Weak State Routing for Large Scale Dynamic Networks

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***Abstract*—Forwarding decisions in routing protocols rely on information about the destination nodes provided by routing table states. When paths to a destination change, corresponding states become invalid and need to be refreshed with control messages for resilient routing. In large and highly dynamic networks, this overhead can crowd out the capacity for data traffic. For such networks, we propose the concept of *weak state*, which is interpreted as a probabilistic hint, not as absolute truth. Weak state can remain valid without explicit messages, by systematically reducing the confidence in its accuracy. Weak State Routing (WSR) is a novel routing protocol that uses weak state along with *random directional walks* for forwarding packets. When a packet reaches a node that contains a weak state about the destination with higher confidence than that held by the packet, the walk direction is biased. The packet reaches the destination via a sequence of directional walks, punctuated by biasing decisions. WSR also uses random directional walks for disseminating routing state, and provides mechanisms for aggregating weak state.**

Our simulation results show that WSR offers a very high packet delivery ratio ($\geq 98\%$). Control traffic overhead scales as $O(N)$ and the state complexity is $\Theta(N^{3/2})$, where N is the number of nodes. Packets follow longer paths compared to prior protocols (OLSR [2], GLS-GPSR [3], [4]); but the average path length is asymptotically efficient and scales as $O(\sqrt{N})$. Despite longer paths, WSR's end-to-end packet delivery delay is much smaller due to the dramatic reduction in protocol overhead.

I. Introduction

In this paper, we consider the problem of designing robust and scalable routing protocols for large and dynamic networks like large scale mobile ad-hoc networks (MANETs) or metropolitan scale vehicular networks, where every vehicle provides an open compute/storage/communication platform. Though such networks are not prevalent today, they show an immense potential for future deployment. We seek to anticipate and understand the fundamental problem of routing, and the nature of routing tables in such future networks.

Routing protocols in communication networks rely on routing table entries ("states") to decide where to forward a packet. The routing table state typically maps an ID (e.g.: destination address) or an aggregate (e.g.: a destination network) to an entity such as a next-hop, a sequence of hops, a location in plane etc. If a destination moves significantly within the network, the corresponding routing table states become invalid and need to be refreshed. As the network size increases and it becomes more dynamic, routing table entries at several routers must be refreshed leading to a huge increase in control traffic. In fact, it has been recently shown that the control overhead that is required for reliable routing may asymptotically use the entire capacity of the network [5], [6]. On the other hand, if the state information is not refreshed rapidly enough, the invalid routing table entries lead to wrong routing decisions and wandering packets that wastefully consume network capacity without leading to end-to-end goodput.

For such large and dynamic networks, we propose to use probabilistic routing tables, where routing table entries are considered as probabilistic hints, and not absolute truth. Such state information is called *weak state*. Weak state can be locally refreshed by reducing the associated confidence value, a measure of the probability that the state is accurate. This way, weak state captures the inherent uncertainty (or weak semantics) of the state information without the need for explicit control traffic that traverse the network, consuming network capacity. In other words, even though the network is large and highly dynamic, the state information at routers is more stable and yet useful when interpreted as probabilistic hints. Weakening the state is similar to aging the state, albeit in terms of semantics. The state is associated with an implicit "soft timeout", i.e. once the associated confidence value is below a threshold the state is removed from the system.

We propose a novel protocol called Weak State Routing (WSR) that uses probabilistic state information in the context of a scalable routing protocol for large, dynamic networks. WSR utilizes the new concept of *random directional walks* (i.e. walks in randomly chosen directions) as a primitive *both* for disseminating weak state, and for forwarding packets. In particular (see Fig. 1), the source node initially assigns a random direction to the data packet. The packet is forwarded along this direction until it is first received by an intermediate node that contains probabilistic information about the location of the destination. The intermediate node *biases* the packet in the direction towards this location and the new confidence value is carried by the packet. This directional walk continues until the packet reaches another node that contains a weak state providing information about the destination ID with a higher confidence value or greater accuracy of localization (i.e. stronger state) than what is carried in the packet. The packet's directional walk is now biased using this information. This

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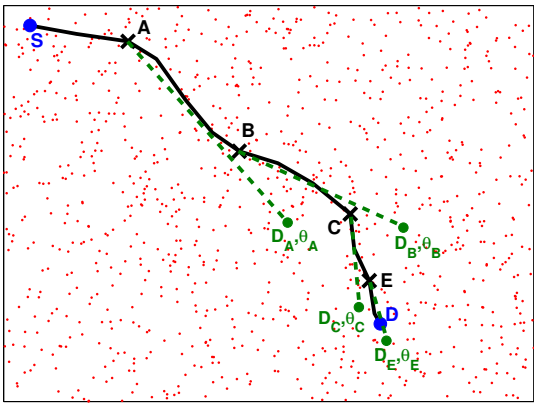


Fig. 1. An illustration of routing with WSR. A data packet is forwarded from node S to D using random directional walks. The packet is successively biased in intermediate nodes, A, B, C and E in directions, towards D_A, D_B, D_C and D_E, respectively, which the nodes believe to lead to destination. The strength of the bias at each intermediate node is θ_A, θ_B, θ_C, θ_E, respectively. Weak state biasing the packet at an intermediate node yields stronger information than the previously biasing state, i.e. $\theta_A < \theta_B < \theta_C < \theta_E$

process of the walks being biased with increasing confidence continues until the packet reaches the destination.

The above forwarding mechanism assumes that a random directional walk will encounter a node with probabilistic state information about the destination with high probability. Further, as the successively biased walk approaches the destination, it will encounter, with high probability, nodes with increasingly stronger state information. To support this assumption, WSR disseminates state information periodically in random directional walks from each node. Two random lines (one the forwarding walk, and the other, the dissemination walk) in a plane intersect with high probability [7]. Even with mobility, the presence of multiple dissemination walks on the plane that inject state at $O(\sqrt{N})$ nodes assures that within $O(\sqrt{N})$ hops, with high probability, a packet forwarded in the form of a directional walk will encounter a node that can bias it with stronger information. WSR also provides mechanisms for aggregating weak state to achieve scalability.

We use extensive simulations to evaluate the performance of WSR. The simulation results show that WSR offers a high packet delivery ratio, more than 98%. The total routing protocol overhead scales as $O(N)$, N being the number of nodes. WSR offers a scalable state maintenance method by aggregating weak states. Through asymptotical analysis, we show that the state complexity of WSR is $\Theta(N^{3/2})$. The cost of WSR is the increased path length. Even though packets follow routes that are longer than the shortest paths, the average path length is asymptotically efficient and scales as $O(\sqrt{N})$. Despite the longer paths, due to the dramatic reduction in control traffic overhead, the average end-to-end packet delivery delay is much smaller than comparable protocols. In particular, our simulations with large and dynamic networks indicate that the average path length in WSR can be 3 times as large as that of GLS-GPSR [3], [4] while control traffic overhead in GLS-GPSR can be over 10 times larger than WSR overhead. Even though the packets take longer paths with WSR, the average end-to-end delay is up to 15 times less than that of GLS-GPSR.

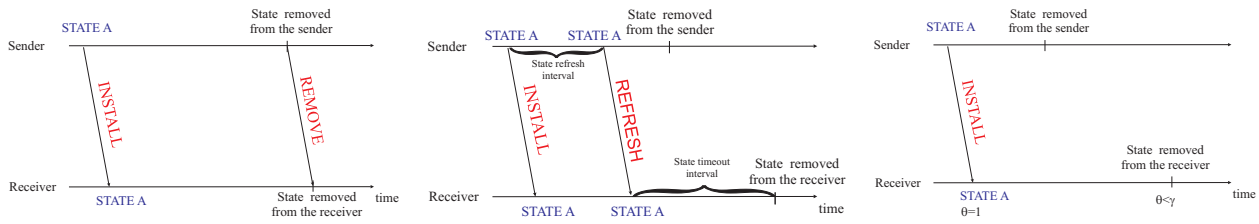
The rest of this paper is organized as follows: In Section II, we review related work. We define our weak state concept and present our routing mechanism in Section III. In Section IV, we provide simulation results. We present an asymptotical analysis in Section V. We conclude the paper in Section VI.

II. Related Work

Traditional state concept can be classified into two broad categories: hard and soft state approaches. *Hard state* is maintained at a remote node until it is explicitly removed using state-teardown messages by the node that installed the state. Since the state is removed explicitly, reliable communication is essential. *Soft state*, which was first coined in [8], *times out* unless it is refreshed within a time-out duration. The node that installed the state periodically issues refresh messages. Once a message is received by the node maintaining the soft state, the timer corresponding to the state is rescheduled. If the timer expires, the state times out and it is removed from the system. Soft state does not require explicit removal messages, unlike hard state. Hence, reliable signaling is not required. Analytical comparisons of hard state, soft state and the hybrid approaches are presented in [9] and [10].

