration

In this strategy, instead of considering the global result (and following its dynamical changes, either decreasing or increasing), the ants are migrated based on a predefined "competition" among them:

1. In the iteration when the migration should arise, two species are randomly chosen from all available ones.
2. From these species, the better one (having the best current result) is selected.
3. Now, one ant from the worse species is migrated to the better one.

Migration in this method is run periodically; the length of the period is one of its crucial parameters.

Stochastic migration

In this method, certain probabilities are computed in each iteration:

- probability of leaving one species by an ant,
- probability of joining a new species by an ant.

It is to note that the probability of leaving the best species (and joining the worst) is equal to zero.

The probabilities of leaving a certain species by an ant may be computed based on the quality observed in the species (i.e., the quality of the best ants) as follows:

1. For each i-th species (excluding the best one in the current iteration), a difference between the quality of its best individual diff_i according to the following equation:

$$\mathit{diff}_i = \mathit{fitness}_i - \mathit{fitness}_{best} \tag{1}$$

   where $\mathit{fitness}_{best}$ is the quality of the solution for the best of the species, while $\mathit{fitness}_i$ describes the quality of the solution in the current iteration for the species for which the difference is computed.

2. Next, for each i-th species (besides the best in the current iteration), a probability is computed for an ant leaving this species:

$$p_i = \frac{diff_i}{\sum\limits_{j \neq best} diff_j} \tag{2}$$

being the fraction of the difference computed by equation 1 and the sum of differences for each of the j-th species (besides the best one).

The probabilities of an ant joining certain species i (besides the worst one) are computed in an analogous way, while the equation for the difference of the quality is as follows:

$$diff_i = fitness_{worst} - fitness_i \tag{3}$$

where $fitness_{worst}$ is the quality of the solution in the current iteration for the worst of the species.

Having the probabilities computed, two species are chosen: one that is about to be left by an ant, and the other that the ant will join.

5. Experimental results

The experiments involved 100 iterations, the total number of the ants in the population was 100 for all of the experiments conducted (of course, the population consisted of dynamically-changing species), and the problem tackled was the Traveling Salesman Problem [13], using the selected classic TSPLIB[2] benchmarks.

In the beginning, let us observe the actual efficiency of the proposed emergent migration strategies tackling three problems of varying difficulty: **eil51**, **berlin52**, and **kroB200**. In this section, the emergent behavior of the ants is evaluated, and the efficacy of such a dynamically adapting metaheuristic is compared to the classic ACO and one of its best socio-cognitive versions (**egoWithoutBad** from [5] containing 60% EC, 20% AC, 20% GC, and 0% BC ants).

Migration from worst to best species

In this case, the migration arises only when the global results are worsening (while each iteration is observed) by a certain percentage. In Figure 2, the fitness and number of particular ants in the species are presented, assuming a 2% worsening of the best quality between the subsequent iterations.

In the case of tackling small problem (**eil51**), this emergence method made the system achieve slightly better results than the competitors and retained until the end, increasing slowly starting from the 40th iteration. In the case of medium problem (**berlin52**), the slight domination over the classic and socio-cognitive ants is lost in the final iterations of the experiment. However, this domination is present significantly

[2] `http://www.iwr.uni-heidelberg.de/groups/comopt/software/TSPLIB95/`

longer than in the case of the small problem (the classic ants begin to dominate around the 70th iteration). In the case of big problem (**kroB200**), the results of the emergent population are comparable to the **egoWithoutBad**; however, they are significantly better than the classic ACO.

