AUTOMATIC PARAMETERIZATION FOR EXPEDITIOUS MODELLING OF VIRTUAL URBAN ENVIRONMENTS
A New Hybrid Metaheuristic

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Abstract: Expeditious modelling of virtual urban environments consists of generating realistic 3d models from limited information. It has several practical applications but typically suffers from a lack of accuracy in the parameter values that feed the modeller. By gathering small amounts of information about certain key urban areas, it becomes possible to feed a system that automatically compares and adjusts the input parameter values to find optimal solutions of parameter combinations that resemble the real life model. These correctly parameterized rules can then be reapplied to generate virtual models of real areas with similar characteristics to the referenced area. Based on several nature inspired metaheuristic algorithms such as genetic algorithms, simulated annealing and harmony search, this paper presents a new hybrid metaheuristic algorithm capable of optimizing functions with both discrete and continuous parameters and offer competitive results in a highly neglected field of application.

1 INTRODUCTION

There has been a growing need for expeditious modelling systems for urban environments in recent years. Applications include virtual city tours, georeferenced services, urban planning.

Creating urban models that are accurate representations of the real world can be extremely hard in terms of information gathering and invested man power. Close resemblances to the real world is often an acceptable compromise for some applications. It often occurs that it is quite impossible to gather information from the entire city you are trying to model but it is somewhat easy to extract detailed information from certain key-defining small areas from within the city. Generating expeditious modelling rules that will match such information is an important requirement. The artificial intelligence field of optimum search includes meta heuristic algorithms that can determine optimum parameter values.

The work described in this paper focuses on solving this problem by creating a new hybrid meta heuristic algorithm, competitive and capable of handling both discrete and continuous parameters. Adapting ideas from several other nature based meta heuristic algorithms such as genetic algorithms, simulated annealing and harmony search.

This paper is divided into 5 sections: the first serving as the introduction, the second section referring to related work, the third describing the developed system, the fourth presenting and discussing the results achieved, and the fifth presenting the conclusions and future work.

2 RELATED WORK

2.1 Expeditious Modelling of Virtual Urban Environments

The modelling of virtual urban environments has many different applications including virtual city tours (Schilling and Coors, 2003), georeferenced services (Ito et al., 2005), cultural heritage preservation (Hildebrand et al., 2000) (Zach et al., 2001) and urban planning. Often there is a need for realistic or semi-realistic models of cities, however, modelling accu-

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rate realistic models grows problematic considering increasing needs in size and complexity.

Using principles of l-system (Lindenmayer, 1968) (Prusinkiewicz, 1986), it is possible to define sets of production rules to model all kinds of urban environment elements (Parish and Muller, 2001) based on limited georeferenced data (Muller et al., 2006). It's often difficult to acquire reliable data of an entire city we are trying to model, however it is relatively easy to gather information from certain key-defining sections of a city and assign the data to a georeferenced database. The production rules with the data collected will enable the creation of models resembling the area of gathered information.

2.2 Meta Heuristic Algorithms for Solving Optimization Problems

The field of artificial intelligence branches many areas (Russel and Norvig, 2003), one of the most relevant ones is the field of optimum search. Meta heuristic algorithms play an important role in this field. Different meta heuristic variants and hybrid versions refer to evolutionary computation or nature inspired behaviors: genetic algorithms (Holland, 1992) (Goldberg, 2002), simulated annealing (Kirkpatrick et al., 1983) (Aarts et al., 2005) and harmony search (Lee and Geem, 2005) (Mahdavi et al., 2007).

The common principle is to find the best combination of parameters of a given vector function such that a related objective function is maximized or minimized. This process is iterated through educated random guesses following the heuristic logic of the algorithm. There is no best heuristic, performance varies according to the constraints of problem. A big number of proposals for hybrid or customized adaptations is found in recent literature (Deep and Thakur, 2007) (Arumugama et al., 2005) (Kumar et al., 2007) (Lee and Geem, 2005) (Mishra et al., 2005).

3 IMPLEMENTATION

3.1 Problem Statement

An l-systems based expeditious modeler for the generation of realistic urban environments becomes more valuable with an optimum parameterization system.