In both hard state and soft state, the state information is regarded as absolute truth. We refer to such state information as having *strong* semantics or that it is an example of *strong state*. When the original state changes, the strong state value at the remote nodes should be explicitly refreshed in both approaches (hard or soft). *Weak state* on the other hand has "weak" or probabilistic semantics. The state can be refreshed *locally*, by weakening or decaying the confidence value associated with the state over time. The confidence value is an estimate of the probability that the true state is valid. Once the confidence in the state is below a threshold value, the state is removed from the system. Weakening the state is similar to aging it and is equivalent to a soft timeout. Hence, weak state is a generalization of soft state. A comparison of hard, soft and weak states are given in Fig. 2. The notion of state weakness and its effect on the consistency of protocol decisions have been evaluated in our more recent work [11], not included in this paper.

Position based routing protocols, such as Greedy Perimeter Stateless Routing (GPSR) protocol [4], provide a scalable solution to the routing problem (in moderately dynamic networks) by leveraging the geographic coordinates of nodes to route packets. A packet is forwarded to the next-hop in the direction of the destination. However, GPSR-like protocols still require the knowledge of the location associated with a destination node ID. They have to be used in conjunction with a location service protocol such as Grid Location Service (GLS) [3] to retrieve the location information of a destination ID. GLS partitions the network into structured grids forming a geographical hierarchy. These structures tend to be hard to maintain as the network size and dynamism increase. Weak State Routing (WSR) uses the unstructured approach of random directional walks *both* for forwarding packets and disseminating state. In geographical routing, the traditional approach isolates the location discovery (e.g. GLS) and packet forwarding (e.g. GPSR). Even though WSR utilizes geographical information as well, these processes take place concurrently.



(a) Hard State (b) Soft State (c) Weak State

Fig. 2. A comparison summary of hard state, soft state and weak state approaches. Hard state requires explicit control message to be removed. Soft state times out if it is not refreshed within the timeout interval. Weak state is associated with a confidence value θ which is a decreasing function of time. When the confidence is below a threshold value γ, it is removed.

MANET routing that use link states has two subclasses: proactive routing [12] (for large, but less dynamic networks) and reactive or on-demand routing [13], [14] (for dynamic, but relatively smaller networks). Recent protocols such as FRESH [15] and EASE [16] utilize node encounter histories as "state". They use iterative searches to find nodes that encountered the destination more recently. FRESH forwards a packet to an intermediate node that encountered the destination more recently whereas EASE sends it to the location where the destination is encountered by such an intermediate node.

Flooding in proactive or reactive protocols to handle dynamism is a core issue that limits scalability. Optimized Link State Routing (OLSR) is a link-state proactive protocol that uses a multipoint relaying mechanism, where only a subset of recipients redistribute control packets [2]. Hazy Sighted Link State (HSLS) is a scalable protocol that propagates link state information to farther nodes at decreasing rates by flooding link state update messages with variable TTL values [17]. Though these protocols reduce flooding, they face challenges when the network becomes both large and highly dynamic. Increased dynamism of nodes leads to routing state updates in a large subset of nodes, and increase in control traffic. In addition, the cumulative number of routing table entries in these protocols (especially OLSR) scales as $O(N^2)$. In WSR, the cumulative state complexity is $\Theta(N^{3/2})$.

The directional forwarding mechanism we utilize has some similarities to the *Orthogonal Rendezvous Routing Protocol* (ORRP) proposed for static networks in [7]. The paper uses the property that a pair of orthogonal lines from the source and destination intersect ("rendezvous") in bounded 2-D Euclidean space with high probability. In a mobile environment, it is difficult to maintain fixed, orthogonal straight lines. Instead, WSR uses random directions and requires multiple biasing nodes to get the packet to the destination.

In Delay Tolerant Networks (DTN), some routing protocols may maintain oracles about the global future view of the network [18]. Opportunistic, stateless techniques are deployed where the nodes have no global information about the network. Instead, they rely on the natural node mobility [19], [20]. These works are inspired by Tse-Grossglauser model [21]. If the mobility scope is small relative to the size of the network, packets may not be delivered to the destination. PROPHET [22] positions itself between the two extremes. It maintains transitive probabilities for each destination, such as a probabilistic distance vector. The state information is used to create gradients towards the destination rather than an explicit mapping as in WSR.

Unstructured pure random walks, which proceed without being biased, are used to locate an object in P2P networks in [23] and [24]. In [25] and [26], Bloom filters are used to bias random walks. Kumar et al. introduce Exponentially Decaying Bloom Filters (EDBF) in [26], which is a "weak" representation of a set of objects. We apply this concept to store a probabilistic set-of-IDs. The difference between EDBF and our weak states is that in EDBF, Bloom filters are decayed hop-by-hop as they propagate in the network. EDBF is used to set up implicit gradients between the nodes by comparing the signals obtained in successive nodes. On the other hand, we decay Bloom filters over time and use them to set up explicit mappings from a weak set-of-IDs to a geographical region.

WSR functions as a distributed hashing method. Therefore, WSR resembles the distributed hash tables (DHT) that provide lookup services at large scale P2P networks [27]. In a DHT, every node stores a range of keys and any node can locate the node in which a particular key is stored using *consistent hashing* [28]. A DHT relies on a structured overlay network. In [29], it has been shown that maintaining such a structure is hard and may require substantial overhead in P2P systems. This is also true for mobile networks. A routing protocol for wireless networks inspired by DHTs, Virtual Ring Routing (VRR), is proposed in [30]. The authors show that increasing the node mobility and network size degrades the network performance significantly even though the protocol does not require network flooding. WSR provides distributed hashing functionality without a structured overlay as in traditional DHTs and with more tolerance of dynamism.

GIA [29] is a scalable unstructured lookup technique for P2P networks that depends upon the heterogeneity and leverages nodes with higher storage and connectivity capabilities. Bubblestorm [31] on the other hand hybridizes random walks with flooding to replicate both data and queries in sub-graphs. Once the sub-graph where the query is replicated overlaps with the sub-graph in which requested resource is replicated, the search is successful. With this scheme, paths are shorter than what random walks provide and hence the delay is smaller. Similar to GIA, Bubblestorm too exploits the heterogeneity of nodes. In contrast, WSR can achieve similar objectives of scaling and rare-object recall without constraints on the degree distribution or dependence on super-nodes in the context of large-scale dynamic networks.

III. Weak State Routing

This section presents the details of the WSR protocol. Specifically, we address the following:

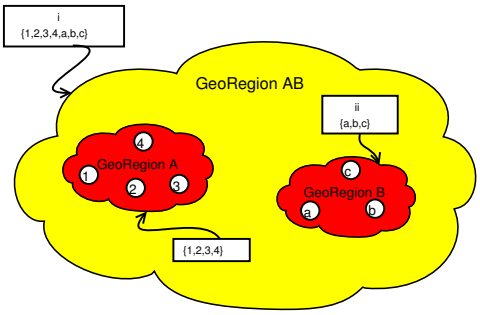


Fig. 3. Weak State Concept: A set of nodes (SetofIDs) are mapped to an aggregated geographical region (GeoRegion). Mappings are more definite for closer nodes.

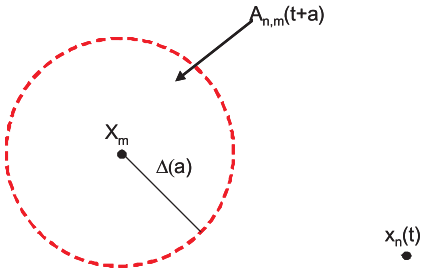


Fig. 4. Geographical decaying: If node n knows that node m was located at X_m at time t, at $t + a$ the node is located within the circle centered at X_m with radius $\Delta(a)$, worst case displacement in a.

1) Assumptions made by WSR.
2) Weak state and its semantic strength
3) Proactive location announcements from destinations using random directional walks.
4) Packet forwarding strategy using successively biased random directional walks.

A. Assumptions

The assumptions WSR makes are similar to those made by traditional location based routing protocols: nodes know their positions on a 2-D plane, either using a GPS device or through any other localization techniques. By using periodic single hop beacon messages, each node also knows its neighbors and their positions. The nodes have uniform omni-directional antennas. The source nodes in general do not know the location of the destination nodes.