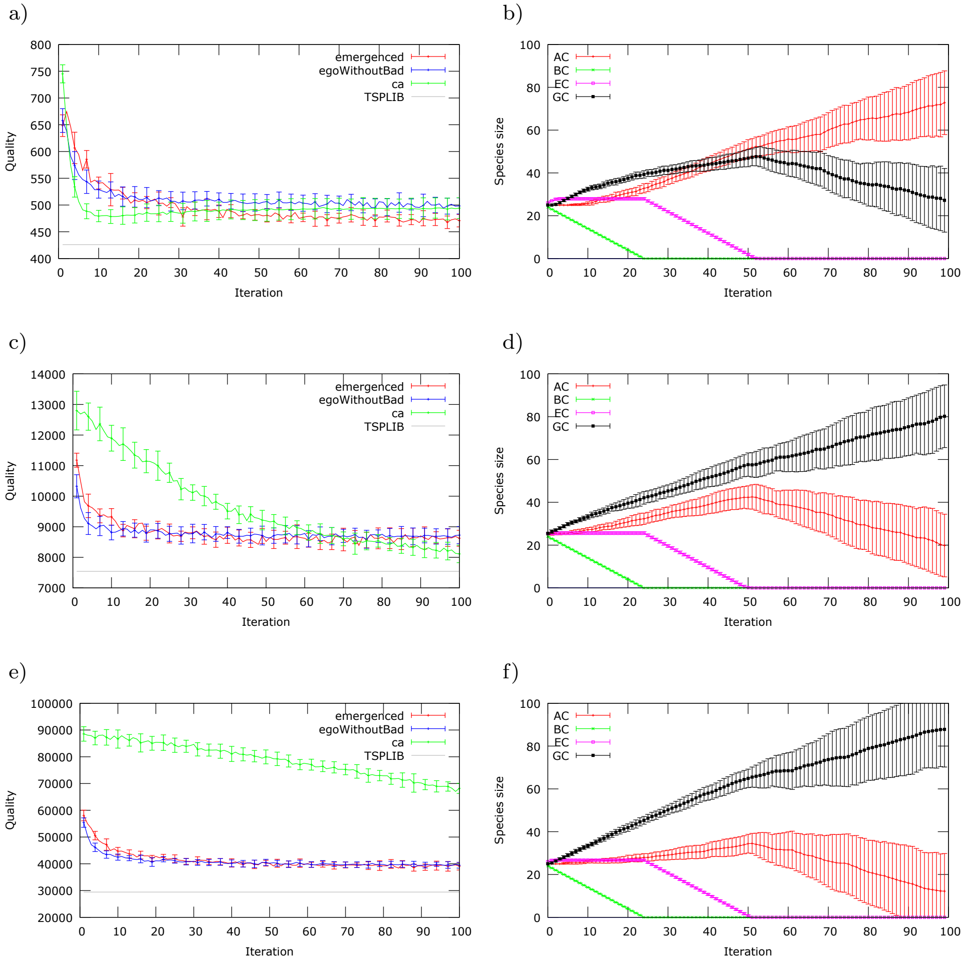

Figure 2. Instances **eil51**, **berlin52**, and **kroB200**, migration from worst to best species with 2% decrease in quality: a) best quality for **eil51**; b) population structure for **eil51**; c) best quality for **berlin52**; d) population structure for **berlin52**; e) best quality for **kroB200**; f) population structure for **kroB200**

Observations of the percentage of particular species in this experiment reveals that the AC ants gradually dominated the other species for the small problem at around the 70th iteration; however, in the case of bigger problems, the GC ants dominated the other species. In all of the experiments, the BC and EC ants are removed from the system by the 50th iteration. It seems that, in the case of the small problem, there is no need to employ complex techniques for perspective-taking and inspiration on the other's solutions; simply following the others is good enough. It is quite self-explanatory: one does not need sophisticated methods to solve simpler problems. At the same time, the more-sophisticated methods prevailed in the bigger problems, especially in the case of the biggest problem tackled.

Stepwise migration of one ant

The emergent behavior in the stepwise migration starts when the global quality drops between the iterations by a predefined percentage. In the tested instances, a 2% worsening was assumed.

In Figure 3, the results showing the quality and percentage structure of the population are presented for the small problem. For this instance (similar to the previous experiment), the stepwise migration is a little better than the competitive algorithms.

In the medium problem, the results are again similar to the previous setting, as the advantage is lost near the end of the computation (around the 70th iteration).

For the biggest instance tested, again the results of the emergent and socio-cognitive populations are very similar, and they are both much better than the classic ACO.

The percentage of a particular species is again quite similar to that of the previous setting. Moreover, just like in the previous experiment, the AC ants prevail for the smallest problem, while the more-sophisticated GC ants dominate the population for the bigger problem. Therefore, the conclusions resulting from the previous experiment may be repeated here: complex problems need more-sophisticated solutions.

Stepwise migration of many ants

Similar to the concept of the stepwise migration of one ant, emergent migration is possible in this case when the best quality decreases by a certain percentage value (see Fig. 4). However, the number of migrating ants currently depend on the extent of the quality decrease. In the tested cases, the decrease value was 2%.

