Collective Self-Awareness and Self-Expression for Efficient Network Exploration

Michele Amoretti(✉) and Stefano Cagnoni

Department of Information Engineering, Universita degli Studi di Parma, Parma, Italy
{michele.amoretti,stefano.cagnoni}@unipr.it

Abstract. Message broadcasting and topology discovery are classical problems for distributed systems, both of which are related to the concept of network exploration. Typical decentralized approaches assume that network nodes are provided with traditional routing tables. In this paper we propose a novel network exploration approach based on collective self-awareness and self-expression, resulting from the simultaneous application of two strategies, namely hierarchy and recursion, which imply the adoption of unusual routing tables. We show how the proposed approach may provide distributed systems with improved efficiency and scalability, with respect to traditional approaches.

Keywords: Collective self-awareness · Collective self-expression · Hierarchy and recursion · Network exploration

1 Introduction

Network exploration is the bottom line of several problems for distributed systems, *i.e.*, systems consisting of multiple autonomous nodes that communicate through a network. Example of such problems are message broadcasting [1,2] and topology discovery [3,4]. Centralized solutions are not scalable and highly inefficient. Thus, decentralized approaches are usually adopted, assuming that network nodes are provided with traditional routing tables — *i.e.*, data tables that list the routes to particular network destinations and, in some cases, metrics associated to those routes.

In this paper we propose a novel network exploration approach based on *collective self-awareness and self-expression* [5], resulting from the simultaneous application of two strategies, namely *hierarchy and recursion*, which imply the adoption of unusual routing tables. With respect to traditional approaches, the one we propose may provide distributed systems with improved efficiency and scalability.

The paper is organized as follows. In Section 2, related work on network exploration and self-aware computing is discussed. In Section 3, the concepts of collective self-awareness and self-expression are summarized, with particular focus on their implementation based on hierarchy and recursion (HR). In Section 4,

M. Gavanelli et al. (Eds.): AI*IA 2015, LNAI 9336, pp. 3–16, 2015.
DOI: 10.1007/978-3-319-24309-2_1

our HR-based network exploration algorithm is illustrated. In Section 5, simulation results are presented and discussed. The last section concludes the paper presenting future research lines. As an appendix, a short survey on consciousness, self-Awareness and self-Expression in psychology and cognitive science is proposed.

2 Related Work

Network exploration is a necessary task in several contexts. Among others, multiple-message broadcasting is particularly important for wireless sensor networks (WSNs), since it is a basic operation in many applications, such as updating of routing tables and several kinds of data aggregation functions in WSNs. Classical Flooding (CF) is the simplest way of implementing multi-hop broadcast: when a node receives a broadcast packet for the first time, it forwards the packet to its neighbors (duplicates are detected and dropped). However, CF can be very costly in terms of wasted bandwidth, and also inefficient, because of broadcast storms that may be generated by concomitant packet retransmissions [6]. Considering also that in Low power and Lossy Networks (LLNs) nodes are extremely energy-constrained, a finite message budget is a realistic assumption [1]. The optimal solution consists of building a minimum Connected Dominating Set (CDS), defined as the minimum set of relays that guarantees network connectivity. However, finding a minimum CDS is known as an NP-hard problem [7] to which several authors proposed distributed approximate solutions. Recently, the IETF ROLL working group standardized RPL, the routing protocol for LLNs [8], and also proposed Multicast Protocol for Low power and Lossy Networks (MPL), a forwarding mechanism for LLN networks [9]. Later, La *et al.* [10] have introduced Beacon-based Forwarding Tree (BFT), an energy-efficient multi-hop broadcasting scheme that achieves performance similar to MPL, although it fits better the case of nodes with low radio duty cycling[1] MAC layers of the type of beacon-enabled IEEE 802.15.4. More generally, Yu *et al.* [2] have proposed a distributed algorithm for multiple-message broadcasting in unstructured wireless networks under a global interference model, as well as a lower bound for randomized distributed multiple-message broadcast algorithms under the assumed network model.

Another domain where network exploration plays a prominent role is topology discovery. Several authors have proposed agent-oriented approaches based on learning [3,11,12]. Agents explore the network to i) acquire information, on their own, about visited nodes (first-hand knowledge); ii) collect information from other agents, by means of direct or implicit communication. Not using agents, Li *et al.* [4] have recently proposed an IPv6 network router-level topology discovery method, combining the topology information obtained by *traceroute* and OSPF [13].