We consider the scenario where the nodes move independently and the network density is high enough for connectivity at any time. The maximum node speed is known. Though this value can be large, we assume that the average displacement in unit time is small in comparison to the maximum distance between any two points in the area covered by the network.

B. Weak State Realization

In WSR, a *weak state* corresponds to a mapping from a persistent node ID or a collection of IDs (*SetofIDs*) to a geographical region (*GeoRegion*) in which the node (or the set of nodes) is believed to be currently located. The state information captures the uncertainty in the mapping.

An explicit mapping from a SetofIDs to a GeoRegion can be used to "bias" the random directional walks of packets being forwarded. If the destination ID is an element of the SetofIDs, the packet can be biased towards the center of the associated GeoRegion (subject to other conditions described later in this section). The bias can be reinforced as the packets get closer to their destinations. This is achieved by maintaining more definite, or stronger, mappings for nodes located closer to the destination. We capture the uncertainty in the mappings by weakening the two components of these mappings: SetofIDs and GeoRegion. We also aggregate the location information about a number of nodes. In Fig. 3 for example, node i maps node a (and a large set of nodes) to a large GeoRegion AB, whereas node ii, which is inside this GeoRegion AB, maps a subset of nodes to a smaller GeoRegion B. The confidence in the information provided by node ii is higher than the confidence in the information provided by node i because it deals with a smaller set, and a smaller GeoRegion.

Weak state has two aspects of probabilistic behavior: the SetofIDs portion is probabilistic in terms of the membership, and the GeoRegion is probabilistic in terms of the scope. The weakness of the SetofIDs allows the state to exhibit persistence, i.e. the state remains valid unlike strong state that is quickly invalidated with node dynamics. Importantly, the weak state can be locally updated without explicit protocol messaging.

Let $x_n(t)$ denote the location of node n at time t and consider the case where node n knows that node m is located at point X_m at time t, $x_m(t) = X_m$ (See Fig. 4). At time $t + \tau$ where $\tau \geq 0$, node n is not certain about the location of node m. The location now becomes a random process based on the mobility pattern of the node. To capture this uncertainty, we decay the location information stored at node n: if node n knows the maximum possible speed v_{max} a node can move with, it can determine the region, $A_{n,m}(t)$ in which the probability of node m being located is 1, $P\{x_m(t+\tau) \in A_{n,m}(t) | x_m(t) = X_m\} = 1$. $A_{n,m}(t)$ is a circular area centered at X_m with radius $\Delta(\tau)$, the worst case displacement of a node in a time interval of a, i.e. $\Delta(\tau) = v_{max} \times \tau$. Now, the state corresponds to a mapping from a node ID to a GeoRegion $A_{n,m}(t)$.

What we have above is a mapping from a node ID to a geographical region. We can now combine several such mappings for which the GeoRegion parts are close enough, into one aggregated state. Consider the scenario in Fig. 5, where node n maintains two states with the corresponding GeoRegions A_1 centered at x_1 and A_2 centered at x_2. If the angular distance between the two GeoRegions according to node n, $(\phi_1 + \phi_2)$, is small, node n aggregates these two mappings. The GeoRegion of the new aggregated mapping is the smallest circle A centered at x, midpoint of x_1 and x_2, that contains both A_1 and A_2. The corresponding SetofIDs portion of the new mapping is the union of the SetofIDs parts of the two mappings before the aggregation. After the mappings are aggregated, we keep decaying the new mapping geographically, i.e, broaden the radius. This way, the mapping gives the smallest area that contains all the nodes in the SetofIDs portion of the new mapping with probability 1.

By broadening the GeoRegion portion of the mapping, we weaken the spatial semantics of the state information: the uncertainty in the location of a node that is an element of

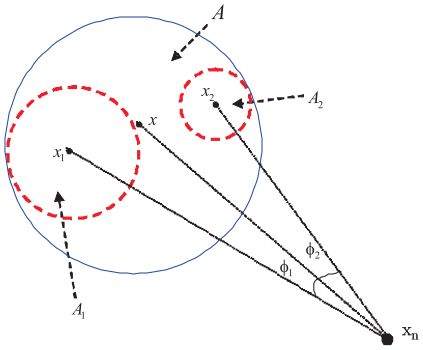


Fig. 5. If the GeoRegion portions of two mappings are located close to each with respect to the location of the node maintaining these mappings, i.e. ϕ_1 and ϕ_2 are small, they are combined into one mapping. The new GeoRegion is the smallest circle that contains both GeoRegions

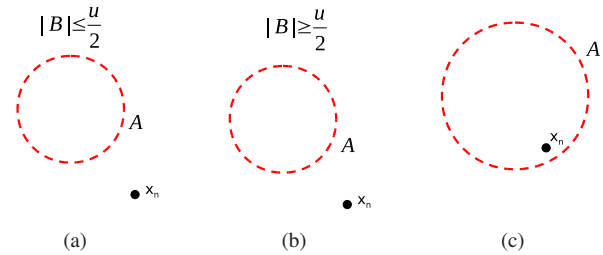


Fig. 6. Conditions on decaying of mapping with GeoRegion A and SetofIDs portion B that is maintained at node with location x_n. u is the length of the filter. At each decaying instant, if the node is located outside the GeoRegion and the cardinality of the SetofIDs portion $|B|$ is below $u/2$ (a), the GeoRegion is decayed. Weakening the SetofIDs portion is triggered if the filter fills up (b), or the GeoRegion grows so that the node is located within the GeoRegion (c).

the SetofIDs portion of the mapping increases every time the GeoRegion is expanded. However, a mapping with a very large uncertainty level is not useful for making forwarding decision. Therefore, we use a limit on the radius of the GeoRegion portion of the mapping. This threshold is not static and depends on the distance between the center of the GeoRegion and the location of the node maintaining this state because we want to have more definite information for closer destinations. Once the perimeter of the GeoRegion reaches the location of the node, we no longer broaden GeoRegion portion of the mapping. Instead, we then turn to weakening the SetofIDs component of the weak state.

To represent the SetofIDs part of the mapping, we use a variant of the Bloom filter data structure [32]. A Bloom filter is described by an array of u bits, which are all initialized to 0. A fixed number k of independent hash functions are employed. When inserting an element m (node ID in our case) to the filter, the bits in k array positions $h_1(m), \ldots, h_k(m)$, which are obtained by feeding the hash functions with m, are set to 1. The union of two filters is a new filter with the same size and characterized by the same hash functions, and obtained by the bitwise OR operation. In a regular Bloom filter, the membership query for an element n yields *yes* only if all the bits in array positions $h_1(n), \ldots, h_k(n)$ are 1.

Bloom filters are subject to false positives and the false positive rate increases with the number of elements added to the filter. To reduce the false positives, we also use a limit on the total number of bits set to 1 in Bloom filter B, which we call the cardinality of B and denote by $|B|$. Similar to the limit on the radius of the GeoRegion portion of the mapping, reaching the cardinality limit triggers the decay of SetofIDs portion the mapping. The decaying schedule of a mapping is summarized in Fig. 6. In addition, if the union of two mappings violate either criteria, we do not combine them.

Once either the radius of the GeoRegion portion of a mapping or the cardinality of its SetofIDs reaches their respective limits, the SetofIDs portion of the mapping is decayed. We refer to this weakened SetofIDs portion of the mapping as a "weak Bloom filter" (WBF). A WBF is similar to the Exponentially Decaying Bloom Filter (EDBF) concept proposed for P2P networks in [26]. In that method, the Bloom filter data structure is used to represent a set of resources that can be reached through a particular node either directly or over multiple hops after that node. The filters are decayed at every hop they propagate by setting a random subset of bits to 0. In other words, the filter becomes a probabilistic or fuzzy set, and a query yields a *signal* (or probability) of membership, rather than a binary yes/no or 0/1 answer. A random walk in a P2P network would sense a local gradient in the "signal" between a node and its neighbors and use that information for biasing its progress.

In WSR, the state information consists of a SetofIDs and an associated GeoRegion. This is an explicit mapping to a geographical region rather than a implicit gradient between neighbors. In contrast to EDBF, WSR decays the SetofIDs portion of the states periodically *over time* rather than over hops. At each decaying instant, the bits set to 1 are reset to 0 with a fixed probability p. This way the number of 1's corresponding to every node in the SetofIDs decay exponentially with time. Using WBF, we do not need a hard timeout value to remove the stale state information of any node. Once the cardinality of the WBF is below a threshold value, we remove the mapping since it is too old to bias any packet accurately enough. WBF also allows us to represent a number of node IDs in a scalable way.