In this case (contrary to the migration of one ant), the optimization of the smallest problem resulted in achieving a slightly better result than in the competitive algorithms; however, these results become visible starting at the 40th iteration. In the case of the medium and big problems, the emergence yields practically the same result as **egoWithoutBad**; however, it fares much better than the classic ACO.

It is to note that, in the case of the small and medium problems, the configuration of the population becomes more or less stable (about 50% of the GC and AC ants) starting at the 30th iteration.

At the same time, it seems that the GC ants prevail very quickly and dominate the other species for the big problem. In the first two experiments, the stability of the population structure is probably an effect of exchanging more ants (besides only one ant in the previous experiments). Moreover, the number of exchanged ants depend on the decrease in the quality. Therefore, it seems that achieving certain stability here is easier.

This observation is, however, false for the biggest problem – here, the GC ants prevail very quickly and yield much-better results than in the case of the classic ants; however, they are the same as **egoWithoutBad**.

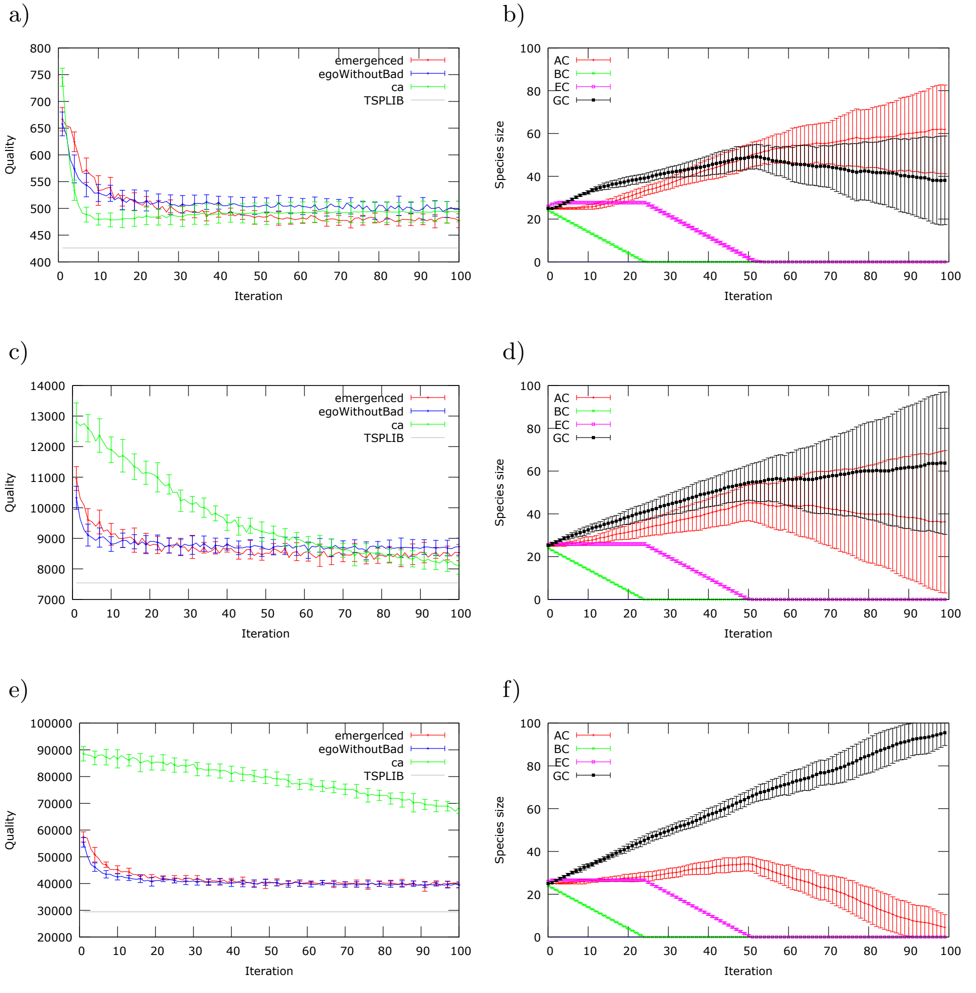

Figure 3. Instances **eil51**, **berlin52**, and **kroB200**, stepwise migration of one ant assuming quality decrease of 2%: : a) best quality for **eil51**; b) population structure for **eil51**; c) best quality for **berlin52**; d) population structure for **berlin52**; e) best quality for **kroB200**; f) population structure for **kroB200**

