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# Hierarchical Decentralized Averaging for Wireless Packet Network

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***Abstract***: *Describing and analyzing a hierarchical algorithm, for solving the distributed average consensus problem in wireless sensor networks and overhead of message. The algorithm deals the problem by recursively partitioning a given network into sub networks. Initially, nodes at the finest scale gossip to compute local averages. Using multi-hop communication and geographic routing to gossip between nodes that are not directly connected, local averages are used to compute global average. To attain hierarchical scheme with k levels this is competitive with state-of-the-art randomized gossip algorithms in terms of accuracy, message complexity, node memory. In networks this results in less congestion and resource usage by reducing message retransmissions. Simulations of the proposed scheme compared with theory and existing algorithms based on averaging along paths. Characterizing scaling laws or the rate at which the communication cost increases as a function of network size and to achieve two goals the longest distance a message travels should be much shorter than previous methods and also Distributing the computation evenly across network.*

***Keywords***: *distributed signal processing, hierarchical processing, Wireless sensor Networks, Consensus algorithms.*

## I. Introduction

Distributed signal and information processing applications arise in a variety of contexts including Wireless sensor networks, smart-grid, mobile social networks and large-scale unmanned surveillance. Applications demand protocols and algorithms that are robust, fault-tolerant, and scalable. Energy-efficiency is an important factor [1]. When a system is using battery powered nodes or agents equipped with wireless radios for transmission. Such as in wireless sensor networks energy-efficiency require few message transmissions since consumes bandwidth, each wireless transmission consumes battery resources [2]

Always there is a tradeoff between algorithmic simplicity and performance [3,4]. If we only allow pair wise communication between neighboring nodes, we cannot beat barriers. If we have the additional knowledge of geographical information for each node and its neighbors, we can make use of geographic routing [5] and with the added complexity of averaging [6] over paths we can bring the message complexity down to linear at the expense of messages having to travel potentially over hops [7]. However to improve upon the performance achievable using pair wise communication between neighboring nodes, additional complexity is introduced. In this, rather than averaging along paths, convergence is achieved faster when we decompose computation in a multiscale manner.

The multiscale approach considered assumes that the nodes know their own and their neighbor's coordinates in the unit. Using geographic information, we derive a hierarchical algorithm that asymptotically achieves a communication cost of messages, however, in multiscale gossip, information is only exchanged between pairs, and there is no averaging along paths. At the expense of extra complexity for building the logical hierarchy, we achieve two important goals [8]. First, the longest distance a message travels in multiscale approach should be much shorter compared to geographic gossip or path averaging. Second, multiscale gossip must distribute the computation quite evenly across the network and does not overwhelm and deplete the nodes located closer to the center of the unit square as is the case for path averaging. Finally including a thorough set of experiments to evaluate the performance of multiscale gossip Primary measure of performance is communication cost the number of messages required to compute an estimate of accuracy. We are interested in characterizing the rate, or scaling laws at which the communication cost increases as a function of network size[9,10]. In the analysis of scaling laws for gossip algorithms [11,12], a common study measure of convergence rate is the averaging time.

*Challlenges:* Self-Configuration and Adaptation, Energy Efficiency, Responsiveness, Robustness, Scalability, Heterogeneity, Systematic Design, Privacy and security.

*Disadvantages of existing methods:*

*i.* If message lost, large number of nodes affected
ii. If messages sent over many hops , size increases because accumulates information of intermediate nodes
iii. Message size depends on
– length of path and

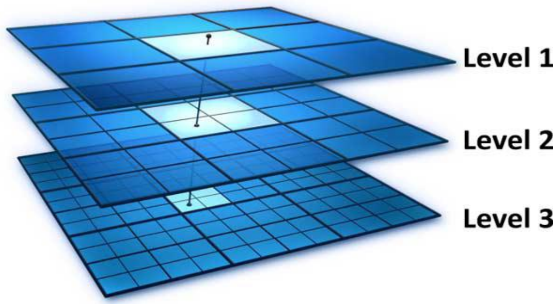
– network size

## II. HELPFUL HINTS

Multiscale gossip performs averaging in a hierarchical manner. At each moment only nodes in the same level of hierarchy do computations at a local scale and computation at one level begins after the previous level has finished. Decomposing the initial graph into sub graphs in hierarchically, we obtain order in the computation. for a specific decomposition it is possible to divide the overall work into a small number of linear sub-problems and thus obtain very close to linear complexity in the size of the network.

Assume we have a random geometric graph G = (V,E) and each node knows its own coordinates in the unit square and the locations of its neighbours. Each node knows the total number of nodes n in the network and k levels desired of hierarchy levels. Figure 1 illustrates an example with k = 3. We use the convention that level k is the lowest level where the unit square is split into small cells. Level 1 is at top level where we have big cells. All cells at the same level have the same area. We split each cell into subcells is directed by a subdivision constant a = 2/3. If a cell contains n nodes, it is split into $n^{1-a}$ cells.

