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Diffusive capture processes for information search

Sungmin Lee, Soon-Hyung Yook*, Yup Kim

Department of Physics and Research Institute for Basic Sciences, Kyung Hee University, Seoul 130-701, Republic of Korea

Abstract

We show how effectively the diffusive capture processes (DCP) on complex networks can be applied to information search in the networks. Numerical simulations show that our method generates only 2% of traffic compared with the most popular flooding-based query-packet-forwarding (FB) algorithm. We find that the average searching time, $\langle T \rangle$, of the our model is more scalable than another well known n-random walker model and comparable to the FB algorithm both on real Gnutella network and scale-free networks with $\gamma = 2.4$. We also discuss the possible relationship between $\langle T \rangle$ and $\langle k^2 \rangle$, the second moment of the degree distribution of the networks.
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The study on the complex networks has been attracted many researchers in diverse fields [1,2]. Due to the inherent complexity in their structures, the dynamical properties of many physical systems on the networks have shown rich behaviors which depend on the structure of the underlying networks and are far from the mean-field expectations [3]. The diffusive capture process (DCP) on complex network is one such example [4,5]. The DCP or the moving trap model has been studied in many physics literatures [6] on chemical kinetics, wetting, melting, etc. This process can be mapped into coupled random walks (RWs), in which n predator (lions or moving trap) stalk a prey random walker (a lamb or a moving particle). On a d-dimensional regular lattice, the survival probability $S(t)$ of the lamb is given by [7–9]

$$S(t) \sim \begin{cases} t^{-\beta} & \text{for } d < 2, \\ (\ln t)^{-n} & \text{for } d = 2, \\ \text{finite} & \text{for } d > 2, \end{cases} \tag{1}$$

where the exponent β varies as n and the ratio of diffusion constant of walks. Like many physical systems on complex networks, we have found that the $S(t)$ of the DCP on complex networks also deviates from the mean-field expectation depending on the degree distribution of the underlying networks. This anomalous behavior

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*Corresponding author. Tel.: +82 2 9610253; fax: +82 2 9578408.
  E-mail addresses: syook@khu.ac.kr (S.-H. Yook), ykim@khu.ac.kr (Y. Kim).

has been found to come from the existence of dominant hubs in complex networks [4,5] and can be applied to information search in complex networks.

The searching information in complex networks, such as peer-to-peer (P2P) networks and the world-wide-web (www), using random walkers [10,11] is an interesting and important application in diverse areas including physics, computer science, and neuroscience [11–13]. The efficiency of the information search can be defined by two factors: (1) amount of traffic at time t defined by the total number of packets existing on the network at t and (2) searching time which corresponds to the average life time of a lamb in the DCP. In general, these two factors are competing to each other, i.e., reducing the traffic congestion causes long waiting time to find a given information. Therefore, it is very important and difficult to design a less traffic congesting model with short searching time. In this paper, we consider the *pure* P2P networks as an example of information search by taking notice of the fact that the most of traffic generated by P2P applications consists of the query packets to find out the node which has the requested file out of the P2P jungle [1]. A *pure* P2P network does not have the notion of clients or servers, but only equal peer nodes that simultaneously function as both clients and servers to the other nodes on the network. Thus, there is no central server managing the network and no central router. By applying the anomalous behavior of the DCP on complex networks, we drastically reduce the traffic congestion. We will also show that our model can provide implementable searching time. We expect that our results can be easily generalized to apply many other information search problems and communication networks, such as neural networks.