The system must handle the input of boolean, integer and real based parameters. The system must allow a configuration easily adaptable to the problem. When solving linear constrained problems the system must out-perform simple random based algorithms such as hill climber and random search. When solving problems with multiple local maximums the system is required to perform above par of classic meta heuristic algorithms such as simulated annealing, genetic algorithm and harmony search.

3.2 Hybrid Optimizer Meta Heuristic Algorithm

The hybrid meta heuristic is inspired by basic principles of real based genetic algorithms and concepts from simulated annealing and harmony search.

There are two families of populations resident in memory at all times, the original parent family and the top list family. Their dimensions can be configured by XML. Each iteration step of the meta heuristic algorithm consists on creating a new original parent family generation. The top list family maintains in memory the best solutions ever found so far, sorted by quality.

Each solution stores values for all parameters being calibrated. Each parameter has information regarding its type (integer, boolean, real) and scope (minimum and maximum values). The type and scope for each parameter are pre-configured by XML. The values for the first generation of the original parent family are calculated randomly within its scope boundaries. The first generation of the top list family is obtained by sorting the first generation of original parent family. These values can also be loaded from disk to test scenarios in same starting terms.

Each following original parent generation is obtained by cross-breeding the original parent family with a chosen member of the top list family. Ensuring an elitist selection behavior inspired by genetic engineering. Several threshold variables further influence the selection of the new solution to ensure a wider search space scope not limited to the first generation. These variables incorporate monte carlo methods (Metropolis and Ulam, 1949) using probability thresholds inspired by simulated annealing and harmony search. Some are, or can be, affected by what is referred to as *globalentropy*, an internal value increasing by each passing iteration as described in (1). There are a total of five threshold parameters which must be calibrated considering the problem.

Random New Struct Threshold (*trns*), affects the probability of choosing a completely random new solution. The higher this value the more probable it becomes to occur a total random creation of a new solution as seen in formula (3).

$$globalentropy = iterationstep/maxsteps \quad (1)$$

$$trns = thresholdRandomNewStruct \quad (2)$$

$$randSol = rand() * globalentropy < trns \quad (3)$$

Random New Type Threshold (*trnt*), affects the probability of choosing a completely random new value for each of the solution parameter types. The higher this value is the more probable it is to occur a totally random new value for the current parameter type of the solution as seen in formula (5).

$$trnt = thresholdRandomNewType \quad (4)$$
$$randType = rand() * globalentropy \; < \; trnt \quad (5)$$

Toplist Dispersion Threshold (*ttld*), affects the probability of choosing lower ranking *toplist* parents to cross the solution with. The higher this value the wider the scope of choice as seen in formula (8).

$$ttld = thresholdToplistDispersion \quad (6)$$
$$ttld > 1.0 \; : \; ttld = 1 - globalentropy \quad (7)$$
$$victim = (rand() * ttld * maxFamilySize) \quad (8)$$

Typevalue Dispersion Threshold (*ttvd*), affects the parental gene influence for each value of the parameter types of the solution as seen in formula (13).

$$tlv = topslistParentValue \quad (9)$$
$$orv = originalParentValue \quad (10)$$
$$ttvd = thresholdTypevalueDispersion \quad (11)$$
$$ttvd > 1.0 \; : \; ttvd = 1 - globalentropy \quad (12)$$
$$newvalue = (ttvd * orv) + ((1 - ttvd) * tlv) \quad (13)$$

Typevalue Entropy Threshold (*ttve*), affects the probability of scope jitter for each value of the parameter types of the solutionas can be seen in formula (17).

$$ttve = thresholdTypevalueEntropy \quad (14)$$
$$ttve > 1.0 \; : \; ttve = 1 - globalentropy \quad (15)$$
$$scope = \|(OParentValue - TLParentValue)\| \quad (16)$$
$$igl = (1.0F - globalentropy) \quad (17)$$
$$ttvss = igl * igl * igl \quad (18)$$
$$range = MaxParamValue - MinParamValue \quad (19)$$
$$scope < ttvss * range \; : \; maxscope = range * igl \quad (20)$$
$$scope > ttvss * range \; : \; maxscope = scope * ttve \quad (21)$$
$$maxscope = scope * rand() \quad (22)$$
$$newvalue = newvalue + scope - (maxscope/2) \quad (23)$$

4 RESULTS

A test-case was prepared involving the parameterization of a set of production rules which would model several buildings with certain height values missing. The known information from all of the buildings included georeferenced location and the values of the buildings perimeter, area and *bottomzvalue*. The unknown information from some of the buildings comprised solely the *topzvalue*.