All the aforementioned network exploration strategies assume that network nodes are provided with traditional routing tables. Our approach, instead,

[1] Radio duty cycling is the proportion between the periods nodes are on and off.

implies the adoption of unusual routing tables. Before introducing them, we need to recall some background concepts.

Self-aware computing systems and applications proactively maintain information about their own environments and internal states [14]. In detail, self-expression refers to i) goal revision and ii) self-adaptive behavior, which derives from reasoning about the knowledge associated with the system's self-awareness.

According to Faniyi *et al.* [14], a self-aware node "possesses information about its internal state and has sufficient knowledge of its environment to determine how it is perceived by other parts of the system." Self-awareness produces behavioral models of the node. Self-expression encompasses goal revision and self-adaptive behavior deriving from reasoning about such models. The same authors [14] have also developed a computational translation of the layered self-awareness model proposed by psychologist Neisser [15] (a short survey on consciousness, self-awareness and self-expression in psychology and cognitive science is proposed at the end of this paper). From the bottom up to the top of the stack, there are five levels of self-awareness, with increasing complexity: stimulus awareness, interaction awareness, time awareness, goal awareness and meta-self-awareness. This latter layer is the node's awareness of its own self-awareness capabilities (or its lack). The conceptual framework is illustrated in Figure 1. Self-awareness implies processing information collected from the internal and external sensors of the node. Data provided by the internal sensors contribute to *private* self-awareness construction. Information about the node's interactions with the physical environment and other nodes, instead, contributes to *public* self-awareness construction.

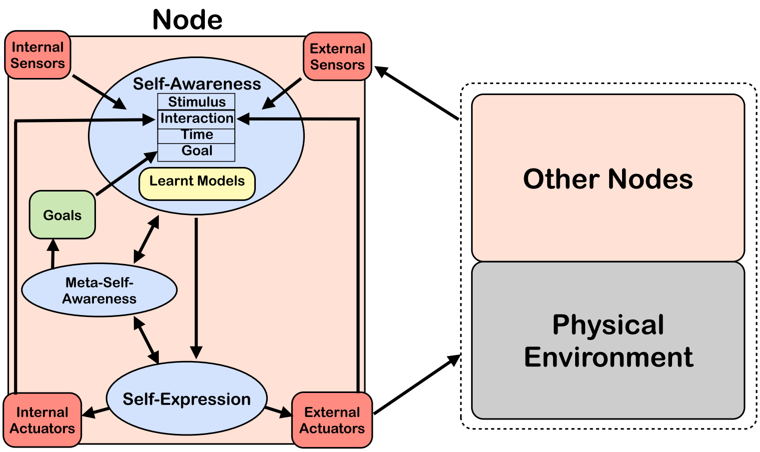


Fig. 1. Representation of a self-aware and self-expressive node, according to the models defined by Faniyi *et al.* [14].

Our recent contribution to self-aware computing is the definition of collective self-awareness and self-expression [5], which is the baseline for the network exploration approach we present in this paper. In the following section, we illustrate the main principles of collective self-awareness and self-expression.

3 Collective Self-Awareness and Self-expression

According to Mitchell [16], complex systems are dynamic systems composed of interconnected parts that, as a whole, exhibit properties that could not be inferred from the properties of the individual parts. Ant colonies, immune systems and humans are examples of complex systems, where collective self-awareness is an emergent effect [14].

In computing/networking systems, the adaptive mechanisms that can be implemented within a single node coincide with self-expression, if they are based on the node's self-awareness capabilities. What about self-awareness and self-expression of a distributed system as a whole? Can actual global self-awareness be achieved only by providing the distributed system with a centralized omniscient monitor? Luckily, the answer is no.

A computing node exhibits self-expression if it is able to assert its behavior upon either itself or other nodes, the relevance of such a behavior being proportional to a notion of authority in the network [14]. The behavior of the node is affected by its state, context, goals and constraints.

Self-expression for ensembles of cooperating computational entities is the ability to deploy run-time changes of the coordination pattern, according to Cabri *et al.* [17]. In other words, the distributed system expresses itself (meaning that it still does what it is supposed to do) independently of unexpected situations and, to accomplish this, it can modify its original internal organization. For example, suppose that each component of a distributed system knows three different collaborative approaches to complete a given task: master-slave, peer-to-peer and swarm. Self-expression here is seen as the capability to collaboratively select the most suitable strategy.

In our view, self-expression for ensembles is the assertion of collective self-adaptive behavior, based on collective self-awareness. As in global self-awareness, achieving collective self-expression in a distributed system that lacks centralized control appears to be a difficult task.