The performance of searching algorithm is crucially affected by the underlying topology [14]. Many studies on the large-scale topology of P2P networks have uncovered that the probability distribution of a node with degree k follows the power law,

$$P(k) \sim k^{-\gamma}, \tag{2}$$

with $\gamma < 3$ [1,11,14,15], or highly skewed fat-tailed distributions [16]. The network satisfying Eq. (2) is called a scale-free (SF) network [2]. In these networks with $\gamma < 3$, several nodes have most of degrees or connections. These nodes are called hubs and many important properties of complex networks are dominated by them [1,2]. However, most of the popular algorithms used in many P2P networks do not take advantage of the underlying structure. In those algorithms, a query packet is generated by a node and forwarded to the nearest neighbors until it finds the requested information during a query event. For example, the flooding-based query-packet-forwarding (FB) algorithm [14], which is used in BitTorrent [17,18], spreads the query packets to all nodes within a pre-assigned diameter. Thus, this algorithm causes significant traffic congestion. The n-random walker (n-RW) model, which is used in LMS (Edutella) [17,19], is another well studied model for searching information [14,11]. n-RW model can cause long waiting time because of the dynamical properties of RWs on complex networks [20]. Gnutella and Kazaa use both algorithms [21,22]. Other P2P applications are structured and use global information such as distributed hash table (DHT) [17,23]. Thus, the traffic generated by those P2P applications using global information can be ignorably small compared with the pure P2P applications. However, pure P2P protocols mentioned above and their clones are still used very widely and listed in the most popular P2P protocols (for example see Ref. [24]). Therefore, we focus on the searching algorithm of *pure* P2P networks without global information in this paper. Inspired by our recent discoveries in the DCP [4,5], we introduce a new model for information search in which not only the query packets but also the information packets take RWs on the network. We will show that our new model has two main benefits compared to the other algorithms: (1) the amount of traffic is always constant and much less than FB algorithm. (2) Much less searching time than that for n-RWmodel. Using these two benefits, we expect that our algorithm can provide more optimized algorithm compared to FB or n-RW for *pure* P2P networks.

We now explain our model based on the anomalous behavior of DCP on the complex networks in detail. In the model, each node sends out an information packet whose main part, for example, consists of names of files stored in it, without regard to the existence of query events. Each of these packets takes RWs along the network connections. Thus, if there are N nodes in the network then N information packets take RWs. Independently, a randomly chosen node sends out one query packet to find a specific file. The query packet also takes RWs. The special feature in our model is thus in the fact that not only the querying packet moves but the information of all files moves on the network. If the query packet meets an information packet which has the requested file name in its list, then the RW of the query packet is terminated but the information

packet continues RWs for the next query. Thus, our model for information search can be mapped into the DCP, i.e., the query packet and the N information packets correspond to the one random walking lamb and N random walking lions, respectively. Therefore, we will call our model the N lions and one lamb (NLL) model.

We assume n_f available files on the given network. For the distribution of files and frequency of queries, we use two kinds of file distribution and frequency of queries. In the first kind, we assume that each node of the network has one randomly chosen file among n_f, and sends out an information packet with the name of the file stored in it, its IP address, etc. And a randomly chosen node sends out a query packet to find one randomly chosen item among n_f files. Thus the popularity of files and frequency of queries are uniform. In the second kind which is invoked by more realistic P2P network [25], the popularity of files or the probability to find the rth most popular file in the network is assumed to be proportional to $1/r$ (Zipf's law) [26–28]. The frequency of queries to find the rth most popular file is also assumed to be proportional to $1/r$ which is consistent with some empirical observations [26–28]. We call the first kind uniform distribution and the second kind Zipf-distribution from now on. The empirically obtained Zipf-distribution also implies that it is more probable to increase the number of more popular files rather than new or rare files when a new user joins the P2P network. Thus, we assume that n_f is fixed for each given network for simplicity.