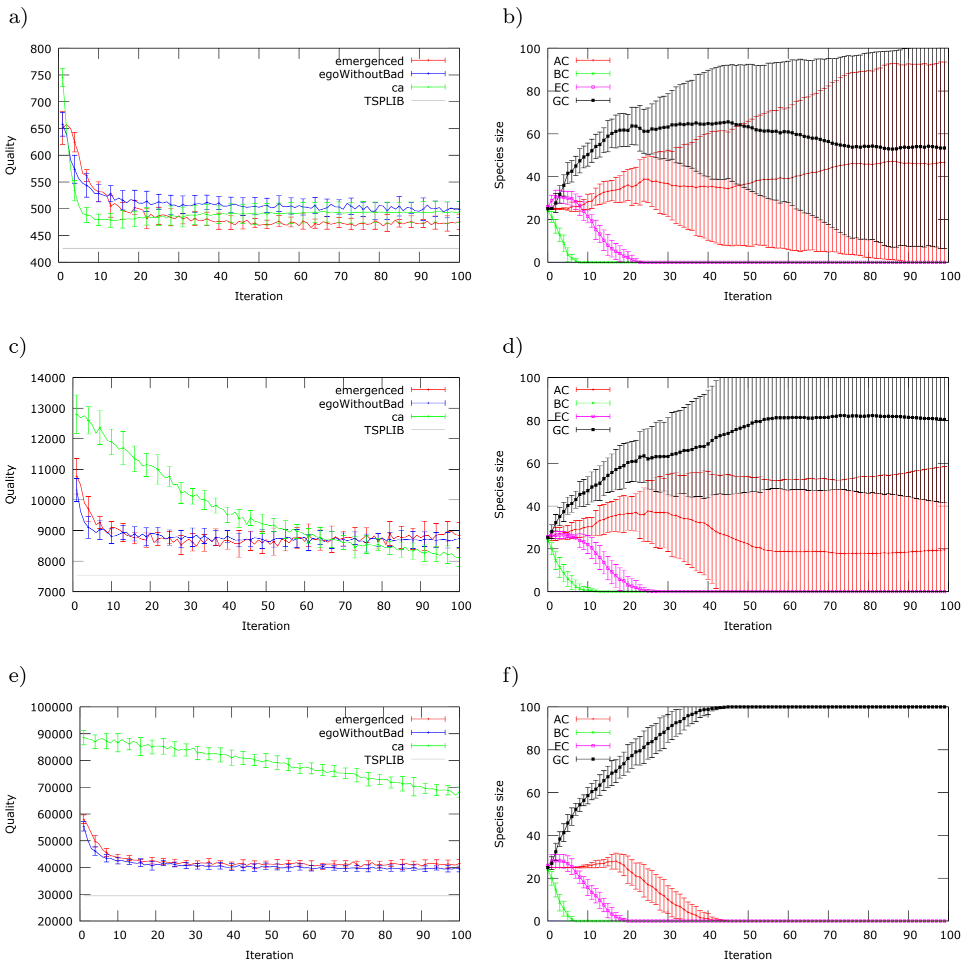

Figure 4. Instances **eil51**, **berlin52**, and **kroB200**, stepwise migration of many ants assuming quality decrease of 2%: a) best quality for **eil51**; b) population structure for **eil51**; c) best quality for **berlin52**; d) population structure for **berlin52**; e) best quality for **kroB200**; f) population structure for **kroB200**

Competition-based migration

In this case, the emergence consists of running a tournament between the ants that are about to change species periodically. The frequency tackled in this experiment is two steps.

In the current case (see Fig. 5), the outcome is generally the same as in the previous cases; however, the situation in the population structure is quite different. It seems that almost all species are present to the final iteration; only the random ants (BC) become extinct. This apparent diversity is caused by the type of emergence used, and the diversity of the population should assure the diversity of the search; therefore, this emergence method should be one of the most-preferred when tackling difficult problems.