C. Semantic Strength of Mappings

The forwarding decisions of the intermediate nodes are based on the quality of information that the mappings offer. We now explain the mapping quality using two strength parameters: spatial strength and temporal strength.

Spatial Strength: The spatial strength of the mapping involves the uncertainty in the GeoRegion portion of the mapping. Consider two mappings M_1 and M_2 with GeoRegion portions A_1 and A_2, respectively. Given that $P\{x_m(t) \in A_1\} = P\{x_m(t) \in A_2\}$ for node m, we say that M_1 is spatially stronger if A_1 represents a smaller region, i.e. its radius is smaller than that of A_2 and it yields a more definite region.

Temporal Strength: The temporal strength of the mapping is associated with the probability of a node being placed in the GeoRegion part of the mapping. Again, consider two mappings M_1 and M_2 with corresponding GeoRegions A_1 and A_2. We say that M_1 is temporally stronger for node m at time t if node m is placed in A_1 at time t with a larger probability, i.e. $P\{x_m(t) \in A_1\} > P\{x_m(t) \in A_2\}$.

Given that node m is located within a region A at time t, i.e. $x_m(t) \in A$, the probability of the node being in the same area in a future time $t+\tau$, $P\{x_m(t+\tau) \in A | x_m(t) \in A\}$ is a non-increasing function of $\tau \in [0, \infty)$. Therefore, a temporal strength parameter should capture the fact that among two mappings, the one that provides more recent information about a node should be temporally stronger.

In our mechanism, temporal strength of a mapping is reduced only if the probability that a node being in that region is not 1. In this case, we reset each 1 in the WBF part of the mapping by a fixed collision probability, p. For a mapping whose WBF part is denoted by B, let $\theta(m) = |\{i; B[h_i(m)] = 1, i = 1, \ldots, k\}|$ be the number of 1's in B corresponding to node m. A larger $\theta(m)$ indicates that the mapping contains more recent information about node m with high probability. Therefore, the probability that the node is located within the area that the GeoRegion portion of the mapping represents is higher. Hence, we use $\theta(m)$ as an indicator of the temporal strength and the value $\theta(m)/k$ as a rough (not actual) measure of the probability $P\{x_m \in A\}$, i.e. state confidence.

D. Dissemination of Location Information

Our routing mechanism is based on forwarding data packets toward the region where the node believes the destination is located, using the information given by weak states.

Initially, nodes have no information about the location of the destination. Nodes know the location of their neighbors through periodic beacon messages. Once two nodes which were neighbors become non-neighbors, i.e. get out of each other's transmission range, they create mappings for each other using their last known locations. For nodes farther away, WSR uses periodic announcements from destinations in random directions (*random directional walks*) to disseminate location information. Note that a random directional walk is different from a standard random walk; in random walks the random walker can proceed to each neighbor with equal probability. In random directional walks, a node selects the direction of the announcement packet randomly and sends the announcement in that direction, and the walk proceeds in that chosen direction. The node first picks an angle uniformly between 0 and 2π radians. The direction on which the location announcement is sent is determined by this angle. WSR calculates the position of a point that is far from the location of the node along this direction (a point outside the area covered the network) and use geographical routing to forward the announcement.

When a node receives an announcement from node m, it creates a weak state entry: a WBF is created with bits at indices $h_1(m), \ldots, h_k(m)$ are 1, and an associated GeoRegion where the center is the location of node m and the radius is 0. After creating this state, the node checks if it can combine this mapping with a already existing state.

By radially sending announcements in random directions at different points in time, we increase the probability that a packet that is also sent as random directional walk will intersect with one of these lines on which the announcements are sent. Also note that with this mechanism, the nodes that are close to a particular node receive location announcements from this node at a higher rate than the nodes further away. Therefore, the uncertainty in the location of a node decreases as the distance to this node decreases. Even though a node has uncertain information about the location of this destination, it can bias the packet towards a region where the packet will encounter a node that has more definite information.

Algorithm 1 Algorithm for biasing packets in WSR

```
ForwardPacket (P)
//Consider the bias previously given to the packet P
m ← destination(P)
θ ← Temporal(P)
R ← Spatial(P)
(x, y) ← TargetLocation(P)
//Find the strongest local mapping indicating the whereabouts of the node
for all mapping i do
    θ_i ← Lookup(i, m)
    if (θ_i > θ) OR (θ_i = θ AND R_i < R) then
        θ ← θ_i
        R ← R_i
        (x, y) ← Center_i
    end if
end for
Temporal(P) ← θ
Spatial(P) ← R
TargetLocation(P) ← (x, y)
Use a geographic forwarding scheme to send the packet to TargetLocation(P)
Lookup(i, m)
Φ ← 0
for all q ∈ {1, 2, ... k} do
    Φ ← Φ + WBF_i[h_q(m)]
end for
Return Φ
```

E. Forwarding Data Packets

Our data forwarding mechanism is a simple greedy geographical forwarding algorithm, albeit using random directional walks, and consulting the weak state at intermediate nodes. Similar to announcement packets, a data packet is initially sent in a random direction (assuming the source does not have any weak state information about the destination). But, unlike location announcements, a data packet is subsequently biased at an intermediate node if the node has a weak state about the location of the destination. We leave the problem of acknowledgements and reliability, i.e. recovery of lost packets, to the higher layers (transport).

The strategy we use for biasing the direction taken by data packets at intermediate nodes is similar to the longest-prefix-match method (summarized in Algorithm 1, called "strongest semantics match"). We first consider the temporal strength of the mapping to find the area that the destination node is most likely located. To achieve this objective, the destination node ID, m, is looked up in the WBF (i.e. SetofIDs) part of each mapping maintained by the current node. For each mapping i, the result of this lookup is the total number of bits set to 1 in locations indexed by $h_j(m), j \in 1 \ldots k$ in the WBF part of the mapping i, i.e. the temporal strength of the mapping for

node m, $\theta(m)$. If the temporal strength of a mapping is below a threshold γ, the mapping is discarded. The temporal and spatial strength values of the biasing state (i.e. the state which influenced its current direction) are carried on the packet. If a mapping at a subsequent node is stronger than strength associated with the packet's current direction (as indicated by its header), the packet is now biased in a new direction determined by this node's mapping. Specifically, the node's state should be either temporally stronger or spatially stronger with the same temporal strength. The packet is forwarded toward the center of the associated GeoRegion. The actual forwarding happens through a geographic forwarding scheme such as GPSR. An illustration of a route determined by WSR is given in Fig. 1. In this figure, θ values can be interpreted as both temporal and spatial strength, with temporal strength has priority over spatial strength.

With high probability, this mechanism does not result in stable loops for any given packet. Specifically, we have two cases. For Case 1, if a packet's direction does not change, due to the geographical forwarding, (such as GPSR), an intermediate node does not receive a packet more than once. For Case 2, consider the case where the packet's direction has changed since a node (say node-A) received the packet for the first time. It is possible, with low probability that node-A may receive a packet for the second time if the packet is biased by another node (say node-B), especially if node-A is also mobile. Since the packet has previously visited node-A, and was subsequently biased by node-B, the most recent bias (from node-B) is stronger than any mapping the node-A maintains regarding the location of the destination (unless node-A has received a new update from the destination). Therefore (assuming node-A does not have new updates from the destination), node-A cannot bias the packet's direction again. In other words, even if the packet touches a node more than once, it does so, only in the context of making progress towards the destination and the loop is not stable. Moreover, since every packet is sent in an initial random direction, the chance of multiple packets in a conversation being trapped in loops is very small. In addition, the abrupt and sudden changes in the node location may cause a node to receive a packet more than once. This may lead to a persistent loop only if the node mobility is repetitive and node speed is very high. Note that this is not specific to WSR, but common in all geographical routing mechanisms. Still, it is very unlikely because the node displacement within a time interval is typically very small in comparison to the distance traversed by a packet during the same interval.

IV. Simulations

In this section, we evaluate the performance of WSR. We compare WSR with OLSR and GLS location service combined with GPSR protocol(GLS-GPSR). OLSR is an optimization of link state protocols and does not contain flooding. Similar to WSR, GLS is also based on a distributed hashing mechanism. However, GLS relies on an underlying structure similar to DHTs. In GLS-GPSR, GPSR forwarding is done after the GLS protocol locates the geographic position of the destination. Even though WSR uses geographical forwarding as well, location discovery and packet forwarding take place concurrently and cannot be isolated as in GLS-GPSR. Note that WSR itself could be optimized further if a higher level acknowledgement from the destination to the source conveys its location after the first receipt of a packet (and thereby makes future packets take shorter paths). We do not examine these optimizations in this paper.