**Fig.1: Hierarchical multiscale subdivision of the unit square**




Algorithm describes multi-scale gossip in a recursive manner. The initial call to the algorithm has as arguments, the vector of initial node values (xinit), the unit square (C = [0; 1] x [0; 1]), the network size n, the top level q = 1, the desired number of hierarchy levels k and the desired error tolerance € to be used by each invocation of randomized gossip. In down-pass unit square is split into smaller and smaller cells all the way to the C(k;) cells. After gossiping in the G(k;_) subgraphs in Line 15, the representatives adjust their values (Line 16). if k is large enough, each G(k;_) is a complete graph. Each node knows the locations of neighbours (needed for geographic routing), at level k we can compute the size of each G(k;_) graph which is needed for the reweighting. The up-pass begins with the L(k;_) representatives forming the G(k-1;_) grid graphs (Line 8) and then running gossip in all of them in parallel. Between consecutive levels we use a = 2/3 to decide how many C(r+1;_) cells fit in each C(r;_) cell. Notice the pseudocode mimics a sequential single processor execution. However, it should be emphasized that the algorithm is intended for and can be implemented in a distributed fashion. The notation $x_{init}(C)$ or $x_{init}(L)$ indicates that we only select the entries of $x_{init}$ corresponding to nodes in cell C or representatives L.

*Algorithm*: MultiscaleGossip ($x_{init}$, C, n, q, k, €)
*1: a = 2/3*
*2: if q < k then*
*3: Split C into* $m_{q+1} = n^{1-a}$ *cells:* $C_{(q+1,1)}, \ldots, C_{(q+1,mq+1)}$
*4: Select a representative node* $L_{(q+1,i)}$ *for each cell* $C_{(q+1,i)}$, $i$ €$\{1, \ldots, m_{q+1}\}$
*5: for all cells* $C_{(q+1,i)}$ *do*
*6: call MultiscaleGossip(xinit(*$C_{(q+1,i)}$*),*$C_{(q+1,i)}$*,*$n^a$*; q + 1; tol)*
*7: end for*
*8: Form grid graph* $G_{(q,.)}$ *of representatives* $L_{(q+1,i)}$
*9: call Randomized Gossip(*$x_{init}(L_{(q+1;1:mq+1)})$*;*$G_{(q,.)}$*,€)*
*10: if q = 1 then*
*11: Spread value of* $L_{(2,i)}$ *to all nodes in each* $C_{(2,i)}$
*12: end if*
*13: else*
*14: Form graph G(k;.) only of nodes in V (G) contained in C*
*15: call Randomized Gossip(* $x_{init,}G(k,.)$*, € )*
*16: Reweight representative values as :*
$x(L_{(k,i)}) = x(L_{(k,i)}) \mid V(Gk) \mid m_{k-1} / \mid V(G) \mid$
*17: end if*

Multiscale gossip has several advantages over Path Averaging. All the information relies on pair wise messages. In contrast, averaging over paths of length more than two has two main disadvantages First, if a message is lost, a large number of nodes are affected by the information loss. Second, when messages are sent to a remote location over many hops, they increase in size as the message body accumulates the information of all the intermediate nodes. The message size now depends on the length of the path and ultimately on the network size. Our messages are always of constant size and independent of the hop distance or network size. The ideal scenario for multiscale gossip is if computation inside each cell stops automatically when the desired accuracy is reached. This way no messages are wasted .However in practice for cells at the same level may need to gossip on graphs of different sizes that take different numbers of messages to converge. This needs for a node synchronization so that all computation in one level is finished before the next level can begin. To alleviate the synchronization issue, we can fix the number of randomized gossip iterations per level so that all computation between different sub graphs at the same level takes practically the same amount of time.

## III. RESULTS

In addition to theoretical results, compare multiscale gossip with path averaging via simulation in MATLAB. The experiments, presented, suggest that multiscale gossip has superior performance for graphs of up to many thousands or nodes. Also include an evaluation in scenarios with unreliable transmissions.