3.1 Hierarchy and Recursion

We claim that both self-expression and self-awareness, for ensembles of cooperating computational entities, can be achieved by the simultaneous application of two strategies, namely *hierarchy* and *recursion*. Hierarchy is the categorization of a group of nodes according to their capability or status. Recursion is the repeated use of a single, flexible functional unit for different capabilities over different scopes of a distributed system.

A possible implementation of this principle is *recursive networking*, developed to describe multi-layer virtual networks that embed networks as nodes inside other networks. In the last decade, recursive networking has evolved to become a possible architecture for the future Internet [18]. In particular, it is a prominent approach to designing quantum networks [19].

Moreover, in the context of Content-Centric Networking (CCN) [20], an emerging approach which is particularly promising to face the scalability issues that the Internet of Things is raising, there is room for both static and dynamic hierarchies.

For example, consider the network illustrated in Figure 2. The routing table at node 4.2 contains information on how to reach any other node in the network. For scalability purposes, the table has more precise information about nearby destinations (node 4.4 and node 4.7), and vague information about more remote destinations (NET9), obtained using hierarchy and recursion. Routing tables are initialized and updated with information exchanged between directly attached neighbors.

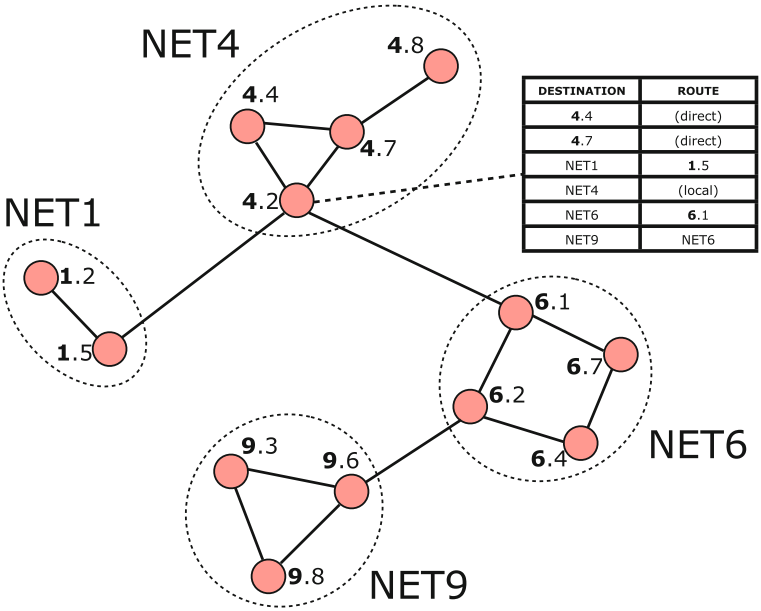


Fig. 2. Hierarchy and recursion: the routing table at node 4.2 contains information on how to reach any other node in the network.

By means of hierarchy and recursion, global self-awareness is available at every node and enables global self-expression. In the network example, packets are forwarded according to routing tables. Forwarding too many packets to the same neighbor may cause congestion on that node. Having a feedback about such a negative effect of the forwarding node's behavior (*i.e.*, having local self-awareness) may lead to a modification of that behavior, supported by the routing table (which is a way of building global self-awareness). Namely, an alternative destination for packets may be chosen. This local self-expression process may also trigger a routing table update. On the other hand, a routing table update may also derive from the exchange of routing information with known nodes. The simultaneous and collaborative update of HR-based routing tables, which may also take into account the possibility of changing hierarchies, is actually a global self-expression process.

More precisely, the networking example in Figure 2 (and further developed in the subsequent sections) fits the conceptual framework in the following way:

- stimuli-awareness: the network is stimuli-aware, meaning that nodes know how to manage messages;
- interaction-awareness: nodes and subnets interact by exchanging messages and control information, i.e., routing table updates; they are interaction-aware, meaning that they can distinguish between other nodes and subnets;
- time-awareness: the network has knowledge of past events or likely future ones, like in learning-based routing;
- goal-awareness: the HR approach enforces the global goal of high efficiency (e.g., simplifying the search for the shortest path towards a specific destination); goal-awareness is thus implicit in how routing tables are populated and updated;
- meta-self-awareness: a way to implement it is to concurrently apply different routing strategies, choosing the best one at runtime.