We empirically show that WSR achieves a high delivery ratio, it incurs only $O(N)$ overhead, its state complexity is $\Theta(N^{3/2})$ and the average path length scales as $O(\sqrt{N})$. We also present how we select the WSR parameters. We obtain the results in this section using random waypoint mobility model [13] and with fixed node density. We also validate the WSR performance trends with other mobility models as well.

A. Setup

In our simulations, the mobile nodes move in a square area, which maintains an average node density of 75 nodes per square kilometer. At the MAC layer we use IEEE 802.11 standard. The nodes have 250 m omnidirectional transmission range.

We simulate WSR for 1000 seconds and other protocols for 500 seconds because OLSR and GLS simulations require too much memory. In WSR, we deploy constant bit rate connections between 60 randomly selected source-destination pairs. In OLSR and GLS, the number of connections is 30. For each connection a 512 byte data packet is sent every second for 100 seconds. All results are averaged over 5 different instances.

The vertical bars in the graphs shown in throughout this section correspond to the 95% confidence interval.

B. Parameter Selection

The parameters we used in our protocol are given in Table I. We now explain the procedures for selecting WSR parameters. In order to limit the hashing collisions in a Bloom filter to a certain level, the number of bits in the filter, u, should increase in the same order as the average number of nodes (IDs) a WBF consists of. For example, if the average number of nodes in a WBF scales as $O(N^{\nu})$, where ν is a constant, u should also scale as $O(N^{\nu})$ in order to achieve a certain collision probability. Therefore, the state complexity of the protocol in terms of bits is only characterized by the average number of nodes that an intermediate node maintains information. We use a constant u value and a constant value for the number of hash functions for WBFs, k. This leads to using a constant γ value, minimum number of 1's in a WBF that corresponds to a node ID. If the temporal strength is below γ, the mapping is timed out and discarded for that node ID. In our simulations, we have $u = 2048$ bits, $k = 32$ and $\gamma = 5$.

In order to determine the decaying probability p, we look at how long it is useful to maintain a given mapping. Remember that the semantics of weak state is reduced over time and the state is removed once the confidence is below a threshold value. The time after which the state is removed is also probabilistic. Here, we present a lower bound on the duration for which a mapping is useful for after we start decaying the SetofIDs portion. Note that the mapping is always useful when we decay it geographically because the node is in the corresponding GeoRegion with probability 1.

Parameter	Description
u	WBF width in bits
γ	Minimum temporal strength (# 1-bits in a WBF for a node below which the state is timed out)
k	Number of hash functions in the WBF
p	Decaying probability
T_A	Announcement TTL
T_D	Data packet TTL

TABLE I
PROTOCOL PARAMETERS

We periodically decay the mappings in discrete decaying instants that are separated by Δt seconds. In a WBF, each node is represented by k bits each given by feeding the node ID to a hash function. The mapping for a node is useful only if at least γ bits corresponding to that node are set to 1. Without loss of generality, let the SetofIDs portion of the mapping start being decayed at time 0. In each decaying instant, each bit is reset to 0 with probability p. Let $b_i^{(m)}(t), 1 \leq i \leq k$ represent the value of the ith bit for a node m at the tth decaying instant. For convenience, we omit the superscript. We have $P(b_i(t) = 1) = (1-p)^t$ for all i.

Let,

$$B(t) = \sum_{i=1}^{k} b_i(t) \quad (1)$$

$$E[B(t)] = k(1-p)^t. \quad (2)$$

Note that $B(t)$ is a binomial random variable with parameter $q = (1-p)^t$. In other words,

$$P(B(t) = a) = \binom{k}{a} q^a (1-q)^{k-a}.$$

The probability that a state is timed out at time t_o is $P\left(B(t_o) < \gamma\right)$. Since the CDF of a binomial random variable cannot be expressed in closed form, we cannot formulate the upper bound in t_o but numerical methods can be used to show that it is finite (See [33]).

In order to find the lower bound on the timeout value, we use Chernoff bound:

$$P(B(t) \leq k(1-p)^t - ka) \leq e^{-2ka^2}.$$

Let $\gamma \leq k(1-p)^t$, and say $k(1-p)^t - ka = \gamma$ and $a = \frac{k(1-p)^t - \gamma}{k}$ Then,

$$P(B(t) \leq \gamma) \leq e^{\frac{-2(k(1-p)^t - \gamma)^2}{k}}.$$

To obtain the timeout value t_o, we look at $P(B(t_o) \leq \gamma) = \beta$. Using simple derivations,

$$t_o \geq \frac{\ln\left[\frac{1}{k}\left(\gamma + \sqrt{\frac{k\ln(1/\beta)}{2}}\right)\right]}{\ln(1-p)}. \quad (3)$$

The lower bound on t_o can be interpreted as the minimum number of times a SetofIDs has to be decayed for state timeout with probability β. To determine p, we use (3) with $\beta = 1$:

$$t_o \cong \frac{\log k - \log \gamma}{p}. \quad (4)$$

Note that (4) also relates to $E[B(t_o)] = \gamma$. The information about this node is lost $t_o \Delta t$ seconds after the SetofIDs begins to be decayed. For convenience, we use $\Delta t = 1$.

The mapping should be useful as long as the location information it provides is correlated to the actual location. So, t_o should be in the order of average time that it takes a node to finish a journey which is called the *transition time*, t_l. We assume this duration scales as $O(\sqrt{N})$. This also captures the average distance between two points in the area that the network covers. Since the average node speed does not change with the number of nodes, the assumption is reasonable. Random waypoint model is one of the mobility models that complies with this assumption along with vehicular mobility models. The expected transition time in random waypoint model is

$$t_l = \frac{0.5214x}{v} \quad (5)$$

if the network covers the area of size $x \times x$ m^2 and nodes move with a constant speed with v [34]. Note that x scales as $\Theta(\sqrt{N})$ to maintain a fixed node density. t_o should be smaller than $2t_l$ because the current position of a node is uncorrelated with the location of the same node after two transitions [35]. Remember that we assume the nodes only know their maximum possible speed, v_{max}. Also, a node that is a member of a SetofIDs may not be located in the boundary of the corresponding GeoRegion. In both cases, setting $t_o = t_l$ causes elimination of useful information. So, t_o should be larger than the expected transition time. We have $t_o = \alpha t_l$ where $1 \leq \alpha \leq 2$. We use $\alpha = \sqrt{2}$. We calculate t_l using (5) with $v = v_{max}$.

Setting p in this manner maintains that each node keeps information about a particular node for a duration of $\Theta(\sqrt{N})$ seconds. Hence, the number of nodes that contain information about this destination is $T_a\Theta(\sqrt{N})$, where T_a is the average number of times an announcement is forwarded. In Section V, we show that the state complexity of $\Theta(\sqrt{N})$ achieves an average path length that scales as $O(\sqrt{N})$. Therefore, we would like to have $T_a = \Theta(1)$. To achieve this, we use $T_A = \Theta(1)$ where T_A is the maximum number of times an announcement can be forwarded. In general, T_a is smaller than T_A because an announcement can be dropped due to reasons other than TTL expiration such as reaching the boundary of the area. We set $T_A = 16$ and make sure that each announcement is forwarded at least once.

In a mobile, connected network the average shortest path between any source-destination pair increases in the order of $O(\sqrt{N})$ with the number of nodes. T_D is the maximum number of times a data packet can be forwarded. In order to a high achieve delivery ratio, we increase T_D in the order of $\Theta(\sqrt{N})$. We set $T_D = 100$ in a network where $x = 2000$m and adjust it so that T_D/x remains approximately constant.

