GENETIC OPTIMIZATION ALGORITHMS APPLIED TOWARD
MISSION COMPUTABILITY MODELS

MEE SEONG IM AND VENKAT R. DASARI

Abstract. Genetic algorithms are modeled after the biological evolutionary processes that use natural selection to select the best species to survive. They are heuristics based and low cost to compute. Genetic algorithms use selection, crossover, and mutation to obtain a feasible solution to computational problems. In this paper, we describe our genetic optimization algorithms to a mission-critical and constraints-aware computation problem.

1. Introduction

Mission critical computations are often needed in the tactical edge where the computational and energy resources are limited and impose a limit on the computational complexity of a chosen algorithm to accomplish mission computational objectives. A trade off must be made between the degree of optimization, speed of the computation and the minimal computational accuracy needed to achieve the computation objectives like decision making, objection detection and obstacle detection. Genetic algorithms are well suited to deploy in resource constrained tactical environments because they are fast, use low resources and their degree of computation accuracy is just enough to meet mission computation objectives in many cases.

In [1], Im and Dasari analyze and optimize the parameters of the communication channels needed for quantum applications to successfully operate via classical communication.

Key words and phrases. bio-inspired algorithms, genetic optimization, optimization models, mission computability, constraints-aware distributed computation.
channels. We also develop algorithms for synchronizing data delivery on both classical and quantum channels. The authors in [2], together with Billy Geerhart, investigate computational efficiency in terms of watt and computational speeds to match mission requirements in mission-oriented tactical environments since it plays an important role in determining the fitness of an application for mission deployment; the application we study in this manuscript relates to context-aware and mission-focused computational framework by restricting to a subclass of deterministic polynomial time complexity class of languages. We focus on a constraints-aware distributed computing algorithm, where if too many jobs are assigned to an array of cores, an algorithm can be written to minimize the number of failed jobs.

The authors address the complexity of various optimization strategies related to low SWaP computing in [3], and due to the restrictions toward optimization of computational resources and intelligent time versus efficiency tradeos in decision making, only a small subset of less complicated and fast computable algorithms can be used for tactical, adaptive computing. And an efficiency tradeo we consider in this manuscript is a job scheduling system for batch jobs and remote desktops for graphical applications, and discuss a way to optimize the heterogeneous computing environment. In [4], Dasari–Im–Beshaj discuss classical image processing algorithms that will benefit from quantum parallelism.

Genetic algorithms mimic ideas from evolutionary biology techniques (cf. [5, 6, 7, 8, 9, 10, 11]). An instance of such algorithms is called ant colony optimization technique (cf. [12, 13, 14, 15]). In this manuscript, we investigate a mission computability model that will benefit from genetic optimization algorithms.
2. Bio-inspired algorithms

Genetic algorithms begin with an initial generation of feasible solutions that are tested against the objective function. Subsequent generations evolve through notions called selection, crossover, and mutation. Selection is to retain the best performing (binary) bit strings from one generation to the next (see e.g., Example 2.1). Crossover is a notion where we select common similarity between the different person variables and keep those to be the same to create a child variable that appear in the subsequent generation. Finally, mutation is where we mutate certain variables from person to take on random values and create a child based off of the mutation. Mutation allows genetic algorithms to avoid falling into a local minima and helps them to explore the space of possible solutions.

Example 2.1. Consider

\[
\text{person}_1 = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{pmatrix} \\
\text{person}_2 = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}
\]

from the previous generation, where the binary digits are the variables in the optimization problem. We use selection

\[
\text{person}_1 = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{pmatrix} \\
\text{person}_2 = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix},
\]

and favor them for reproduction; thus, red and green digits are kept for the next generation since they performed well in the previous generation. Because they performed well, they
might be used for crossover, i.e.,

\[
person_1 = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{pmatrix},
\]

\[
person_2 = \begin{pmatrix} 1 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}, \text{ and}
\]

\[
child = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}.
\]

Mutations may occur, assisting the genetic algorithm to better analyze the solution set:

\[
person_1 = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 1 & 0 \end{pmatrix} \text{ and}
\]

\[
child = \begin{pmatrix} 1 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 \end{pmatrix}.
\]

