Expert Systems With Applications 54 (2016) 351–363

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

A social-aware routing protocol for opportunistic networks

Ana Cristina Kochem Vendramin[a,b,*], Anelise Munaretto[a,b], Myriam Regattieri Delgado[a,b], Mauro Fonseca[a,b], Aline Carneiro Viana[c]

[a] Graduate Program in Applied Computing (PPGCA)
[b] Graduate Program in Electrical and Computer Engineering (CPGEI), Federal University of Technology - Parana (UTFPR). Av. Sete de Setembro, 3165. CEP 80230-901, Curitiba, Brazil
[c] Institut National de Recherche en Informatique et en Automatique (INRIA) Saclay - Ile de France. 4, rue Jacques Monod, 91893 Orsay Cedex, France

ARTICLE INFO

Keywords:
Cultural algorithms
Ant colony optimization
Social analysis
Routing protocol
Intermittently connected networks

ABSTRACT

Understanding nodes mobility is of fundamental importance for data delivery in opportunistic and intermittently connected networks referred to as Delay Tolerant Networks (DTNs). The analysis of such mobility patterns and the understanding of how mobile nodes interact play a critical role when designing new routing protocols for DTNs. The Cultural Greedy Ant (CGrAnt) protocol is a hybrid Swarm Intelligence-based approach designed to address the routing problem in such dynamic and complex environment. CGrAnt is based on: (1) Cultural Algorithms (CA) and Ant Colony Optimization (ACO) and (2) operational metrics that characterize the opportunistic social connectivity between wireless users. The most promising message forwarders are selected via a greedy transition rule based mainly on local information captured from the DTN environment. Whenever global information is available, it can also be used to support decisions. We compare the performance of CGrAnt with Epidemic, PROPHET, and dLife protocols in two different mobility scenarios under varying networking parameters. Results obtained by the ONE simulator show that CGrAnt achieves a higher message delivery and lower message redundancy than the three protocols in both scenarios. The only exception is in one of the scenarios, when messages have a time to live lower than 900 min, where CGrAnt delivers a bit less messages than dLife, although with a lower message redundancy.

1. Introduction

The pervasiveness of computing devices and the emergence of new applications are factors emphasizing the increasing need for adaptive networking solutions. In most cases, this adaptation requires the design of interdisciplinary approaches as those inspired by nature, social structures, games, and control systems. The approach presented in this paper combining solutions from different, but yet complementary domains, i.e., networking, artificial intelligence, and complex networks. The aim addresses the problem of efficient data delivery in opportunistic and intermittently connected networks referred to as Delay Tolerant Networks (DTNs)(Chaintreau et al., 2007; Khabbaz, Assi, & Fawaz, 2012; Tournoux et al., 2011). Movement of nodes in such networks is not random and is a manifestation of their routine behavior. Together with contact-based interactions among nodes, this movement generates a mobile social network where contacts occur opportunistically in social environments such as conferences sites, urban areas, or university campuses.

We note that the complex environment of opportunistic DTNs challenges the application of any routing protocol. On the other hand, given that adaptation in nature is a permanent and continuous process, we believe that Swarm Intelligence (SI) methods, including approaches based on Ant Colony Optimization (ACO) (Dorigo, Maniezzo, & Colorni, 1996) and Cultural Algorithms (CAs) (Reynolds, 1994) can be adopted even in these complex environments. Among ACO characteristics that can contribute to routing on opportunistic DTNs, we point out: (i) auto-organization that induces no need of a central element to coordinate ants action (partial paths construction in the routing context); (ii) due to its parallel and scalability characteristics, ACO is suitable for complex routing processes involving high dimensions networks; (iii) the use of pheromone that can take advantage of the repetitive behavior of nodes in opportunistic networks; (iv) the use of heuristic-based decisions that can be useful for intermittent connections; (v) the capability of trading-off between local and global searches by constructively building a set of solutions that can be partially

* Corresponding author. Tel.: +55 41 3310 4750; fax: +55 41 3310 4646.
E-mail addresses: criskochem@utfpr.edu.br (A.C.K. Vendramin), anelise@utfpr.edu.br (A. Munaretto), myriamdelg@utfpr.edu.br (M.R. Delgado), maurofonseca@utfpr.edu.br (M. Fonseca), aline.viana@inria.fr (A.C. Viana).

http://dx.doi.org/10.1016/j.eswa.2016.01.039
0957-4174/

maintained or discarded depending on the dynamic of the current environment. Besides, the environment of opportunistic DTNs presents certain features in the mobility patterns of the network nodes that can be well explored by Cultural Algorithms (e.g., knowledge stored in the belief space can guide the swarms through new or already constructed partial paths depending on the node behavior).