C. Results

Fig. 7 shows the fraction of data packets successfully delivered. We use two dynamism levels for WSR and GLS-GPSR. In the low mobility scenario (L), the minimum speed is 5 m/s and the maximum speed is 10 m/s. In the high mobility scenario (H), the minimum speed is 10 m/s and the maximum speed is 20 m/s. In either case, WSR succeeds delivering

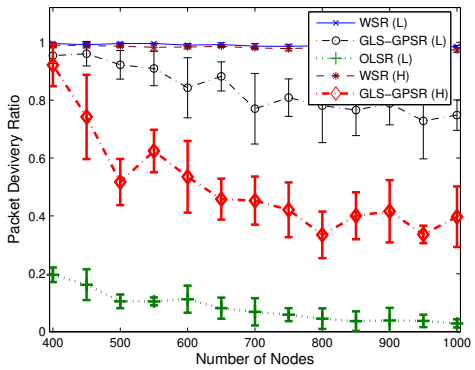


Fig. 7. Packet delivery success rate with respect to the number of nodes. WSR consistently delivers a very large fraction of packets. OLSR has a low delivery rate and GLS performance degrades with the network size and network dynamism. In low mobility scenario (L), the $v_{min} = 5$ m/s and $v_{max} = 10$ m/s and in high mobility scenario (H), the $v_{min} = 10$ m/s and $v_{max} = 20$ m/s

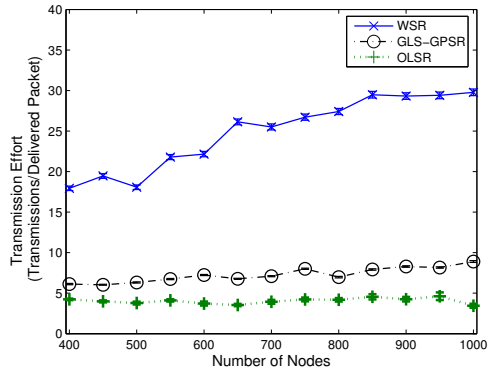


Fig. 9. Path efficiency vs. Number of Nodes in the Network. $v_{min} = 5$ and $v_{max} = 10$. The path efficiency is given by the number of transmissions per successfully delivered packet. OLSR can only deliver packets to close destinations. GLS only delivers packets to destinations whose exact location can be looked up. WSR are paths are much longer but still scalable $O(\sqrt{N})$.

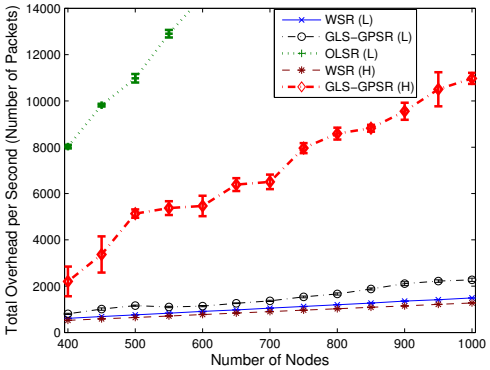


Fig. 8. Control Packet Overhead vs Number of Nodes. In WSR, the overhead scales as $O(N)$ regardless of the dynamism. Yet, GLS incurs superlinearly increasing overhead especially when the dynamism is high.

at least 98% of the packets. OLSR is a mechanism that is optimized over flooding. However, the scope of dissemination is still the entire network. The control packets traverse the entire network periodically. Therefore, a great number of control packets are generated in the network which causes congestion in intermediate nodes and a large fraction of packets are dropped. GLS is a structured mechanism that works fine in low mobility scenario when the number of nodes is small, which is consistent with the results reported in [3]. However, as the level of dynamism increases, the structure becomes hard to maintain. As a result, a large fraction of location request packets cannot find the correct location servers hence the delivery ratio drops.

Fig. 8 shows the protocol overhead. We adjusted the scale of the graph for clarity. It can be seen OLSR overhead is much more in comparison to WSR and GLS even in small number of nodes. The control packets for WSR consist of the periodic beacons and the location announcements. Since both the beacons and the location announcement packets are sent proactively, the expected number of control packets generated by a node within a fixed time interval is constant. The beacons are one hop packets and they are not further forwarded. Since an announcement packet has a fixed TTL, the number of times it is forwarded is bounded by a constant. Hence, the total overhead of WSR scales as $O(N)$. The location announcement packets are dropped in case of transmission failures and the overhead slightly decreases with increasing mobility level because of more frequent link failures. The overhead exponentially increases with the number of nodes in OLSR because the control packets whose scope is the entire network disseminate within the network periodically. GLS causes overhead in order to maintain the structure. The rate of location change is not significant in low mobility, hence the overhead is comparable to that of WSR. On the other hand, as the level of dynamism increases, the overhead becomes excessive because the nodes have to update their location information in the location servers more frequently in order to cope with dynamism. The result is superlineary increasing overhead. For example, in a highly dynamic 1000 node network, GLS overhead is more than 10 times what WSR incurs.

The transmission cost of routing protocol also includes increased length of paths that the data packets take. The efficiency of WSR in the control overhead performance comes at the cost of increased path length. Since we simulate very large networks, calculating the shortest path for every generated packet is extremely computationally expensive and hence not possible. Even though we are unable to compare the length of paths with the shortest paths, the relative comparison of "transmission effort" of each protocol is useful. The transmission effort metric is the average number of transmissions for each successfully delivered packet. Note that this metric also includes the number of retransmissions.

In WSR, packets follow longer paths as shown in Fig 9. However, the number of transmissions increases in the order of $O(\sqrt{N})$ (Please refer to Section V for detailed discussion). In GLS and OLSR, the packets that are successfully delivered mostly originate from sources that are close to the corresponding destinations which are easier to locate. Especially in OLSR, this situation together with the proactive topology information update mechanism results in small number of transmissions for delivered packets. In a network that utilizes

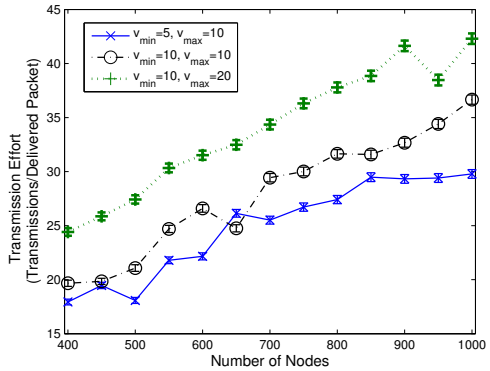


Fig. 10. Path efficiency of WSR vs. Number of Nodes. The average path length increases with the maximum node speed but in all cases it scales as $O(\sqrt{N})$.

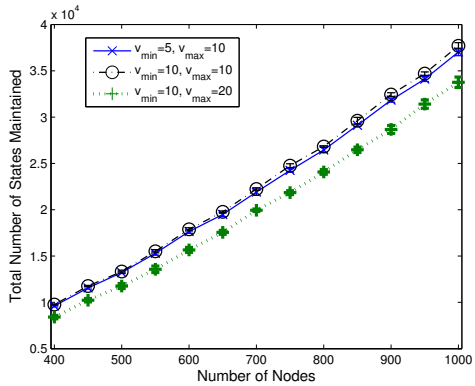


Fig. 12. Number of mappings stored vs. Number of Nodes. Each state corresponds to a WBF and a GeoRegion. The number of mappings stored in the network scales as $\Theta(N^{3/2})$

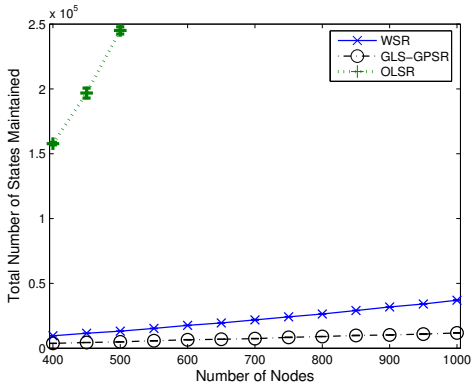


Fig. 11. Total States Stored vs. The Number of Nodes. $v_{min} = 5$ and $v_{max} = 10$. Total storage size increases as $\Theta(N^{3/2})$ in WSR, $O(N \log N)$ in GLS and $O(N^2)$ in OLSR.

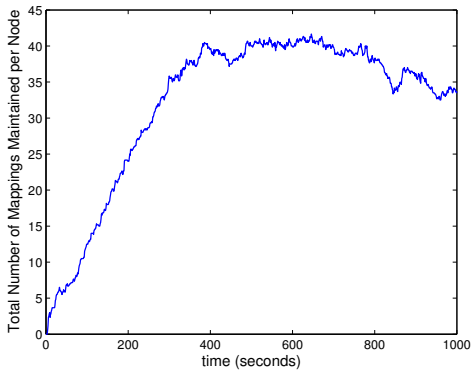


Fig. 13. Evolution of the number of mappings in a node. The total number of nodes in the network is 1000. $v_{min} = 10$ and $v_{max} = 10$. Announcement rate matches with the decaying aggregation rate and hence the number of states stored is bounded.

GLS, a node uses reactive location request packets when it has a packet to send to a destination. For successfully delivered packets, it is certain that the exact location of the destination node is known. Therefore, the data packets follow the efficient routes given by geographic forwarding scheme. We see that average path length for delivered packets in GLS is about one third of that in WSR.

We now look at how the path length changes with the node mobility in WSR. In Fig. 10, we see that packets take longer paths in the high mobility scenario. In WSR, the decaying probability is a function of the maximum node speed. When $v_{max} = 20$ m/s, the decaying probability is the twice the value when $v_{max} = 10$ m/s under same conditions. As a result, the mapping for a particular node is available for a shorter time and it takes more transmissions for a packet to be received by a node containing location information about the destination for the first time.