4 HR-based Network Exploration

Let us consider a network consisting of N nodes and S subnetworks. We are interested in evaluating the approximate number of forwardings needed by a probe message to propagate through the whole graph. The probe message is generated by a random node, which sends it to one of its neighbors. Then it is forwarded to another neighbor, and so on. A node that receives the probe message is marked as "visited".

The simplest search strategy is the *Random Walk (RW)*, where the next hop is randomly selected among the node's neighbors. Even if the network is recursive and hierarchical, such features are not exploited by RW. As a consequence, RW is quite expensive, in terms of probe message propagations needed to explore the whole network — even if the network topology has good features, such as scale invariance [21].

Another simple strategy is Classical Flooding (CF) (see also Section 2), where every probe message received by a node is forwarded to all the neighbors of the node. To avoid network congestion, probe messages are always associated to a Time To Live (TTL), which is the maximum number of times they can be forwarded. The main advantage of CF is that, if a packet can be delivered, it will actually be (probably multiple times). However, CF can be very costly in terms of wasted bandwidth and also inefficient, as it may originate broadcast storms [6].

Our HR-based network exploration approach takes subnetworks into account and exploits collective self-awareness. Every node is member of a subnetwork NETs ($s \in \{1, .., S\}$) and has an identifier Node$n$ ($n \in \mathbb{N}$) which is unique within that network. The *name* of the generic node is denoted as NETs.Node$n$. A node may have neighbors that are members of other subnetworks. For example, the routing table illustrated in Figure 2 allows NET4.Node2 to forward messages i) to other nodes of NET4 that are directly reachable, ii) to NET1 and NET6 through directly reachable nodes that belong to those subnetworks, and iii) to NET9 through NET6. Importantly, the size of the routing table is $O(S)$.

The neighbor to whom the probe is forwarded belongs to the same subnetwork of the sender. If all neighbors of the same subnetwork have been already visited, the probe is forwarded to one neighbor from another subnetwork, excluding the previous hop. If there is only one neighbor belonging to other subnetworks and it is the previous hop, then the neighbor that grants access to the longest route is chosen. The flowchart of the HR-based network exploration approach is shown in Figure 3.

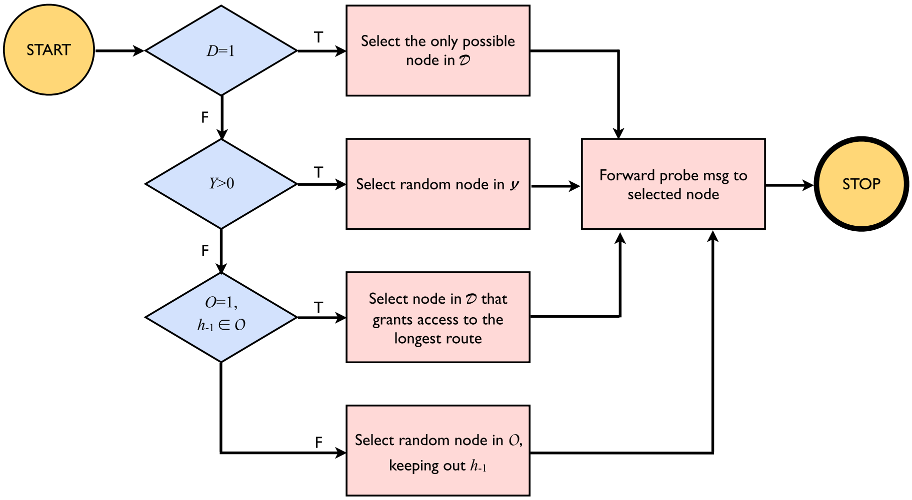


Fig. 3. HR-based network exploration approach. $\mathcal{D}$ is the set of neighbors of the considered peer ($D = |\mathcal{D}|$). $\mathcal{Y}$ is the set of neighbors belonging to the same subnetwork of the considered peer ($Y = |\mathcal{Y}|$), that have not been visited yet. $\mathcal{O}$ is the set of neighbors that belong to other subnetworks ($O = |\mathcal{O}|$). h_{-1} denotes the previous hop.

5 Performance Evaluation

To evaluate the proposed HR-based network exploration algorithm, we adopted the general-purpose discrete event simulation environment called DEUS[2] [22,23], whose purpose is to facilitate the simulation of highly dynamic overlay networks, with several hundred thousands nodes, on a single machine — without the need to simulate also lower network layers (whose effect can be taken into account,

[2] DEUS project homepage: https://github.com/dsg-unipr/deus/

in any case, when defining the virtual time scheduling of message propagation events).