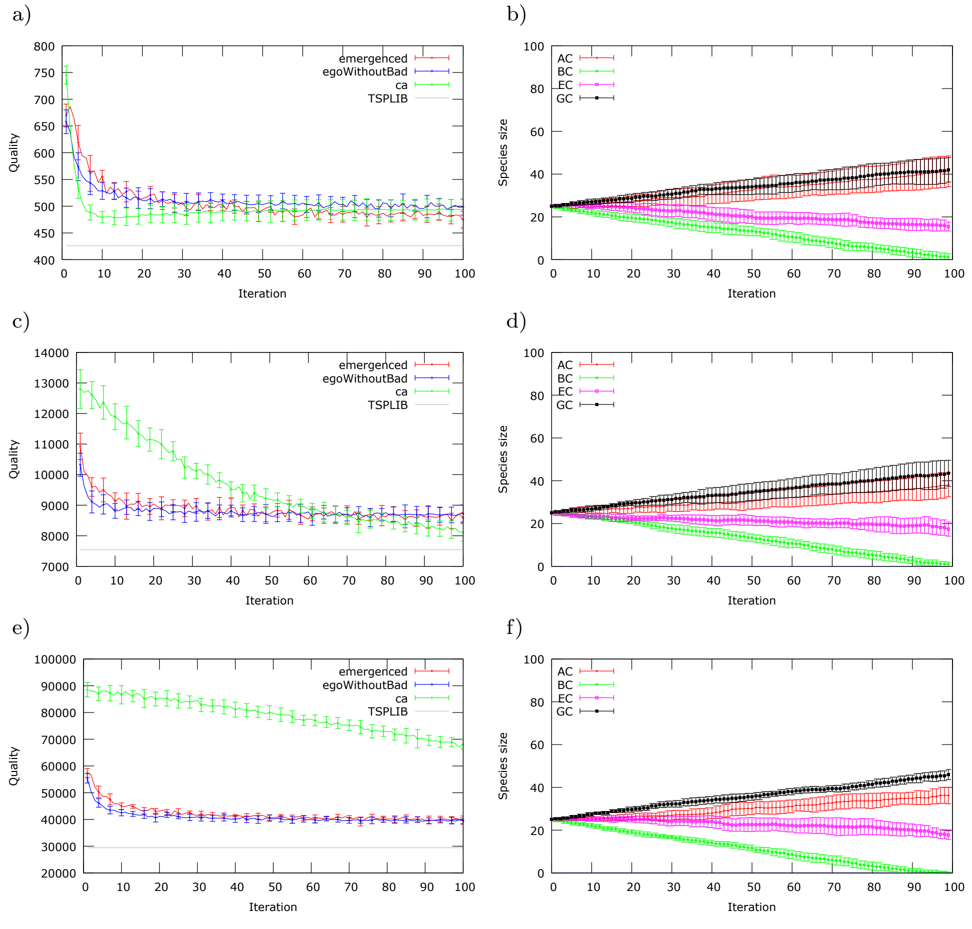

Figure 5. Instances **eil51**, **berlin52**, and **kroB200**, competition-based migration with period of 2: a) best quality for **eil51**; b) population structure for **eil51**; c) best quality for **berlin52**; d) population structure for **berlin52**; e) best quality for **kroB200**; f) population structure for **kroB200**

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Stochastic migration

According to the idea of stochastic migration, one of the ants leaves a randomly selected species and moves to another in each iteration (also randomly chosen).

