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MAX-MIN Ant System in Image Preprocessing

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Introduction

Ant Colony Optimization [3] belongs to evolutionary computation methods, based on the swarm intelligence approach. The main advantage of swarm intelligence approach [4] is that system of simple communicating agents is capable of solving complex problems [8, 9]. Max-Min Ant System is one of the representatives of Ant Colony Optimization algorithms [1, 2]. Max-Min Ant System (MMAS), together with Ant Colony System algorithm proved to be an effective instrument, solving Traveling Salesman and Quadratic Assignment problems [2, 3].

Image preprocessing is inevitable process performed in any image processing application. Commonly it uses image processing operators to prepare image for further analysis. Idea to do image processing by Ant Colony Optimization algorithm is not new, but fresh [10, 11] and promising [5]. In this work we provide modifications to MMAS algorithm including modifications for initial ant placement for better exploration of the search space, applying algorithm for image processing operators' sequence selection for preprocessing synthetic images. Modifications of algorithm model are presented, estimation of parameters and experimental results are provided.

Main structure of image preprocessing task by MMAS is presented on Fig. 1, here MMAS is used for selection of image processing operators' sequence.

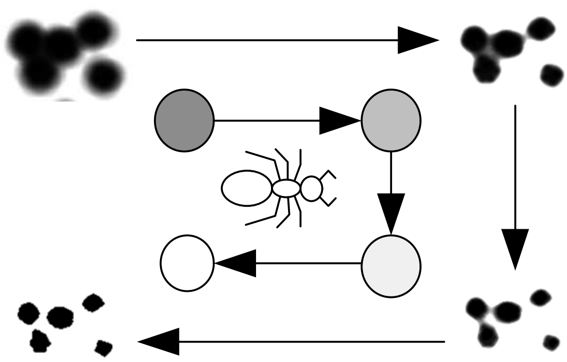

Fig. 1. Image preprocessing task structure

We start with introductory presentation of selected Max-Min Ant System model – describe model itself as also as modifications for its use for image preprocessing. Then we present experimental setup, necessary steps of image preprocessing, synthetic experimental data. Afterwards we show and comment the results of experimentation on the selection of suitable MMAS model parameters. Finally we present results of MMAS use for preprocessing of images and discuss possible further ways for preprocessing improvement.

Model of MAX-MIN Ant System

The original Max-Min Ant System model was proposed by Thomas Stützle and Holger H. Hoos [1, 2]. The main difference of Ant System from other Ant Colony Optimization algorithms is the way pheromone is updated. In original formulation of Ant Colony Optimization algorithm each ant places certain amount of pheromone at every step. Differently in MMAS algorithm – only the ant with (usually local) best solution is allowed to place pheromone.

Traveling Salesman problem is a standard way to check how well algorithm solves optimization task. The main task of the problem is for salesman to visit all cities using the shortest path. Commonly number of ants, m is equal to the number of cities, n. Each ant can move from one city to another, until all cities are visited. At the same time ant cannot move to already visited city, so total number of steps for each ant is m. During initialization ants are randomly placed in cities. At every step of solution construction, each ant moves, based on probabilistic decision, to a city it has not yet visited. The probabilistic choice of ant k move is:

$$p_{ij}^{k}(t)=\frac{\left[\tau_{ij}\left(t\right)\right]^{\alpha}\cdot\left[\eta_{ij}\right]^{\beta}}{\sum_{l\in N_i^k}\left[\tau_{il}\left(t\right)\right]^{\alpha}\cdot\left[\eta_{il}\right]^{\beta}},\qquad \text{if } j\in N_i^k. \qquad (1)$$

It is influenced by the pheromone trail $\tau_{ij}\left(t\right)$ and by locally available heuristic information $\eta_{ij}=1/d_{ij}$ that depends on distance d_{ij} between cities i and j. Ants prefer cities that are close and connected by links with high pheromone trail. α and β are two parameters that determine the relative importance of the pheromone trail and the heuristic information. N_i^k is the set of cities ant has not visited yet.

Pheromone trails are updated after all ants have completed their tour construction. Initially pheromone level is lowered due to evaporation parameter ρ (with $0 \le \rho < 1$):

$$\tau_{ij}(t+1) = \rho \cdot \tau_{ij}(t). \tag{2}$$

Then pheromone is added to the best path:

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}^{\mathrm{best}}, \tag{3}$$

here $\Delta\tau_{ij}^{\mathrm{best}} = 1/f\left(s^{\mathrm{best}}\right)$ with $f\left(s^{\mathrm{best}}\right)$ as a solution cost of iteration-best $s^{\mathrm{best}} = s^{\mathrm{ib}}$.