To simplify the configuration of the routing tables in simulation, we consider the (sub-optimal) scenario in which every node knows which subnetworks can be reached through its direct neighbors. No further knowledge is necessary, when S is of the same order of magnitude as the mean node degree $\langle k \rangle$ of the network. Instead, for large networks, with $S \gg \langle k \rangle$, further knowledge — provided by neighbors of neighbors (of neighbors etc.) — is necessary to build meaningful collective self-awareness.

We take into account two network topologies, characterized by different statistics for the *node degree*, that is the number of links starting from a node. The node degree of a network is described in terms of probability mass function (PMF) $P(k) = P\{\text{node degree} = k\}$.

The first network topology we consider is *scale-free*, meaning that its PMF decays according to a power law, *i.e.*, a polynomial relationship that exhibits the property of scale invariance (*i.e.*, $P(bk) = b^a P(k)$, $\forall a, b \in \mathbb{R}$), such as:

$$P(k) = ck^{-\tau} \quad \forall k = 0, .., N-1$$

where $\tau > 1$ (otherwise $P(k)$ would not be normalizable) and c is a normalization factor. In simulation, we have used the widely known generative model proposed by Barabási and Albert (called BA model) [24], which constructs scale-free networks with $\tau \simeq 3$. The BA model is based on two ingredients: growth and preferential attachment. Every node which is added connects to m existing nodes, selected with probability proportional to their node degree. The resulting PMF is

$$P(k) \simeq 2m^2 k^{-3} \quad \forall k > m$$

and the mean node degree is $\langle k \rangle = 2m$. The average path length is

$$\langle l \rangle_{BA} \simeq \frac{\ln N}{\ln \ln N}$$

The second network topology we consider is a purely random one, described by the well-known model defined by Erdös and Rényi (ER model). Networks based on the ER model have N vertices, each connected to an average of $\langle k \rangle = \alpha$ nodes. The presence or absence of a link between two vertices is independent of the presence or absence of any other link, thus each link can be considered to be present with independent probability p. It is trivial to show that

$$p = \frac{\alpha}{N-1}$$

If nodes are independent, the node degree distribution of the network is binomial:

$$P(k) = \binom{N-1}{k} p^k (1-p)^{N-1-k}$$

which, for large values of N, converges to the Poisson distribution

$$P(k) = \frac{\alpha^k e^{-\alpha}}{k!} \qquad \text{with } \alpha = \langle k \rangle = \sigma^2$$

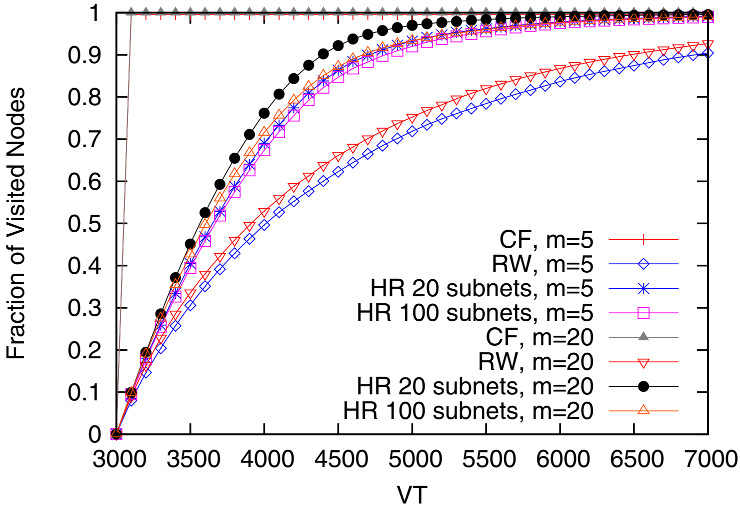
The average path length (*i.e.*, the expected value of the shortest path length between node pairs) is