The production rule used to estimate the unknown *topzvalue* from the buildings is described mathematically in formula (27).

$$av = (cra - 1) * fca * area \quad (24)$$
$$ab = (crb - 1) * fcb * bottomzvalue \quad (25)$$
$$ap = (crp - 1) * fcp * perimeter \quad (26)$$
$$topzvalue = avgz + disp * (av + ab + ap) \quad (27)$$

The formula implies a relation between the building's area (24), perimeter (26) and *bottomzvalue* (25) with the building's height to estimate a realistic *topzvalue* for input to the expedite modeler.

Our formula has a total of 8 unknown fields to be parametrized: *avgz* [100.0 .. 120.0], the average height for all the buildings. *disp* [0.0 .. 1.0], the dispersion rate from the average height. *cra* [0 .. 3], area correlation. *crb* [0 .. 3], *bottomzvalue* correlation. *crp* [0 .. 3], perimeter correlation. *fra* [0.0 .. 1.0], the area value correlation factor. *frb* [0.0 .. 1.0], the *bottomzvalue* correlation factor. *frp* [0.0 .. 1.0], the factor of the perimeter correlation.

Different configurations of the meta heuristic algorithm were tested with a fixed *toplist* family size of 20. The different tested configurations include the behavior of some classic algorithms: random search, hill climber and simulated annealing. A few additional configurations were also tested for comparative performance results. Each test iterated 50 generations with a family size of 8 and were labeled as follows: *h1r8*, hybrid random search. *h1n8*, hybrid new configuration. *h2n8*, hybrid second new configuration. *h3n8*, hybrid third new configuration. *hhc8*, hybrid hill climber. *hsa8*, hybrid simulated annealing.

The calibration parameters of each configuration tested can be consulted in Table 1.

Table 1: Threshold parameters of the different configurations.

config	trns	trnt	ttld	ttvd	ttve
h1r8	1.0	1.0	0.0	0.5	0.5
h1n8	0.01	0.01	0.1	1.1	1.1
h2n8	0.001	0.001	0.4	0.15	1.1
h3n8	0.001	0.001	0.1	0.1	1.1
hhc8	0.01	0.01	0.0	1.0	0.1
hsa8	0.01	0.01	0.0	1.0	1.1

The quality function for the test case is calculated as a weighted sum of the height from the involved buildings. All simulations were performed three times to present some insight on how deeply the performance of the meta heuristics algorithm stochastic nature is affected. Table 2 displays the progressive results obtained from our test case. It shows the quality value of the best solution found at 2%, 40%, 80% and at the end of the iteration process and allow us to speculate on how each configuration depend on the initial state and perform comparatively to known random search, hillclimber and simulated annealing algorithms.

Table 2: Progressive solution quality results from the different configurations.

config	2%	40%	80%	final
h1r8-1	163.95	54.254	44.854	44.854
h1r8-2	373.90	98.338	14.557	14.557
h1n8-1	272.53	9.319	9.319	9.319
h1n8-2	29.479	10.910	8.972	8.972
h2n8-1	438.53	24.047	14.425	14.425
h2n8-2	1038.61	1.758	1.758	1.758
h3n8-1	22.164	6.418	0.175	0.175
h3n8-2	288.56	3.934	0.798	0.798
hhc8-1	117.35	47.728	47.728	32.145
hhc8-2	1069.77	427.75	232.77	104.08
hsa8-1	1207.92	75.354	40.354	40.354
hsa8-2	315.95	137.05	42.689	9.804

5 CONCLUSIONS AND FUTURE WORK

An automatic parameterization system for expeditious modelling of virtual urban environments has been developed with a successful field application. Our test case, despite its relatively low complexity and linear constraints, demonstrates the potential of our new hybrid meta heuristic algorithm in finding optimum parameters for rule sets of expeditious modelling competitively to common optimum search algorithms. Further test results are required to statistically compare the performance of the new hybrid meta heuristic algorithm with other meta heuristic algorithms and parameter optimization problems.

An envisioned improvement to the system involves applying principles of nested partition and linear regression to strengthen performance.

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