In the simulation we use two kinds of networks. One is the theoretical SF network with $\gamma = 2.4$ to mimic the virtual P2P networks. The SF networks are generated by the method suggested by Goh et al. [29]. To compare the scalability of each model or algorithm, we control the number N of nodes in the networks as $N = 10^3 - 10^6$. The other kind is the snapshot of a real Gnutella topology obtained from Ref. [16], which has $1,074,843$ ($\approx 10^6$) nodes. For comparison with the results on the theoretical SF networks, we extract the sub-networks of Gnutella from the huge snapshot without changing the topological properties. Constructing sub-network with $N < 10^6$ from the given snapshot of the Gnutella network without changing the topological properties is not trivial one [30–32]. To extract Gnutella sub-networks having $N = 10^3 - 10^5$ nodes from the snapshot, we use a RW; place a particle at a randomly chosen node and let the particle take RWs until it visits N different nodes. Then construct sub-networks with these N visited nodes and the links which connect any pair of nodes among the N visited nodes in the original network. We have verified that the resulting sub-networks and original Gnutella network have almost the same degree distribution, degree–degree correlations and hierarchical structures [32]. All quantities measured in the simulations are averaged over 10 network realizations and 100 different histories for each network realization.

In Fig. 1(a), we compare the traffic $f(t)$ generated by FB algorithms to that by NLL model on the SF networks with $N = 10^3$ nodes. At each time t, all packets whose pre-assigned time-to-live (TTL) counter is larger than 0 are forwarded to the nearest neighbors. The TTL of each packet decreases by one when the packet is forwarded to its nearest neighbors, and if $TTL = 0$ then the query event is forced to end [1]. The uniform distribution for files and frequency of queries is used. We assign $n_f = 5$ and $TTL = 6$ for FB algorithm. The different values of the n_f and TTL give us the similar results. In order to prevent the overflow caused by a large number of packets in FB algorithm, we assume that a new query event can occur when one of the query packets succeed to find the requested file. In this case, the other query packets, which fail to find the requested file, are forwarded until their TTLs become 0. If all the query packets fail to find the requested file, then a new query event can occur only when the TTLs of the previous packets are expired. The traffic generated by FB algorithm during each query event is known to increase exponentially as

$$f(t = TTL) \approx \langle k \rangle \left(\frac{\langle k^2 \rangle - \langle k \rangle}{\langle k \rangle} \right)^{TTL-1}, \tag{3}$$

where $\langle k \rangle$ and $\langle k^2 \rangle$ are the first and second moments of network degree distribution, respectively [1]. However, the traffic of NLL model is always $N + 1(= 1001)$ for successive query events. The simulation result shows that FB algorithm generates around 50 times more traffic than NLL model on the average. If there are q simultaneous query events, then the average traffic for FB algorithm increases simply by q times of the average traffic shown in Fig. 1(a), but it becomes simply $q + N$ for NLL model. The successive single query events of n-RW model produce the smallest traffic among the algorithms considered in this paper. Since the traffic of n-RW model is qn for q simultaneous query events, if $q = N$, i.e., every node in the network sends out
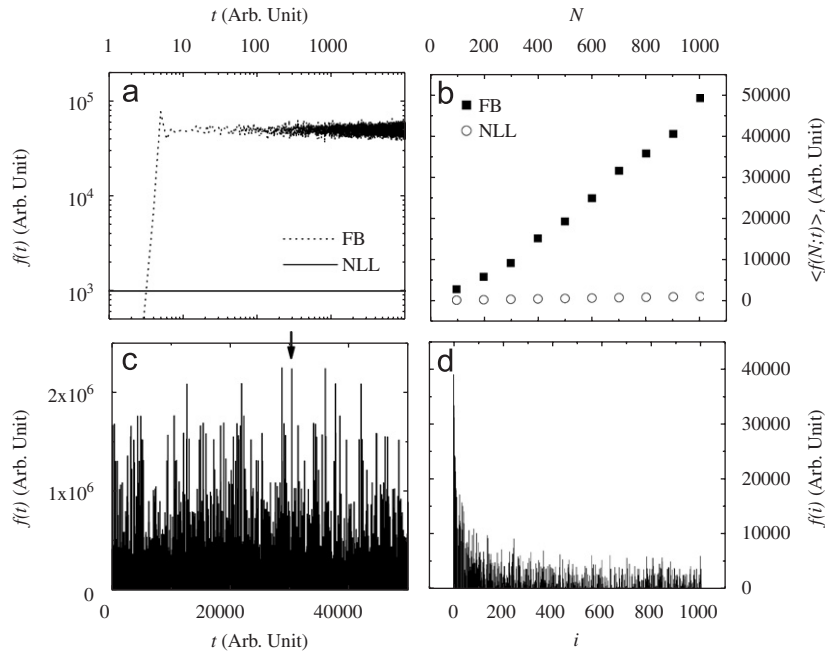
Fig. 1. (a) Plot of traffic $f(t)$ against t. The average traffic of NLL model is calculated from simple theoretical arguments. (b) Time averaged traffic $\langle f(N; t)\rangle_t$ generated by FB and by NLL for various network sizes $N = 10^2 - 10^3$. (c) The time evolution of $f(t)$ obtained from a single run of simulation of FB algorithm. One of the local maxima of traffic generated by FB algorithm is marked by the arrow. (d) The traffic of FB algorithm measured at each node $f(i)$ when $f(t)$ has the local maximum.