$$\langle l \rangle_{ER} \simeq \frac{\ln N}{\ln \alpha}$$

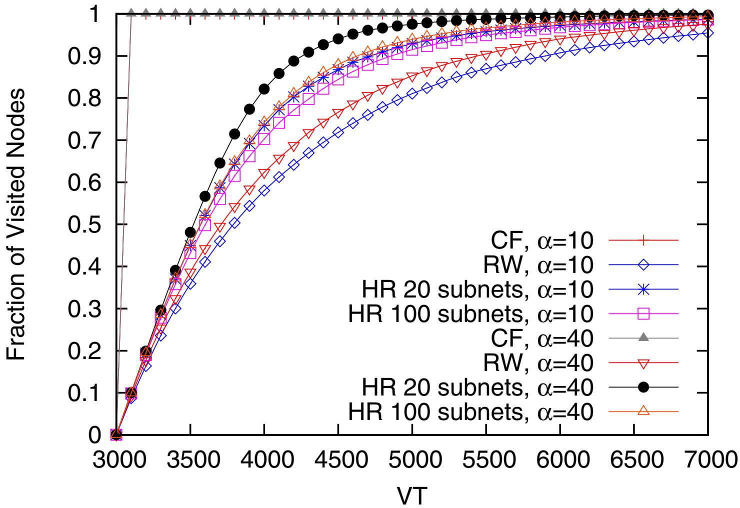
Scale-free and ER are the extremes of the range of meaningful network topologies, as they represent the presence of strong hubs and the total lack of hubs, respectively. It has been recently shown that the degree distribution of the Internet is the composition of the contributions of two classes of connections [25]: the provider-customer connections introduce a scale-free distribution, while the peering connections can be modeled using a Weibull distribution. A large contribution to the deviation from the scale-free distribution is given by the Internet Exchange Points (IXPs), that are physical infrastructures which allow ASs to exchange Internet traffic, usually by means of mutual peering agreements, leading to lower costs (and, sometimes, lower latency) than in upstream provider-customer connections. Since IXP introduce a high number of peering relationships, the higher the number of connections identified as crossing IXPs, the larger the deviation of the degree from the scale-free distribution. The structural properties of the Internet AS-level (Autonomous System level) topology graph can be discovered by means of the concept of *community*, which is informally defined as "an unusually densely connected set of ASes" [26]. The task of detecting communities in a graph is very hard for at least two reasons: firstly, because there is no formal definition of a community and, secondly, because most algorithms are computationally demanding and cannot be applied to dense graphs.

Our simulations compared the HR, RW and CF network exploration strategies, with networks consisting of $N = 1000$ nodes, and either $S = 20$ or $S = 100$ subnetworks. With the BA topology, when $m = 5$ and $m = 20$, the mean node degree is $\langle k \rangle = 10$ and $\langle k \rangle = 40$, respectively. To have the same $\langle k \rangle$ values for the ER topology, we set $\alpha = 10$ and $\alpha = 40$. The virtual time VT of the simulation is represented on the x axis. Before $VT = 3000$, the network is grown and configured — *i.e.*, routing tables are filled after $N = 1000$ nodes have been created and connected. Then, at $VT = 3000$ the probe message is generated and forwarded at every virtual time step. Regarding the CF strategy, $TTL = 4$ is necessary to explore the whole network in all the scenarios we consider (which are characterized by $\langle l \rangle_{ER,\alpha=10} \simeq 3$, $\langle l \rangle_{ER,\alpha=40} \simeq 2$ and $\langle l \rangle_{BA} = 3.6$, respectively). Indeed, when the topology is ER with $\alpha = 10$, CF with $TTL = 3$ reaches 69% of the nodes only.

In Figure 4, the fraction of visited nodes (averaged over 25 simulation runs) is reported on the y axis. As the presence of subnetworks does not affect RW and CF, just one curve is plotted for these cases. Conversely, subnetwork awareness plays a fundamental role in HR. From the results we obtained, it is clear that CF allows to explore the whole network much faster than RW and HR. However, CF produces a large burst of probe message forwardings (see num_f in Table 1), to complete the exploration of the network. Instead, HR and RW require fewer messages to achieve the same result (albeit more slowly). In general, HR and RW have to be preferred, with respect to CF. Then, it is also clear that HR outperforms RW. Indeed, for the topologies under consideration, the HR-based



(a) BA topology



(b) ER topology

Fig. 4. Fraction of visited nodes when the network topology is BA or ER.

algorithm requires about 4000 message propagations to visit the whole network. With the same amount of propagations, instead, RW visits only 90% of the network. The difference is more evident when the topology is BA, because using HR the probe message is forced to visit every hub (*i.e.*, one of the most connected nodes) just once, while with RW the probe message visits hubs very frequently.

On the other hand, since neither RW nor HR exploit hubs conveniently, performance is better with the ER topology (where node degree values are more fairly distributed).

Table 1. No-HR vs HR: number of probe message forwardings until the network has been fully explored.