**Fig. 2 shows the nodes co-ordinates initialization for considered no. of nodes in network (Initialized node)**

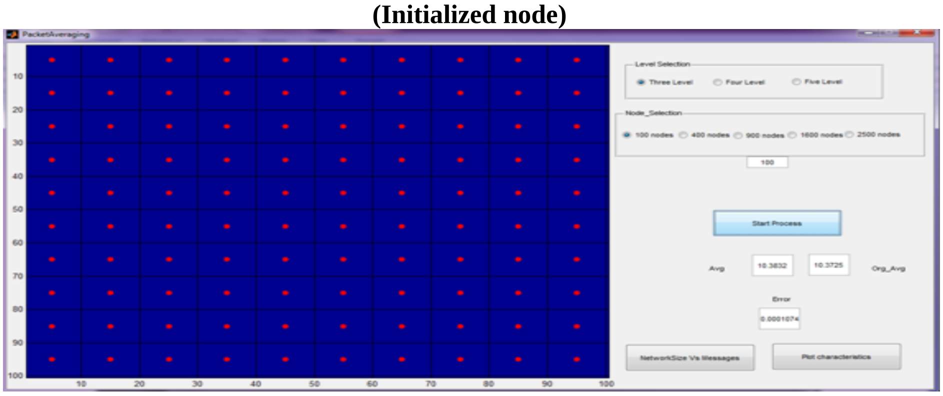


**Fig. 3 indicates splitting the area considered into smaller cell (Initial cell splitting)**

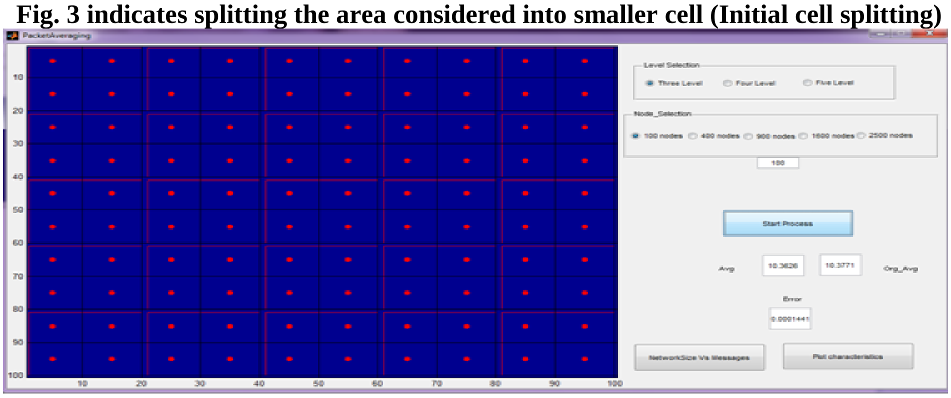


**Fig. 4 indicates gossiping of nodes among the splitted cells (Initialized nodes gossip at level 3)**

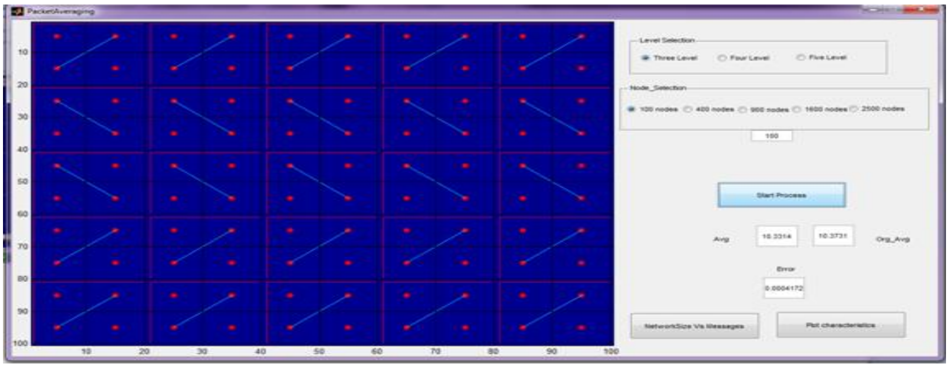


**Fig. 5 indicates the gossiping among the representative nodes of level 3 (Initialized nodes gossip at level 2)**

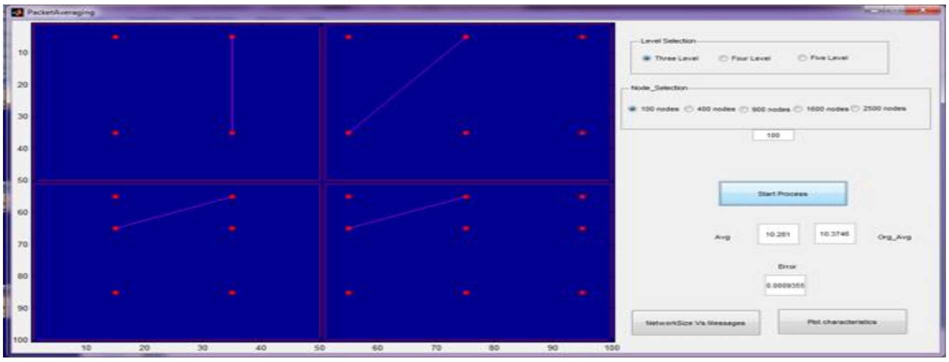