a query packet simultaneously, then the traffic generated by n-RW model can exceed the traffic of NLL model depending on the value of n. We also consider the dependence of $f(t)$ on the network size N, $f(N; t)$. Fig. 1(b) shows the time averaged traffic generated by FB algorithms, $\langle f_{FB}(N; t)\rangle_t$, and by NLL model, $\langle f_{NLL}(N; t)\rangle_t$, on the SF networks with $N = 10^2 - 10^3$. As N increases, $\langle f_{FB}(N; t)\rangle_t - \langle f_{NLL}(N; t)\rangle_t$ considerably increases. Fig. 1(c) displays the time evolution of the traffic obtained from a single run of simulation for FB algorithm. It implies a practical importance. Due to the large fluctuations, for example, around at $t \approx 3.0 \times 10^4$ (marked by the arrow) the traffic on the network can have local maxima exceeding 2×10^6, which is 2000 times larger than the traffic generated by NLL model. At the moment of occurring such large amount of traffic, FB algorithm can causes severe traffic congestion over the network. However, NLL model always guarantees a constant level of traffic, which is much less than that of FB algorithm and comparable to that of n-RW model.

Since the probability that a RW visits a node of degree k is given by $p_v(k) = k/\sum_{i=1}^{N} k_i$ [7,20], the average traffic of NLL model at the node having k links can be estimated by $\langle f(k)\rangle = N(k/\sum_{i=1}^{N} k_i)$. Therefore, the hub can have considerable amount of lion-traffic in the NLL model. In order to find the bottleneck in FB algorithm, we measure the traffic of each node $f(i)$ when $f(t)$ has the local maximum for FB algorithm (Fig. 1(d)). By definition of the static model [29], the smaller node index i has the larger k. From the data, we find that the traffic of the largest hub ($i = 1$) reaches around 4×10^4 which is much larger than the average traffic of NLL model at the largest hub $\langle f(k_{\max})\rangle$ or the possible maximum traffic of NLL model ($f_{\max} = 1001$ for $N = 1000$). The maximum traffic of a link at time t can be estimated by mean-field type arguments as $f(k_{\max}; t) + \langle f(t)\rangle$ for FB algorithm which is much larger than that for n-RW and NLL model, $f(k_{\max}; t)/k_{\max} + \langle f(t)\rangle/\langle k\rangle$. Here, $f(k_{\max}; t)$ represents the traffic on the largest hub at t.