3. Optimization of genetic algorithms

Optimization of genetic algorithms can be thought of as follows. Consider an optimization problem in an \( n \)-dimensional space, with a given initial population \( s_1^{(1)}, \ldots, s_N^{(1)} \), i.e., the first generation solution set, scattered in the \( n \)-dimensional space. Suppose there are \( k \) local minima in the initial population, where, without loss of generality, all are local \( m_1, \ldots, m_{k-1} \) and the last one is global, which we denote by \( m_k \).

The fitness function \( f \) evaluates the first generation solution set, giving us fitness function values \( f(s_1^{(1)}), \ldots, f(s_N^{(1)}) \). A subset of the values are selected as a few good solutions (for e.g., one can use the distance function and a few good solutions are considered to be those solutions \( s_i^{(1)} \) satisfying the inequality \( d(f(s_i^{(1)}), m_j) = \| f(s_i^{(1)}) - m_j \| \leq \varepsilon \) where \( 1 \leq i \leq N \) and \( 1 \leq j \leq k \), and \( \varepsilon > 0 \)). Now using the good solutions, we use selection, crossover, and mutation to generate a new population \( s_1^{(2)}, \ldots, s_N^{(2)} \) of feasible solutions. They are then evaluated.
back into the fitness function, and we repeat this process of generating new generations of solutions until the genetic algorithm converges through a multitude of convergence criteria.

Some examples of convergence criteria include fixing the number of generations so that the genetic algorithm will run until we compute a certain number of generations. Another one is the genetic algorithm will converge and will come to a halt when the best objective function or best fitness function value is no longer changing or it is altering infinitesimally.

4. MISSION COMPUTABILITY MODELS

Mission computability has been explored in [1, 2, 3, 4, 16, 17, 18], to name a few. Fulfilling computational requirement for a given mission is crucial for a successful Army operation. Algorithms generally studied in terms of time and space complexity using limited number of resources often fail due to inefficiency and constraints of the computation or resource. Network specific constraints also need to be taken account when assessing resource efficiency of the distributed computation.

5. APPLICATIONS

In this manuscript, we consider a genetic optimization algorithm for the class of mission computable problems (cf. [2, 3]). That is, consider a constraints-aware distributed computation: given that many jobs are assigned to an array of cores, we incorporate an algorithm to minimize the number of failed jobs.

We program $k$ machines, each with a single core, using integer programming. That is, we arrange the decision variables in an ordered list which is represented as a binary matrix $M = (b_{i,j})_{i,j} \in M_{m+1,k+1}$, where $b_{i,j} \in \mathbb{Z}_2$, since we want to maximize the total number of computations on $k$ machines, where $(i, j)$ represents the $i$-th job on machine $j$ for $i \geq 2$. We
reserve the first column of $M$ to label and distinguish the job, and let us reserve the first row of $M$ to be those computations that have successfully been computed in machine $j$. For the sake of notational simplicity, we label the columns of $M$ by 0 through $k$ (so the $j$-th column corresponds to $j$-th machine). A 1 in $(i, j)$ position in matrix $M$ represents that the $i$-th job has been sent to machine $j$ and is waiting to be processed, while a 0 in $(i, j)$ position represents that the $i$-th job has failed to be sent to machine $j$. Once the computations in row 1 are complete, all $b_{i,j}$ should move up to position $b_{i-1,j}$ for all $i$ and $j$. This action could be viewed as a left multiplication by the $m \times m$ nilpotent matrix

$$u = \begin{pmatrix} 0 & 1 & \ldots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \ldots & \ldots & 0 \end{pmatrix}$$

onto the $m \times k$ lower right submatrix of $M$.