Key difference of MMAS algorithm from others is the use of pheromone limits. Limits are calculated by:

$$\tau_{\max} = \frac{1}{1-\rho} \cdot \frac{1}{f\left(s^{\mathrm{gb}}\right)}, \quad \tau_{\min} = \frac{\tau_{\max} \cdot \left(1 - \sqrt[n]{p_{\mathrm{best}}}\right)}{(avg-1) \cdot \sqrt[n]{p_{\mathrm{best}}}}. \tag{4}$$

Here $p_{\mathrm{best}} = p_{\mathrm{dec}}^n$ is the probability to construct the best solution; p_{dec}^n is a decision at each node; $avg = n/2$; $\tau_{\min} > 0$.

Initially all pheromone values are set to $\tau_{\max}$ and after each iteration pheromone limits are updated. Then validity of limits is checked by the use of rule:

$$\text{if } \tau_{\min} > \tau_{\max}, \quad \text{then } \tau_{\min} = \tau_{\max}, \tag{5a}$$

and pheromone values are placed within limits:

$$\begin{cases} \text{if } \tau_{ij}(t) > \tau_{\max}, & \text{then } \tau_{ij}(t) = \tau_{\max}; \\ \text{if } \tau_{ij}(t) < \tau_{\min}, & \text{then } \tau_{ij}(t) = \tau_{\min}. \end{cases} \tag{5b}$$

Because of pheromone limits, convergence condition is easily formulated: when only one pheromone trail reaches $\tau_{\max}$ and all other trails become $\tau_{\min}$, convergence occurs.

For a task with $n = 20$ cities, typical parameters for MMAS are: number of ants $m = 20$; $\alpha = 1$; $\beta = 2$; $\rho = 0.98$; $p_{\mathrm{best}} = 0.05$.

MMAS model adjustment for image preprocessing

Main idea of applying MMAS for image preprocessing is based on the assumption that ants can select the right sequence of processing operators in order to get required processing effect. Then found preprocessing sequence can be used to preprocess other similar images.

Characteristic initial image together with “preprocessed” one (e.g., by human operator) are needed. Using these two images, MMAS will find the sequence of image processing operators to get the initial image $\mathbf{I}_{\mathrm{in}}$ as close as possible to the provided target image $\mathbf{I}_{\mathrm{tar}}$.

To implement this idea, the table $\mathbf{C}$ of possible processing operators together with possible processing parameters should be created. Each operator with linked parameter should be considered as one city.

For experimental model a table of 85 processing operators with linked parameters was created. Table consists mostly of morphological image processing operators, as these operators are often used. Additionally, rising in power, averaging and edge detector operators are included.

Main steps of image preprocessing algorithm are based on common MMAS application and can be summarized as follow:

1. Initialize.
2. Create solutions.
3. Perform local search.
4. Update pheromone trails.
5. Check convergence condition.
6. If condition is not met, return to Step 2.

During initialization initial $\mathbf{I}_{\mathrm{in}}$ and target $\mathbf{I}_{\mathrm{tar}}$ images are provided, then $p_{\mathrm{best}} = 1/n$ is calculated. Variables $\tau_{\max}$ and $\tau_{\min}$ are initialized according to (4). However $avg = n$ is set, because each operator is equally possible in a path and the worst initial solution cost then is:

$$f\left(s^{\mathrm{best}}\right) = I_{\mathrm{X}} \cdot I_{\mathrm{Y}} \cdot 255, \tag{6}$$

here I_{X} and I_{Y} hold image size values; image intensity range is 255.

Usually solution consists of limited number of operators, so in order to simplify calculations, we limit ant’s path length, i.e., $l_{\max} = 6$.

Standard MMAS model places one ant in each city. Such ants’ placement gives equal probability for search space exploration.

During standard MMAS model execution ant could visit any non visited city. However in image preprocessing application of MMAS, same image processing operator may be used several times. So ant should be able to go to already visited cities. For this purpose heuristic information η is changed to suit image processing model:

$$\eta = \frac{1}{1 + l_{\max} - l^{\mathrm{op}}}, \tag{7}$$

here η depends on distance of used operator in time l^{op}. Increase of iteration number, will raise the probability of operator’s reuse. Thus the operator that was used by ant in last iteration will have lowest probability compared to operator that was not used yet.