In Fig. 2 we show the average searching time, $\langle T\rangle$, for each algorithm. The searching time T is defined by the time taken to find the requested information, and thus, it corresponds to the life time of a lamb in DCP. In the simulations we use infinite TTLs. Since the searching time of n-RW model depends on the value of n, we need a criterion for n. Here we use the condition $f_{n-RW}(t) = f_{NLL}(t)$ when $q = N$, so we fix $n = 2$ in the following simulations. In Fig. 2, we display the average searching time when $n_f = 500$. From the data we
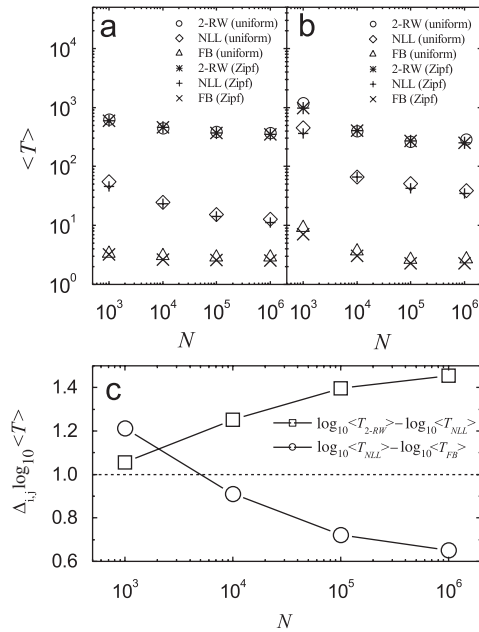
Fig. 2. Log–log plot of the average time $\langle T \rangle$ taken to find the requested information with a fixed value of $n_f (= 500)$ on SF networks with $\gamma = 2.4$ (a) and real Gnutella networks (b). $\langle T \rangle$ decreases as increasing N both for 2-RW and NLL models, while $\langle T \rangle$ for FB algorithm remains almost constant on SF networks (a) and decreases on real Gnutella networks. Open symbols: both the frequency of queries and popularity of files follow the uniform distribution. Crossed symbols: both the frequency of queries and popularity of files follow the Zipf-distribution. (c) Plot of the $\Delta_{ij} \log_{10} \langle T \rangle$ against N. The subscripts i and j represent each model (2-RW, NLL, and FB). Squares correspond to the results for $i =$ 2-RW and $j =$ NLL. Circles denote the results for $i =$ NLL and $j =$ FB. The dashed line represents $\Delta_{ij} \log_{10} \langle T \rangle = 1$. $\Delta_{ij} \log_{10} \langle T \rangle < 1$ implies that the difference in the order of magnitude of $\langle T \rangle$ between the models i and j is less than order 1.

cannot find any significant difference between uniform distribution and Zipf distribution of files and queries. The average searching time of NLL model on SF networks is, at least, 10 times faster than n-RW model on SF networks. For example, $\langle T \rangle_{2-RW} / \langle T \rangle_{NLL} = 365.417/12.84 \approx 28$ on SF networks for $N = 10^6$. However, $\langle T \rangle_{NLL} / \langle T \rangle_{FB} = 12.84/2.9 \approx 4.4$ on the same size of SF networks (see Fig. 2(a)). Therefore, the average searching times satisfy the inequality,

$$\langle T \rangle_{FB} < \langle T \rangle_{NLL} < \langle T \rangle_{2-RW} \tag{4}$$

for all $N \leqslant 10^6$. We also investigate the performance of each models when searching for rare files by assuming that $n_f = N$. From the numerical simulations we obtain $\langle T \rangle_{FB} \simeq 4.7$, $\langle T \rangle_{NLL} \simeq 3938$, and $\langle T \rangle_{2-RW} \simeq 1.67 \times 10^6$ for $N = 10^6$. These results show that the performance of NLL model in this extreme case still satisfies Eq. (4).

Note that $\langle T \rangle$ of NLL model decreases much faster than that of n-RW model as increasing N and approaches to $\langle T \rangle_{FB}$, i.e., the difference between NLL and 2-RW models, $\langle T \rangle_{2-RW} - \langle T \rangle_{NLL}$, increases while $\langle T \rangle_{NLL} - \langle T \rangle_{FB}$ decreases as increasing N (see Fig. 2(a)). We find the same behavior of $\langle T \rangle$'s on the real Gnutella (sub-) networks (see Fig. 2(b)). This can be understood from the dynamical properties of RWs on complex networks. Since the probability that a RW visits a node with the degree k is proportional to k [7,20], the probability that a query packet finds a requested file at a node with degree k is proportional to k in n-RW model. But in NLL model, due to the random walking information packets, the probability is proportional to k^2 [5]. As a result, the hubs in the network can collect more packets in our NLL model than n-RW model, and thus become effective attractors. This effect becomes enhanced if the second moment of degree distribution $\langle k^2 \rangle$ diverges, or for SF networks with $\gamma < 3$. In SF networks the degree of the hub increases with N [1]. Therefore, both $\langle T \rangle_{NLL}$ and $\langle T \rangle_{2-RW}$ decrease but $\langle T \rangle_{2-RW} - \langle T \rangle_{NLL}$ increases as increasing N. These provides an indirect evidence that the $\langle k^2 \rangle$ grows more rapidly than $\langle k \rangle$ as increasing N in the Gnutella network.