Since we want the $i$-th job to successfully wait in-line by at most one machine, we have a constraint equation

$$\text{constraint: } \sum_{j=1}^{k} b_{i,j} \leq 1.$$ 

We have another constraint condition since we want each job to be successfully computed at most once

$$\text{constraint: }$$

if $b_{1,\ell} = 1$ for some $\ell$,

then remove this job from being called again,

but if $b_{1,\ell} = 0$ for all $\ell$, then recall this job by putting it in any entry in the last row of matrix $M$ (so the coordinate being $b_{m+1,j} = 1$ for exactly one $j$).
Now we define a notion of inverse selection. If machines $\ell_1, \ldots, \ell_u$ have more than $w$ jobs waiting, i.e., $\sum_{i=2}^{m+1} b_{i,j} > w$ for $j = \ell_1, \ldots, \ell_u$ (that is, for certain subset of the columns), then we use inverse selection to identify these columns and then use crossover to create a new matrix $M'$ to minimize the number of columns satisfying $\sum_{i=2}^{m+1} b_{i,j} > w$ such that $u \leq \delta$ for some predetermined $\delta > 0$. This eases some of the machines from having too many jobs lined up and from overworking, and possibly breaking down or needing maintenance.

Furthermore, mutation is applied to those rows of $M$ with all 0 such that exactly one 1 appears in such rows, so that dropped jobs are minimized.

Another application is using ant colony optimization algorithm to mission computability models. Ant colony optimization algorithm uses crowding technique and changeable mutations to multiple populations to obtain near-optimal solutions (cf. [19, 20, 21, 22, 23, 24]). It can be thought of as an existence of a higher probability that a population will ultimately move along a path more frequently traveled. The ant colony algorithm can be run continuously, mutate, and adapt in real time, even under incremental modifications and configurations of the system. Some examples include taking the shortest path from point $A$ to point $B$, even if points $A$ and $B$ were to move around in real time, or photons traveling in polarization-maintaining cables for communication purposes.

6. Conclusion

We have discussed genetic algorithms and mission computability, applying genetic optimization techniques to an important computability and processing problem. In particular, genetic algorithm has been applied to jobs sent to and scheduled on a distributed computing
platform, where a global optimizer with constraints determines which jobs should be scheduled or rescheduled. The notion of crossover has been used to move the jobs up along an integral matrix, and since each machine tags each job with appropriate priority level, the notion of selection and mutation in genetic algorithms has been applied to handle dropped jobs.

Applying genetic and ant colony optimization algorithms to many crucial mission-critical problems is a quickly developing field, which we foresee that these techniques will become an important contribution and development in this area of research.

ACKNOWLEDGEMENTS

This work is supported by a research collaboration between the U.S. Army Research Laboratory and U.S. Military Academy. M.S.I. is supported by National Research Council Research Associateship Programs.

REFERENCES

[1] M. S. Im and V. R. Dasari, “Optimization and synchronization of programmable quantum communication channels,” in Quantum Information Science, Sensing, and Computation X, E. Donkor and M. Hayduk, Eds., vol. 10660, International Society for Optics and Photonics. SPIE, 2018, pp. 166 – 172. [Online]. Available: https://doi.org/10.1117/12.2304372

[2] V. R. Dasari, M. S. Im, and B. Geerhart, “Complexity and mission computability of adaptive computing systems,” The Journal of Defense Modeling and Simulation, vol. 17, no. 1, pp. 1–7, 2019. [Online]. Available: https://doi.org/10.1177/1548512919869567

[3] M. S. Im, V. R. Dasari, L. Beshaj, and D. Shires, “Optimization problems with low SWAP tactical computing,” in Disruptive Technologies in Information Sciences II, M. Blowers, R. D. Hall, and V. R.
[4] V. R. Dasari, M. S. Im, and L. Beshaj, “Solving machine learning optimization problems using quantum computers,” *arXiv preprint arXiv:1911.08587, to appear in Proc. SPIE*, pp. 1–6, 2019.

[5] D. Whitley, “A genetic algorithm tutorial,” *Statistics and computing*, vol. 4, no. 2, pp. 65–85, 1994.

[6] U. Maulik and S. Bandyopadhyay, “Genetic algorithm-based clustering technique,” *Pattern recognition*, vol. 33, no. 9, pp. 1455–1465, 2000.