The main innovations and contributions of CGrAnt are listed in the following: (i) differing from other protocols that use either only global or only local information, CGrAnt contains additional flexibility, because the decision is based on all available information (both ACO operators and knowledge stored in the CA belief space); (ii) to reduce the number control messages circulating in the net, search phases start only under demand. However, considering the sparse environment, searchers agents (ants) encapsulate data into the messages; (iii) assuming that DTNs are usually intermittently connected, the proposed protocol aims to avoid missing good paths by using event-guided evaporation mechanisms instead of cyclic ones; (iv) CGrAnt maintains a set of (partial) paths instead of only the best one; (v) in CGrAnt, the total of ants is dynamically defined; (vi) to take advantage of each encounter among nodes, the transition rule of CGrAnt is greedy instead of probabilistic; (vii) due to the absence of a central element, knowledge components and communication between population and belief spaces are spread among the nodes which store only partial information regarding the net. Considering the previous characteristics, we assume that CGrAnt can be suitable for running on different mobile scenarios (ranging from highly connected to sparse connected networks) due to its adaptive nature.

Motivated by those issues, this paper aims to extend a previous work (Vendramin, Munaretto, Delgado, & Viana, 2012a) by evaluating the use of CGrAnt to identify the most promising social-aware forwarders in two different DTN scenarios. Here, opportunistic and complex information (such as frequency and duration of contacts, centrality metrics, and mobility features) is also gathered and favorable paths along which to forward each message are determined hop-by-hop, while limiting data redundancy. However, in this paper we intend to show that the forwarding approach implemented through CGrAnt is adaptive and tailored to match forwarding decisions to different mobility conditions. Hence, we applied CGrAnt to two scenarios and compared its performance with that provided by dLife (in addition to PROPHET and Epidemic).

The remainder of this paper is structured as follows. Section 2 provides an overview of the principles that drive our approach. Section 3 describes the CGrAnt routing protocol in detail, and Section 4 presents the simulation environment. Section 5 investigates how the proposed operational metrics affect the CGrAnt's performance. Section 6 compares the performance of CGrAnt with three known DTNs forwarding protocols under varying networking parameters, and finally, Section 7 summarizes the concluding remarks and future directions.

2. Rationale and background

This section begins with an overview of the addressed problem. The related work is further discussed.

2.1. Problem overview

In DTNs, a fully connected multi-hop path may not exist between a sender and a receiver due to either mobility issues or varying conditions of wireless communications, thus requiring the use of specific mechanisms to ensure robustness in the data communication among nodes. The information exchange must be performed in an opportunistic fashion through so-called store-carry-forward routing techniques (Cerf et al., 2007). The nodes may need to store messages from other nodes in their buffers for long periods of time and carry these messages until a forwarding opportunity arises (Cerf et al., 2007). Additionally, message replication may be necessary to increase the probability of successfully delivered messages. However, certain problems exist in a limited resource scenario: replications are undesirable because they compete with valid data messages in the paths toward a destination, and the storage of neighbors' messages can be a problem due to limited buffer sizes.

The problem of routing in DTNs can thus, be modeled as a multimodal optimization problem attempting to find not just one solution but a set of solutions (i.e., multiple paths between two nodes). The finite set of possible solutions (i.e., paths formed by a sequence of nodes in which each node permutation generates a new solution) characterizes the routing in DTNs as a combinatorial problem. The problem can be also modeled as a dynamic state because the search space characteristics and the location and value of the solutions will change over time. The problem of routing in DTNs presents, therefore, a complex challenge, with several aspects still unexplored by most approaches described in the literature. Therefore, an updated consideration of the DTN dynamics is necessary and can be accomplished by periodically analyzing the neighbor information and selecting more than one path along which to forward each message while limiting message redundancy. The dynamic and complex premises of DTNs characterize it as an environment favorable for the application of SI algorithms, including ACO and CA (Dorigo et al., 1996; Reynolds, 1994).

2.2. Related work

Next sections discuss the most representative results on both DTN forwarding protocol and swarm intelligence methods.

2.2.1. DTN forwarding protocols

The most common forwarding protocol for DTNs take a flooding approach. The Epidemic routing protocol provides an optimal solution in terms of message delivery and latency, when no buffer constraint is present (Vahdat & Becker, 2000). In Epidemic, a node buffers a message and passes it on to all encountered nodes that have not received it before. No good message forwarders prediction is performed. To limit resource utilization, a hop-count field can be set in each message.

Prediction-based approaches try to reduce the message overhead by selecting a few good message forwarders. In this context and more related to CGrAnt, several approaches estimate a delivery probability based on history of encounters like PROPHET (Lindgren, Doria, & Schelén, 2003). In PROPHET, vectors are exchanged to indicate the predictability of each node in delivering messages to others nodes. This predictability increases every time two nodes come into contact and reduces if they fail to meet frequently. When a node *A* establishes a contact with a node *B*, a message will be sent to *B* if its message delivery's prediction to the destination of the message is higher as compared to *A*. The delivery predictability also has a transitive property.

Other approaches study the effect of social networking on routing. BubbleRap (Hui, Crowcroft, & Yoneki, 2008) and SimBet (Daly & Haahr, 2007) use information about social structures and centrality that nodes have in a community to choose good message forwarders. Zhang et al. (2012) introduce four social-aware data diffusion schemes based on the social relationship and data similarity of the contacts. The dLife routing protocol (Moreira, Mendes, & Sargento, 2012), more related to CGrAnt, is a non-community based approach that captures network dynamics, represented by users' daily life routine. dLife represents the dynamics of a social network as a weighted contact graph, where the weights (i.e., social strengths) express how long a pair of nodes is in contact over