In Fig. 11, we compare the number of mappings stored in network in WSR with the number of entries in GLS location database and number of entries in OLSR routing table. The scale of the graph is adjusted for clarity. As we discuss in Section V, the state complexity of WSR is $\Theta(N^{3/2})$. We empirically see this in Fig. 11. In OLSR, every node in the network maintains a routing table entry about every other node in the network because the topology control packets are received by the all the nodes in network even though OLSR does not use flooding. Therefore, the total number of routing table entries scales as $O(N^2)$. The total number of routing table entries in GLS scales as $O(N \log N)$ because of the structure it uses. This way GLS is similar to Distributed Hash Tables and very efficient. On the other hand, WSR trades off the number of mapping for better delivery ratio. The state complexity is still below $O(N^2)$ and WSR can be regarded as scalable.

Fig. 12 shows how the number of mappings stored in the network changes with node mobility in WSR. The results indicate that the number of mappings does not change significantly with the increasing speed. Note that we decay the SetofIDs portion of the mappings using a larger decaying probability if the network is more dynamic. Still, the number of mappings stored within the network remains roughly the same because of aggregation. When the dynamism is low, the average lifetime of the mappings is longer but the nodes have more opportunities to combine mappings and vice versa in highly dynamic scenarios. The combined effect of decaying and aggregation mappings remains the same regardless of the dynamism. Therefore, the number of mappings in the network is approximately the same.

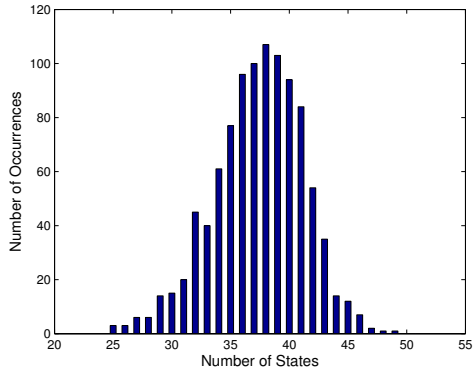


Fig. 14. The distribution of the number of mappings to the nodes in the network. The total number of nodes is 1000. $v_{min} = 10$ and $v_{max} = 10$. States are well distributed with a coefficient of variation 0.1 (with standard deviation of 3.8 and mean 37.4)

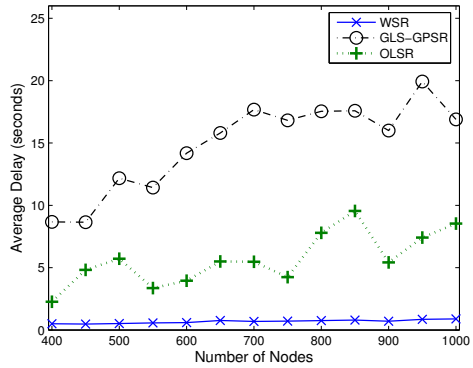


Fig. 15. End-to-end packet delivery delay vs the total number of nodes. $v_{min} = 5$ and $v_{max} = 10$. WSR quickly delivers packets. GLS requires route discovery, which may take a large amount of time. In OLSR, queues quickly fill up and therefore it takes a long while until the packets being served.

Fig. 13 shows how the number of mappings evolve in a random node in a $N = 1000$ node network and the node speed is always 10 m/s. The figure shows that the announcement rate matches with the decaying and aggregation rate. Therefore, the number of mappings maintained at a node is bounded and oscillates within a steady state interval[1].

Fig. 14 shows the distribution of the mappings in a 1000 node network with node speed 10 m/s. The distribution has a mean of 37.4 and a standard deviation of 3.8. The coefficient of the variation (CoV) of the distribution (the ratio of the standard deviation to the mean) is only 0.1. Hence, the distribution has a low degree of variation with respect to the mean and the mappings in the network are well distributed because of the location announcement method in the random directions. Therefore, failure of a single node will not drastically influence network performance.

One drawback of following routes with higher hop-count is that the data packets suffer from larger end-to-end delay values. Fig. 15 presents the average end-to-end delay values. Contrary to GLS, WSR does not require route request or location query packets in order to find the location of the destination. The packet forwarding is opportunistic in nature. In GLS, one request packet is sent for each flow. Yet, until the time the source node receives a route reply, all the arriving packets are queued in the source node. In large networks, GLS makes more than one attempt to locate the destination when the first location request packet is not able to locate the destination which increases the time until the queued packets are sent. Another factor in high end-to-end delay is the overhead. As the number of nodes increases, the number of control packets stored in the intermediate node buffers increases much faster in GLS and OLSR. OLSR in particular is a proactive scheme in which nodes find the routes without requiring route discovery. Still, the delay is higher than WSR because transmission buffers of the nodes quickly filled with the control packets and a data packet may need to wait for the control packets to be served. The transmission of control packets cause extra delay. Since WSR has no location or route discovery phase and average per-node overhead remains the same, the end-to-end delay is smaller than these schemes.

[1]The number of mappings stabilize at around t=300 seconds in all cases. Therefore, we start sending packets at this time in our simulations.

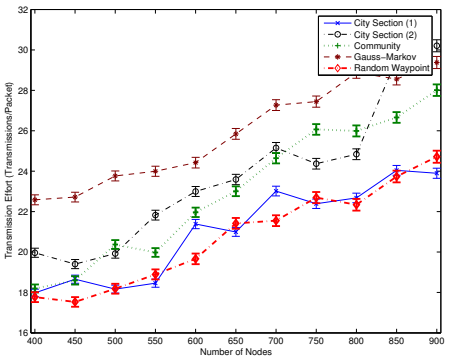


Fig. 16. Path length performance of WSR under a variety of mobility models. The results are consistent with those obtained with random waypoint mobility model.

Note that delay is not the only issue affected by long paths. As the number hops a packet takes increases, a network can serve fewer connections since more nodes participate in forwarding a single session. For networks that require short paths due to reasons like constrained energy or capacity, the simulation results may suggest using GLS. However, it is possible to use WSR as a location service. At the beginning of a connection, a random directional walk that follows weak states can be issued to locate the destination. This way, data packets can follow short paths with slightly increased control overhead and delay.

In Fig. 16, we demonstrate the path length performance of WSR under various mobility models, including Gauss-Markov mobility model and two instances of city section mobility model. In Gauss-Markov mobility model, the transition time for node trips have different scaling properties than the random waypoint mobility model. Still, we used the procedure in Section IV-B to set the protocol parameters. City section mobility model represents vehicular mobility better because the nodes can only move on roads on a given map. Obtaining this figure, we used two instances of city section mobility model. In the first, the nodes move on a fixed map, i.e. the

size of the area covered by the network does not change with the number of nodes. In the second, we used Manhattan Grids with size that maintains a constant node density. In all these scenarios, although the actual numbers can change, the characteristics of WSR performance is the same: packet delivery ratio is at least 98%, paths are longer than the shortest paths but the average path length scales as $O(\sqrt{N})$ and state complexity of the protocol is $O(N^{3/2})$. The difference in path length stems from the node distribution. For example in Gauss-Markov model, the nodes are distributed more evenly to the area in comparison to other mobility models in which the node distribution is denser in the center of the area. As a result, the average path between source-destination pairs is larger in Gauss-Markov mobility. Still, the paths are longer than the shortest paths but the increase in the path length against the number of nodes has the same characteristics for all mobility models. We present the results for other performance criteria in the extended technical report [33] because of space constraints.

V. Asymptotical Performance Analysis

In this section, we present a simple mathematical analysis that characterizes the asymptotical performance of our scheme. We show that the number of mappings stored in the network and the average path length scale as $\Theta(N^{3/2})$ and $O(\sqrt{N})$, respectively. We study the notion of the weakness in terms of consistency of protocol decisions in a separate paper [11].

A. State Complexity

The location announcements are sent along the random directions with a constant TTL value. So, each announcement is received by $\Theta(1)$ nodes. The procedure given in Section IV-B determines the probability for decaying SetofIDs portions of the mappings so that nodes maintain information about a destination for a duration that scales as $\Theta(\sqrt{N})$. Within this duration, $\Theta(\sqrt{N})$ nodes receives the location announcements from a particular node because the announcements are sent in random directions and the nodes move independently. This implies that $\Theta(\sqrt{N})$ nodes maintain information about that node and each node maintains information about $\Theta(\sqrt{N})$ nodes.