In a standard MMAS formulation for a Traveling Salesman problem each ant has equal probability to start in the same city. However for image preprocessing application, beginning of operation from certain city (operator) can lead to better solution. Thus the standard model of MMAS is modified and pheromone control of starting position is. Pheromone matrix in starting position $\boldsymbol{\tau}^{\mathrm{Start}}$ is initialized to $\tau_{\max}^{\mathrm{Start}}$, calculated by:

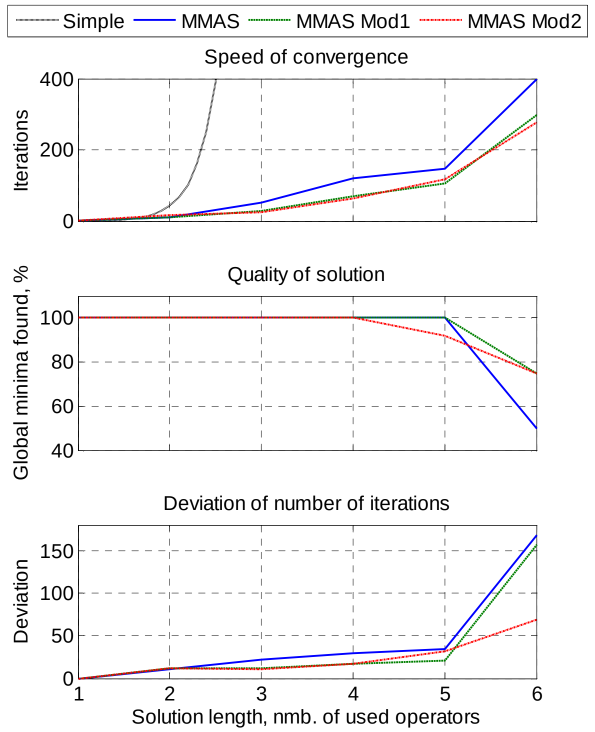

Fig. 2. Results comparison of different MMAS used for image preprocessing task

$$\tau_{\max}^{\text{Start}} = \frac{1}{1-\rho} \cdot \frac{1}{n}, \tag{8}$$

and at each iteration $\boldsymbol{\tau}^{\text{Start}}$ is updated by:

$$\tau_i^{\text{Start}}(t+1) = \tau_i^{\text{Start}}(t) \cdot \rho + \sqrt[n]{\Delta \tau_i^{\text{best}}}. \tag{9}$$

Two modifications of initial ant placement based on pheromone concentration are proposed.

MMAS Mod1 – first modification is based on ant's starting position control:

$$p_i^{\text{Start}\,k}(t) = \frac{\tau_i^{\text{Start}}(t)}{\sum_{l \in N} \tau_l^{\text{Start}}(t)}. \tag{10}$$

Here $p_i^{\text{Start}\,k}$ is the probability of the ant k to start in city i; $\tau_i^{\text{Start}}(t)$ is the pheromone concentration in city i; N is the total number of cities. Starting position is chosen by a roulette well method based on probability vector $\mathbf{p}^{\text{Start}}$.

MMAS Mod2 – second modification is based on ant's placement control, when at each iteration a predefined amount of ants m is moved from the cities with the lowest pheromone level $\tau_{\min}^{\text{Start}}$ to the cities with the highest pheromone level $\tau_{\max}^{\text{Start}}$.

Local search is used to find local best solution choosing the one with maximum $f^{-1}\left(s^{\text{best}}\right)$. Local search not only finds the path with best solution but also is used as a stopping criterion for ant travel.

Results of image preprocessing by MMAS

Prior to MMAS simulation, complexity of the problem should be analyzed and primary parameters supplied. Because ants can visit already visited cities, total number of possible solutions can be $S^{\text{Total}} = n^{l_{\max}}$. Having in mind that number of ants m is equal to number of cities n, during each iteration MMAS model can check n solutions.

For testing purposes synthetic initial image was created and after applying from 1 to 6 image processing operators, resulting images were used as a targets, guaranteeing existence of the solution.

After setting recommended parameters [2]: $\alpha = 1$; $\beta = 2$; $\rho = 0.98$ for MMAS model, numbers of experiments were performed in order to determine model effectiveness comparing it with simple brute force method of finding the sequence.

Results proved (see Fig. 2) that parameters are good and standard MMAS model is quite effective in finding solutions of multidimensional problem. Increase of α led to much quicker solution, however as it also increased the rate of stuck in local minima, it was reverted back. Modification of β and ρ parameters usually led to change in convergence speed but usually ended in local minima. So parameters were left as per recommendation. Increase of solution length to $l_{\max} = 7$ led to increased complexity of the problem and with higher dimensionality of the problem about 50 % of all solutions were stuck in local minima.

As expected, introduction of pheromone controlled start position led to improvement of convergence speed. Two suggested modifications provided similar improvement in convergence speed as we can see it on Fig. 2. When compared to standard MMAS, modifications improvement starts from path length $l = 3$ and with path length $l = 6$ best improvement over standard MMAS without pheromone controlled ants placement was 30 %. MMAS Mod2 showed best results when set amount of moved ants was 20 %, that led to 5 % improvement over MMAS Mod1 $l = 6$. Further increase of percentage of moved ants lead to narrower exploration space and simulation often ended with solution in local minima.