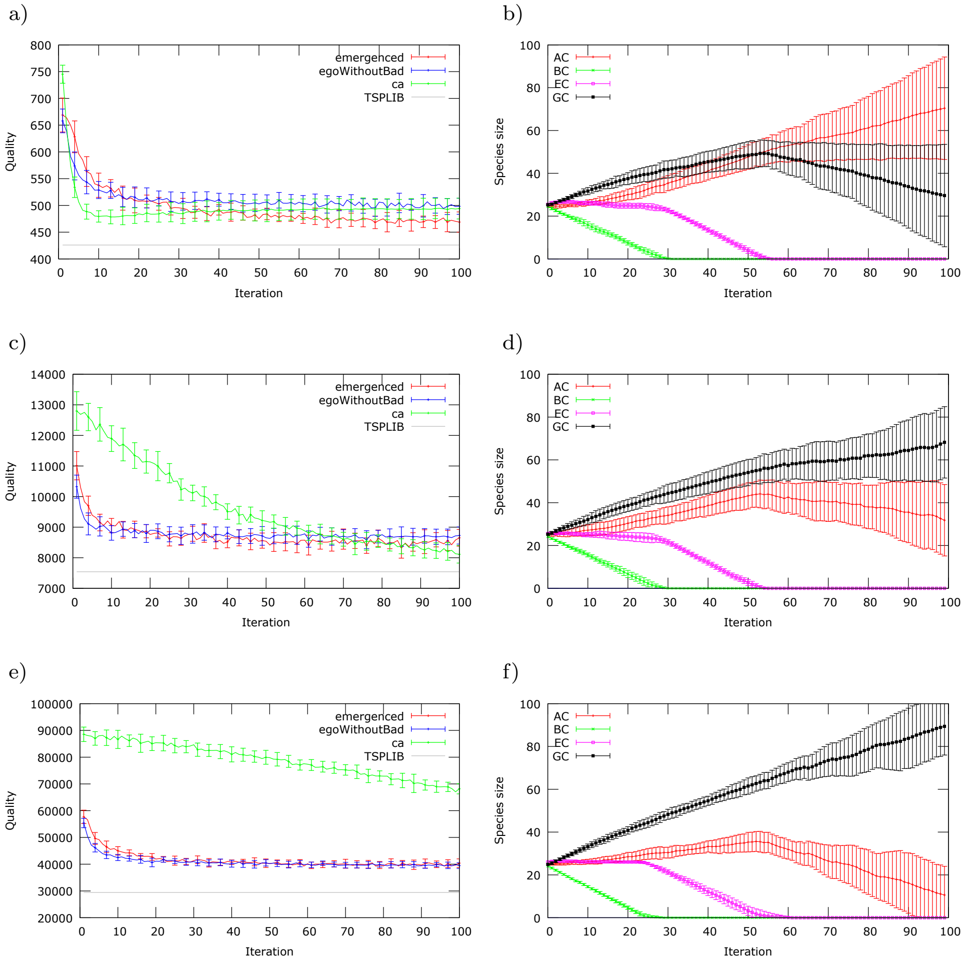

Figure 6. Instances **eil51**, **berlin52**, and **kroB200**, stochastic migration: a) best quality for **eil51**; b) population structure for **eil51**; c) best quality for **berlin52**; d) population structure for **berlin52**; e) best quality for **kroB200**; f) population structure for **kroB200**

In Figure 6, one can see the results of emergence with stochastic migration. It is clear that, in the case of the first problem tackled, the emergent population prevailed in the end. For the next two problems, the results of the emergent population are the same as in the case of **egoWithoutBad**.

The population structure again shows that, in the simplest case, the AC ants are the most-important species, while for the more-complex problems, the GC ants prevail.

Summary

For simpler problems, the results from all of the emergence strategies used were comparable with classic ants and **egoWithoutBad**; in several cases, the emergent population yielded better performances.

Observing the emergence strategies and composition of the population in the case of the three problems tackled, it turns out that AC ants following simple search algorithms perform better for the simple problems; however, for harder problems, more-sophisticated GC ants are required. One should compare this observation with the composition of the population for **egoWithoutBad**, where the most-numerous species was EC, with AC and GC accounting for 20% each.

To sum up, there are many near-equal optimal results of the search for the best composition of the population. However, it is not necessary to do such a search manually using a trial-and-error approach; instead, it is enough to define emergence strategies and wait for a feasible configuration to stabilize.

6. Conclusion

Metaheuristics can be complex, requiring a large number of parameters in the software application to be adjusted before it can efficiently solve a certain problem. Seeking optimal (or rather quasi-optimal) values of these parameters is usually realized by a trial-and-error approach, which can be tedious.

In this paper, we have presented an enhancement of the earlier proposed metaheuristics (namely, socio-cognitive ACO) by introducing emergence mechanisms for automatically configuring the composition of the population (in terms of ant species) to optimize performance. The emergence mechanisms are based on observing the quality value in the population and taking other actions that exchange ants among the species. The efficacy of these proposed mechanisms was tested with several selected benchmark functions from the well-known TSPLIB library.

The results show that the emergence mechanisms yield an outcome very similar to that obtained from manual tuning. In particular, population **egoWithoutBad**, which was found to be the best composition in our previous research, was easily reached by the emergent migration mechanism proposed here, thereby relieving the user from a tedious trial-and-error approach.

We plan to further examine the parametrization of the proposed metaheuristic, employing other means such as the diversity measures introduced in our earlier research ([21]) for assessing the quality of particular configurations.

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