[7] G. R. Harik, F. G. Lobo, and D. E. Goldberg, “The compact genetic algorithm,” *IEEE transactions on evolutionary computation*, vol. 3, no. 4, pp. 287–297, 1999.

[8] D. M. Deaven and K.-M. Ho, “Molecular geometry optimization with a genetic algorithm,” *Physical review letters*, vol. 75, no. 2, p. 288, 1995.

[9] J. Yang and V. Honavar, “Feature subset selection using a genetic algorithm,” in *Feature extraction, construction and selection*. Springer, 1998, pp. 117–136.

[10] D. E. Goldberg and M. P. Samtani, “Engineering optimization via genetic algorithm,” in *Electronic computation*. ASCE, 1986, pp. 471–482.

[11] J. L. Ribeiro Filho, P. C. Treleaven, and C. Alippi, “Genetic-algorithm programming environments,” *Computer*, vol. 27, no. 6, pp. 28–43, 1994.

[12] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE computational intelligence magazine*, vol. 1, no. 4, pp. 28–39, 2006.

[13] M. Dorigo and G. Di Caro, “Ant colony optimization: a new meta-heuristic,” in *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)*, vol. 2. IEEE, 1999, pp. 1470–1477.

[14] M. Dorigo and C. Blum, “Ant colony optimization theory: A survey,” *Theoretical computer science*, vol. 344, no. 2-3, pp. 243–278, 2005.

[15] C. Blum, “Ant colony optimization: Introduction and recent trends,” *Physics of Life reviews*, vol. 2, no. 4, pp. 353–373, 2005.
[16] D. C. MacKenzie, R. C. Arkin, and J. M. Cameron, “Multiagent mission specification and execution,” in Robot colonies. Springer, 1997, pp. 29–52.

[17] C. K. Pang, G. R. Hudas, M. B. Middleton, C. V. Le, and F. L. Lewis, “Discrete event command and control for network teams with multiple military missions,” The Journal of Defense Modeling and Simulation, vol. 12, no. 3, pp. 241–255, 2015. [Online]. Available: https://doi.org/10.1177/1548512912472772

[18] B. A. Brucker, E. W. East, L. R. Marrano, M. P. Case, W. D. Goran, A. Carroll, and G. DeJesus, “Emerging challenges and opportunities in building information modeling for the US army installation management command,” Engineer Research and Development Center Champaign, IL Construction, Tech. Rep., 2012.

[19] H. Chong-hai, J. Wei, and W. Tie-jun, “Continuous ant algorithm based on cooperation in radar network optimization,” in 2010 International Conference on Management Science & Engineering 17th Annual Conference Proceedings. IEEE, 2010, pp. 224–233.

[20] M. T. Davis, M. J. Robbins, and B. J. Lunday, “Approximate dynamic programming for missile defense interceptor fire control,” European Journal of Operational Research, vol. 259, no. 3, pp. 873–886, 2017.

[21] X.-y. WANG, Z.-w. LIU, C.-z. HOU, and J.-m. YUAN, “Modeling and decision-making of multi-target optimization assignment for aerial defense weapon [j],” Acta Armamentarii, vol. 2, 2007.

[22] T.-p. Fu, Y.-s. Liu, and J.-h. Chen, “Improved genetic and ant colony optimization algorithm for regional air defense WTA problem,” in First International Conference on Innovative Computing, Information and Control-Volume I (ICICIC’06), vol. 1. IEEE, 2006, pp. 226–229.

[23] Z.-J. Lee, C.-Y. Lee, and S.-F. Su, “An immunity-based ant colony optimization algorithm for solving weapon–target assignment problem,” Applied Soft Computing, vol. 2, no. 1, pp. 39–47, 2002.

[24] Y.-d. Zhang and S.-b. Huang, “On ant colony algorithm for solving multiobjective optimization problems,” Control and Decision, vol. 20, no. 2, pp. 170–173, 2005.
E-mail address: meeseong.im@westpoint.edu, meeseongim@gmail.com

E-mail address: venkateswara.r.dasari.civ@mail.mil