Conclusions

1. Ant's starting position has great influence for MMAS convergence speed (improvement of 30 % over model without starting position control was achieved).
2. Proposed MMAS with ant placement control showed up to 5 % additional improvement of convergence speed compared to another proposed MMAS with starting position control.

The future work will concentrate on more sophisticated ant placement strategies and application of MMAS for preprocessing of images of two-dimensional electrophoresis gels [6, 7].

ACKNOWLEDGMENTS

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MAX–MIN Ant System (MMAS) application in image preprocessing is investigated. Standard MMAS model for traveling salesman problem is presented together with MMAS model modifications, applying it for image preprocessing. Two modifications of initial ant placement strategy introduced, one based on simplified MMAS without heuristic information (Mod1), second is based on normalized quantity of moved ants (Mod2). Experimentally determined percentage of moved ants is 20%. Provided modifications were tested on synthetic images with evaluation of convergence speed. Additionally test results were compared with simple brute force solution finding method. Initial ants placement based on pheromone concentration proved to be an effective way to increase convergence speed. With solution length of 6 operators 30% increase in convergence speed was achieved compared to MMAS without pheromone control. Mod2 showed 7% decrease in quality on short run problems (5 operators), however on longer solution (6 operators) Mod2 solution quality decrease slope was less rapid (quality decrease 25%) compared to both standard MMAS without initial ant placement strategy and Mod1 (quality decrease 49%). Analyzing deviation of number of iterations Mod2 also showed less rapid increase in deviation compared to MMAS and Mod1. Ill. 2, bibl. 11 (in English; summaries in English, Russian and Lithuanian).

Р. Лаптик, Д. Навакаускас. MAX–MIN муравьинная система в предварительной обработке изображений // Электроника и электротехника. – Каунас: Технология, 2009. – № 1(89). – С. 21–24.

Исследуется применимость MAX–MIN муравьинной системы (ММMC) для предварительной обработки изображений. Кратко представлена стандартная модель ММMC, применимая для решения задачи комивояжера. Предложено несколько модификаций модели для предварительной обработки изображений. Представлены две модификации модели начального расположения муравьев: одна основана на упрощенной модели ММMC (Mod1) без евристической информации, другая – на нормированном количестве переносимых муравьев (Mod2). Экспериментально определено, что количество переносимых муравьев должно составлять 20 %. Предложенные модификации проверялись на искуственных изображениях, оценивая скорость конвергенции. Оценивая скорость конвергенции модели, дополнительно проводплось сравнение с простым методом перебора. Начальное расположение муравьев, основанное на концентрации феромона, оказалось эффективным способом сокращения времени конвергенции. При увеличении длины решения до 6 операторов, был получен 30 % прирост скорости. При короткой длине решения (5 операторов), качество решения ухудшилось на 7 %, хотя при более длинных решениях (6 операторов) спад качества получился 25 %, что лучше, чем у стандартной ММMC (49 %). Mod2 имеет наименьшую дисперсию количества итераций. Ил. 2, библ. 11 (на английском языке; рефераты на английском, русском и литовском яз.).

R. Laptik, D. Navakauskas. Vaizdų pirminis apdorojimas MAX–MIN skruzdžių sistema // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2009. – Nr. 1(89). – P. 21–24.

Tiriamas MAX-MIN skruzdžių sistemos (MMSS) taikymas vaizdų pirminiam apdorojimui. Trumpai supažindinama su standartiniu MMSS modeliu ir jo taikymu keliaujančio prekeivio problemai spręsti. Pristatomos kelios MMSS modelio modifikacijos, pritaikant šį modelį vaizdų pirminiam apdorojimui. Siūlomos šios pradinio skruzdžių išdėstymo modifikacijos: pirmoji pagrįsta supaprastintu MMSS modeliu be euristinės informacijos (Mod1), antroji – perkeliamų skruzdžių skaičiaus normavimu (Mod2). Eksperimentiškai nustatyta, kad 20 % visų skruzdžių turi būti perkeliamos. MMSS modelio modifikacijos buvo tikrinamos naudojant dirbtinius vaizdus ir vertinant algoritmų konvergavimo greitį. Modelių vertinimo rezultatai papildomai lyginami su visų sprendimų perrinkimo Mod1 rezultatais, t. y. pradinis skruzdžių išdėstymas, remiantis feromono kiekiu, efektyviai didina MMSS konvergavimo greitį. Didinant sprendinio ilgį iki 6 operatorių, gautas 30 % greičio prieaugis. Trumpo sprendinio (5 operatoriai) naudojant Mod2 kokybė pablogėjo 7 %, o ilgesnio sprendinio (6 operatoriai) – 25 %, tačiau tai yra geriau negu nemodifikuotos MMSS atveju (pablogėjimas 49 %). Be to, Mod2 būdinga mažiausia rezultatų sklaida palyginti su MMSS ir Mod1. Il. 2, bibl. 11 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).

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