Finally, in order to systematically analyze the data in Figs. 2(a) and (b), we calculate the difference in the order of magnitude of searching time, $\Delta_{i,j} \log_{10}\langle T \rangle \equiv \log_{10}\langle T \rangle_i - \log_{10}\langle T \rangle_j$, between models i and j. Here i and j represent the name of each model (2-RW, NLL, and FB). As a simple criterion, we assume that the $\langle T \rangle$'s of models i and j are comparable if $\Delta_{i,j} \log_{10}\langle T \rangle < 1$. Fig. 2(c) shows the $\Delta_{i,j} \log_{10}\langle T \rangle$ obtained from the data in Fig. 2(a). The data shows that $\Delta_{2-RW,NLL} \log_{10}\langle T \rangle$ increases as N increases. On the other hand, $\Delta_{NLL,FB} \log_{10}\langle T \rangle$ decreases and becomes less than 1 when $N > 5000$. This implies that $\langle T \rangle_{NLL}$ becomes comparable with $\langle T \rangle_{FB}$ when $N > 5000$ on the theoretical networks. We also calculate the $\Delta_{ij} \log_{10}\langle T \rangle$ for real Gnutella network and find the similar tendencies (which is not shown). By extrapolating the result we obtain that $\Delta_{NLL,FB} \log_{10}\langle T \rangle < 1$ when $N > 10^7$ for real Gnutella network.

In this paper we introduce a new model for information search, which can be easily applied to many information search problems such as P2P file sharing networks. By numerical simulations, we verify two important benefits of our model: (1) first of all, our model can drastically decrease the traffic congestion compared to FB algorithm and (2) it can provide more implementable scalability in average searching time than n-RW model. Because of these two benefits, NLL algorithm suggested in this paper can be utilized to optimize information search on *pure* P2P networks. The dynamical properties of NLL model can be easily understood from the DCP and the dynamical properties of RWs on complex networks. Since the probability that a RW visits a node with degree k is proportional to k [7,20], $P(k)$ becomes relevant. If $\langle k^2 \rangle$ diverges then most of the information would be gathered at several hubs without the knowledge of the global information on the distribution of files. Therefore, the hubs spontaneously play a very similar role of the directory servers in structured P2P networks [14] which provide better scalability than n-RW model.

Though P2P network is virtual network, nodes with large number of connections in real network can have large number of degree in P2P network. In certain real P2P networks such as Gnutella, the nodes which satisfy some requirements such as sufficient network resources, CPU speed, etc. are prepared to be the hubs with a large number of degree [21]. For simplicity, we assume the degree of virtual P2P network is approximately proportional to the degree of real network and each node and link can treat an unlimited amount of packets at each time step. However, the detailed studies with more realistic restrictions such as finite buffers, different data transfer rate and *ad hoc* properties of network topology are necessary for further studies to apply NLL model to the real P2P applications.

Finally, some information transfer networks, such as neural networks, satisfy Eq. (2) with $\gamma < 3$ [12] or have huge hub like the Gnutella network [16]. In these networks, we expect that the networks have self-organized their structure to improve the efficiency for finding information such as reducing the traffic or the searching time. By combining our results, we expect that the non-mean-field type behavior of DCP can give a clue to the emergence of SF structure or formation of hubs in information transfer networks observed in nature [12,33].

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