Strategy	**Topology**	S	num_f
CF	BA, $m = 5$	n.a.	$24 \cdot 10^3$
RW	BA, $m = 5$	n.a.	$> 4 \cdot 10^3$
HR	BA, $m = 5$	20	$4 \cdot 10^3$
HR	BA, $m = 5$	100	$4 \cdot 10^3$
CF	BA, $m = 20$	n.a.	$12 \cdot 10^3$
RW	BA, $m = 20$	n.a.	$> 4 \cdot 10^3$
HR	BA, $m = 20$	20	$3 \cdot 10^3$
HR	BA, $m = 20$	100	$3 \cdot 10^3$
CF	ER, $\alpha = 10$	n.a.	$15 \cdot 10^3$
RW	ER, $\alpha = 10$	n.a.	$> 4 \cdot 10^3$
HR	ER, $\alpha = 10$	20	$3 \cdot 10^3$
HR	ER, $\alpha = 10$	100	$3 \cdot 10^3$
CF	ER, $\alpha = 40$	n.a.	$11 \cdot 10^3$
RW	ER, $\alpha = 40$	n.a.	$> 4 \cdot 10^3$
HR	ER, $\alpha = 40$	20	$2.5 \cdot 10^3$
HR	ER, $\alpha = 40$	100	$3 \cdot 10^3$

6 Conclusions

Collective self-awareness and self-expression, based on the simultaneous application of hierarchy and recursion, make it possible to design efficient and scalable network exploration strategies, with limited extra cost in terms of design complexity.

Other than network exploration, message routing and distributed computing, also distributed sensing, mapping and geo-localization systems may benefit from collective self-awareness and self-expression. The networking and computing research communities have already started studying HR-based strategies, but a lot of work still needs to be done. In our opinion, it will be particularly important to find novel strategies for the efficient maintenance of HR-enabling information.

Consciousness, Self-Awareness and Self-Expression in Psychology and Cognitive Science

Psychology as a scientific discipline started in the second half of the nineteenth century. Almost immediately, the notion of consciousness became central. In 1905, Freud separated the unconscious, the preconscious and the conscious. Since then, several other levels of consciousness have been defined and examined. In 1934, Mead proposed the distinction between focusing attention outward toward the environment (consciousness), and inward toward the self (self-awareness). Self-awareness represents a complex multidimensional phenomenon that comprises various self-domains and corollaries. A very clear and comprehensive survey on this topic has been recently published by Morin [15]. Duval and Wicklund defined self-awareness as *the capacity of becoming the object of one's own attention* [27]. In this state one actively identifies, processes, and stores information about the self. The layered self-awareness model proposed by Neisser [28] is particularly appealing to computer engineers. Indeed, a computational interpretation of that model (illustrated in this paper) has been recently developed by Faniyi *et al.* [14]. The lowest level of self-awareness, denoted as *ecological self*, concerns the reactions to stimuli. The highest level, denoted as *conceptual self*, represents the most advanced form of self-awareness, where the organism is capable of constructing and reasoning about an abstract symbolic representation of itself. Eventually, the conceptual self may allow the organism to become aware of its own self-awareness capabilities (*i.e.*, *meta-self-awareness*). Self-expression, in social psychology literature, is a notion that is closely associated with a multitude of positive concepts, such as freedom, creativity, style, courage, self-assurance. Fundamentally, self-expression is the assertion of one's personal characteristics.

References

1. Bertier, M., Kermarrec, A.-M., Tan, G.: Message-efficient byzantine fault-tolerant broadcast in a multi-hop wireless sensor network. In: IEEE Int'.l Conference on Distributed Computing Systems (ICDCS), Genoa, Italy (2010)
2. Yu, D., Hua, Q.-S., Wang, Y., Yu, J., Lau, F.C.M.: Efficient distributed multiple-message broadcasting in unstructured wireless networks. In: IEEE INFOCOM, Turin, Italy (2013)
3. Khazaei, H., Misic, J., Misic, V.B.: Mobile software agents for wireless network mapping and dynamic routing. In: IEEE Int'.l Conference on Distributed Computing Systems (ICDCS) Workshops, Genoa, Italy (2010)
4. Li, M., Yang, J., An, C., Li, C., Li, F.: IPv6 network topology discovery method based on novel graph mapping algorithms. In: IEEE Symposium on Computers and Communications (ISCC), Split, Croatia (2013)
5. Amoretti, M., Cagnoni, S.: Toward Collective Self-Awareness and Self-Expression in Distributed Systems. IEEE Computer **48**(7), 29–36 (2015)