Because of the constant WBF length and the limit on the maximum number of bits set to 1 in WBF, SetofIDs portion of each mapping contains $\Theta(1)$ nodes. Hence, the number of mappings a node stores scales the same way as the number of nodes it maintains information about, i.e. $\Theta(\sqrt{N})$. Since the WBF length is constant, this is also the number of bits a node allocates for state storage. If we consider the entire network, the state complexity of protocol becomes $\Theta(N^{3/2})$.

B. Path Length

In this section, we show that a random directional walk is received by a node that has complete temporal strength about the destination after it is biased by at most a constant times and forwarded $O(\sqrt{N})$ hops, with high probability. At this point, the region where the destination is located is known with certainty and we show that the probability of packet delivery is very high within another $O(\sqrt{N})$ hops.

Given that $\Theta(\sqrt{N})$ nodes maintain information about the destination, the fraction of the nodes with the information about this destination is $q_1 = \frac{c_1}{\sqrt{N}}$ where c_1 is a constant.

Let n_1 denote the number of hops a random directional walk is forwarded until the packet first encounters a node containing information about the destination. We have

$$P(n_1 > n) = (1 - q_1)^n \leq \left(1 - \frac{c_1}{\sqrt{N}}\right)^n. \tag{6}$$

n_1 is a geometric random variable with parameter at least q_1. Hence,

$$E[n_1] = d_1\sqrt{N} \tag{7}$$

where d_1 is a constant. Let p_1 be the probability that it is biased at a node that has information about the destination after it is forwarded $O(\sqrt{N})$ times.

$$1 - p_1 = \left(1 - \frac{c_1}{\sqrt{N}}\right)^{b_1\sqrt{N}} \approx e^{-c_1 b_1}. \tag{8}$$

In words, a packet that is forwarded $b_1\sqrt{N}$ times is biased with an approximately high probability. This probability is high if the product $c_1 b_1$ is large.

In WSR, the protocol first checks the temporal strength of the mappings to bias the packets. Remember that the temporal strength of a mapping is given by the number of 1's in the indices that correspond to destination ID. There are a total of $k - \gamma$ temporal strength levels in the mappings (See Table I for k and γ.). Because of the way the decaying probability is set, the number of nodes that have a weak state with temporal strength ω is in $O(\sqrt{N})$ for each ω such that $\gamma \leq \omega \leq k$.

Let θ_1 denote the temporal strength of a mapping that first biases a packet and say $\theta_1 = \omega_1$, where $\gamma \leq \omega_1 \leq k$. $P(\theta^j > \omega_1)$ is the probability that a a node j has information with a temporal strength higher than ω_1. The number of nodes that contain such information is $c_2\sqrt{N}$, with $c_2 < c_1$. The probability that a consecutive node j, which is along the new direction, biases the packet for the second time is denoted by q_2 and conditional on the information given by the first mapping biasing the packet.

$$q_2 = P(\theta^j > \omega_1 | \theta_1 = \omega_1).$$

Once the packet is biased, the direction it is forwarded is altered so that it is more likely to be received by an intermediate node that contains stronger information about the destination. Hence, q_2 is lower bounded by the unconditional probability $q_2 \geq P(\theta^j > \omega_1) = \frac{c_2}{\sqrt{N}}$.

Based upon equations (6), (7) and (8), we can say that after the first bias, the packet is biased again with probability p_2, which is at least a constant if it is forwarded $b_2\sqrt{N}$ times. This constant is large if $c_2 b_2$ is large. The expected number of hops the packet is forwarded between the first and second bias, $E[n_2]$, is upper bounded by $d_2\sqrt{N}$. Because the number of nodes that contain information with temporal strength ω is in the order of $\sqrt{N}$ for each ω, this argument is true for every p_i and n_i. Note that the difference $P(\theta^j > \omega_i | \theta_i = \omega_i) - P(\theta^j > \omega_i)$ is larger for large values of ω_i. Hence, it is not necessarily true that $E[n_i] > E[n_{i-1}]$ nor $d_i > d_{i-1}$.

The number of hops until a packet reaches a node that has a complete temporal strength k is

$$\nu = \sum_{i=1}^{K} n_i \tag{9}$$

where K is the number of times the packet is biased until it is received by such a node. Because the number of temporal strength values are constant $(k - \gamma)$ as both k and γ are constants, $K = O(1)$. As a result, $E[\nu] = O(\sqrt{N})$. Similarly, the probability that the packet is received by a node with a mapping that has complete temporal strength k is

$$P_t = \prod_{i=1}^{K} p_i. \tag{10}$$

Similar to p_2, we can approximate the lower bound on each p_i as $1 - e^{-c_i b_i}$. In the protocol, we do not control each b_i. Instead, we use a T_D (See Table I) value that increases as $O(\sqrt{N})$, $T_D = b\sqrt{N}$ as explained in Section IV-B. Using a large b, as in our simulations, ensures that the packet is received by a node that has a complete temporal strength about the destination.

Once the packet is biased by a mapping with the complete temporal strength, the region in which the destination is located is known with certainty and the protocol makes decisions using the spatial strength values of the mappings. The radius of the GeoRegion part of the first mapping that biases the packet with complete temporal strength, denoted by R_1, is $O(\sqrt{N})$. The distance between the destination and the biasing node is also in the order of $\sqrt{N}$ hops. Once the packet is received by a node that has a mapping with full temporal strength and a GeoRegion with radius $O(1)$, the packet can be delivered.

In comparison to the entire network size, the number of nodes at which a packet can be biased via spatial strength is small; yet, the concentration of such nodes is high in the given GeoRegion. This is because the nodes in this region are likely the destination's recent neighbors and the announcements that are sent after the one that created first mapping with complete strength are more likely to be received by these nodes since the announcements are sent radially.

Let us first not consider the state aggregation. Recall that we broaden the GeoRegion portion of the mappings by periodically increasing the radius by a constant. Hence, the number of announcements emitted by the destination since the mapping with radius R_1 hops is created is in the order of R_1. If R_1 is large, the packet intersects the line on which one of these announcement is sent (i.e. the packet is received by a node that received that announcement) or received by a recent neighbor of the destination with high probability. R_1 is small, the probability that the packet encounters a current neighbor of the destination or the destination itself is high. Let this happens after L hops. The radius of the new GeoRegion is proportionally smaller than R_1 because of the radius of the GeoRegion is bounded.

$$R = O\left(\frac{1}{L} R_1\right) \tag{11}$$

Because $R_1 = O(\sqrt{N})$, after $L = O(\sqrt{N})$ hops, the packet reaches a node that maintains a mapping with complete temporal strength and a GeoRegion of size $O(1)$, that we assume leads to final packet delivery. As a result, the total average path length is $O\sqrt{N}$.

Recall that with state aggregation, even though the radius of the GeoRegion increases, the deflection in the direction on which a packet is forwarded is limited. This is because WSR does not aggregate two mappings that are angularly far from each other(See Fig. 5). Hence, even though the GeoRegion of a mapping that gives fresh information about a destination is large, forwarding the packet along the direction towards the center of the aggregated mapping gives effectively the same result as the forwarding the packet towards the individual mapping.

VI. Conclusion and Future Work

We present Weak State Routing (WSR) protocol, an unstructured forwarding paradigm based on the partial knowledge about the node locations. The nodes periodically announce their locations on random directions. The nodes use these announcements to create aggregated SetofIDs-to-GeoRegion mappings. A routing state consists of a weak Bloom filter (WBF) which contains a set of nodes and a geographical region where the nodes are believed to be located. WBF also yields the confidence that a node is an element of SetofIDs. When a node has a data packet, the packet is sent in a random direction with the belief that an intermediate node will give the packet a superior hint about the location of the destination node. The packet trajectory is then biased toward the center of the region indicated by this state value.

In all our simulations, WSR provides a high data packet delivery ratio greater than 98%. The total control traffic overhead scales as $O(N)$, where N is the number of nodes. The state complexity of the protocol is $\Theta(N^{3/2})$. The average path length is $O(\sqrt{N})$ and asymptotically efficient in that routes are at most a constant factor longer than the shortest path. We show that the performance of our scheme is not affected by the increasing mobility with speed values up to 20 m/s. Our simulation results show that WSR significantly outperforms OLSR and GLS with GPSR in large scale networks achieving high reachability, low overhead and delay but needing a larger number of hops to reach the destination.

While we have considered WSR in the context of large, mobile and connected ad-hoc networks in this paper, we believe the weak state concept can be also adopted in networks that experience node disconnectedness, i.e. Delay Tolerant Networks (DTNs), though this would require different methods for state dissemination and packet forwarding. Our future plans include the investigation of such methods.

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