6. Ni, S., Tseng, Y., Chen, Y., Sheu, J.: The broadcast storm problem in mobile Ad hoc networks. In: ACM MobiCom, Seattle, WA, USA (1999)
7. Garey, M., Johnson, D.: Computers and Intractability: A Guide to the Theory of NP-Completeness. Freeman, San Francisco (1978)
8. Winter, T., et al.: RPL: IPv6 routing protocol for low power and lossy networks. In: RFC 6550, IETF, March 2012
9. Hui, J., Kelsey, R.: Multicast protocol for low power and lossy networks (MPL). In: Work in Progress draft-ietf-roll-trickle-mcast-11, IETF, November 2014
10. La, C.-A., Varga, L.-O., Heusse, M., Duda, A.: Energy-efficient multi-hop broadcasting in low power and lossy networks. In: 17th ACM Int'.l Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM 2014), Montreal, Canada (2014)
11. Kramer, K.H., Minar, N., Maes, P.: Cooporative mobile agents for dynamic network routing. ACM SIGMOBILE Mobile Computing and Communications Review **3**, 12–16 (1999)
12. Houidi, I., Louati, W., Zeghlache, D.: A distributed virtual network mapping algorithm. In: IEEE Int'.l Conference on Communications (ICC), Beijing, China (2008)
13. Shaikh, A., Goyal, M., Greenberg, A., Rajan, R., Ramakrishnan, K.K.: An OSPF Topology Server: Design and Evaluation. IEEE Journal of Selected Areas in Communications **20**(4), 746–755 (2002)
14. Faniyi, F., Lewis, P.R., Bahsoon, R., Yao, X.: Architecting self-aware software systems. In: IEEE/IFIP WICSA 2014, pp. 91–94
15. Morin, A.: Self-Awareness Part 1: Definition, Measures, Effects, Functions, and Antecedents. Social and Personality Psychology Compass **5**(10), 807–823 (2011)
16. Mitchell, M.: Complex systems: network thinking. Artificial Intelligence **170**(18), 1194–1212 (2006)
17. Cabri, G., Capodieci, N., Cesari, L., De Nicola, R., Pugliese, R., Tiezzi, F., Zambonelli, F.: Self-expression and dynamic attribute-based ensembles in SCEL. In: Margaria, T., Steffen, B. (eds.) ISoLA 2014, Part I. LNCS, vol. 8802, pp. 147–163. Springer, Heidelberg (2014)
18. Touch, J., Baldine, I., Dutta, R., Ford, B., Finn, G., Jordan, S., Massey, D., Matta, A., Papadopoulos, C., Reiher, P., Rouskas, G.: A dynamic recursive unified internet design (DRUID). Computer Networks **55**(4), 919–935 (2011)
19. Van Meter, R.: Quantum networking and internetworking. In: IEEE Network, July/August 2012
20. Jacobson, V., Smetters, D.K., Thornton, J., Plass, M.F., Briggs, N.H., Braynard, R.L.: Networking named content. In: ACM CoNEXT, Rome, Italy (2009)
21. Amoretti, M.: A Modeling Framework for Unstructured Supernode Networks. IEEE Communications Letters **16**(10), 1707–1710 (2012)
22. Amoretti, M., Agosti, M., Zanichelli, F.: DEUS: a discrete event universal simulator. In: 2nd ICST/ACM Int'.l Conference on Simulation Tools and Techniques (SIMUTools 2009), Roma, Italy, March 2009
23. Amoretti, M., Picone, M., Zanichelli, F., Ferrari, G.: Simulating mobile and distributed systems with DEUS and ns-3. In: Int'.l Conference on High Performance Computing and Simulation 2013, Helsinki, Finland, July 2013
24. Barabási, A.-L., Albert, R.: Emergence of Scaling in Random Networks. Science **286**(5439), 509–512 (1999)

25. Siganos, G., Faloutsos, M., Krishnamurthy, S., He, Y.: Lord of the links: a framework for discovering missing links in the Internet topology. IEEE/ACM Transactions on Networking **17**(2), 391–404 (2009)
26. Gregori, E., Lenzini, L., Orsini, C.: k-dense Communities in the Internet AS-Level Topology Graph. Computer Networks **57**(1) (2013)
27. Duval, S., Wicklund, A.: A Theory of Objective Self Awareness. Academic Press (1972)
28. Neisser, U.: The roots of self-knowledge: perceiving self, it, and thou. In: Snodgrass, J.G., Thompson, R.L. (eds.) The Self Across Psychology: Self-Recognition, Self-Awareness, and the Self-Concept. Academy of Sciences, New York