**Fig. 6 indicates the gossiping among the representative nodes of level 2 (Initialized nodes gossip at level 1)**

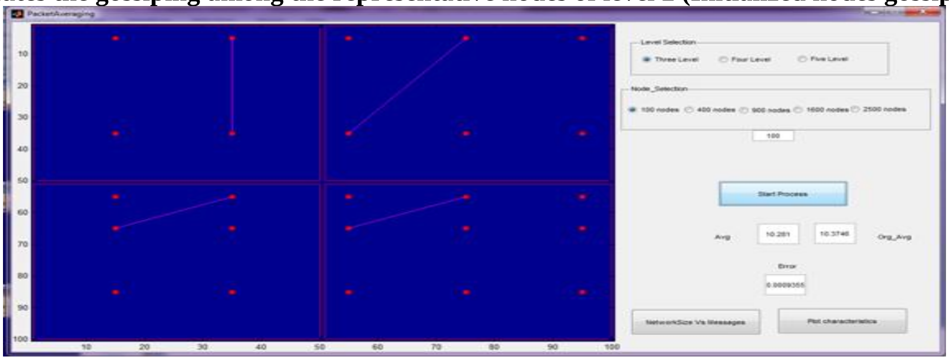


**Fig. 7 shows the comparison graph for simulated hierarchy levels 3, 4& 5, for number of message transmission reduced with varying network size**

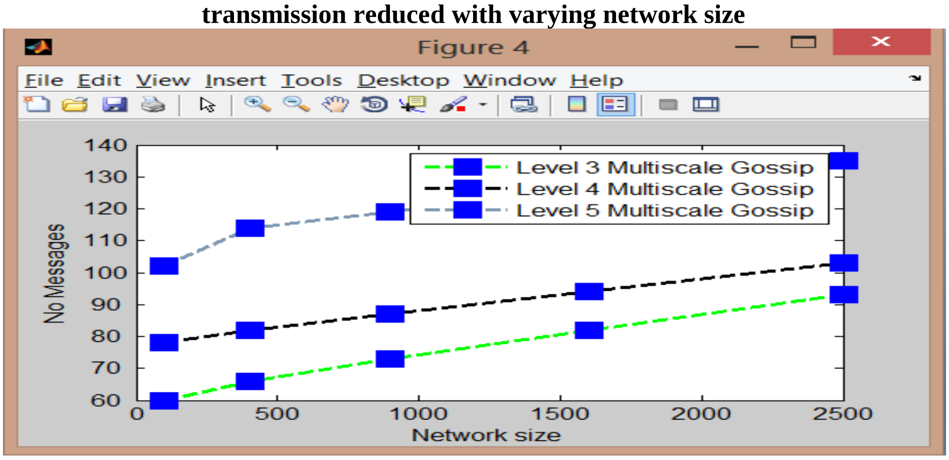



**Fig. 8 indicates the number of message transmission reduced with the varying hierarchy levels 3, 4&5**

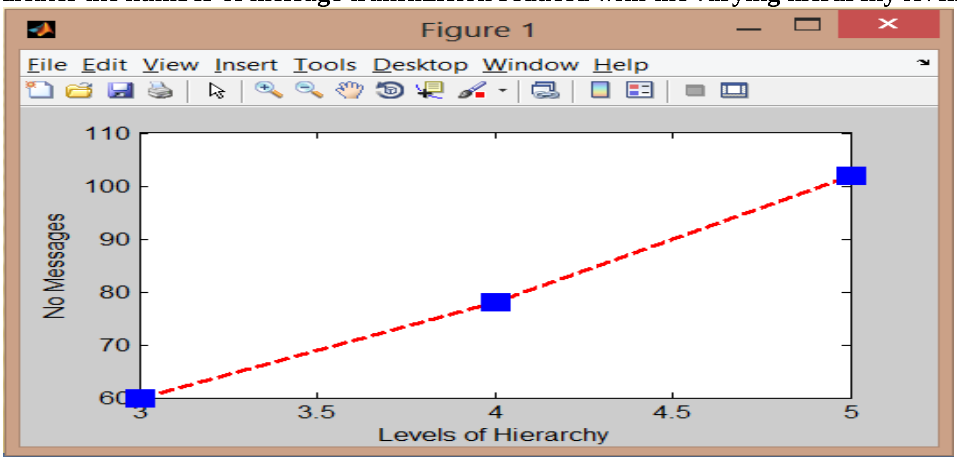



**Fig. 9 indicates the simulated graph for the packet averaging for no. of message transmission reduced with network size.**

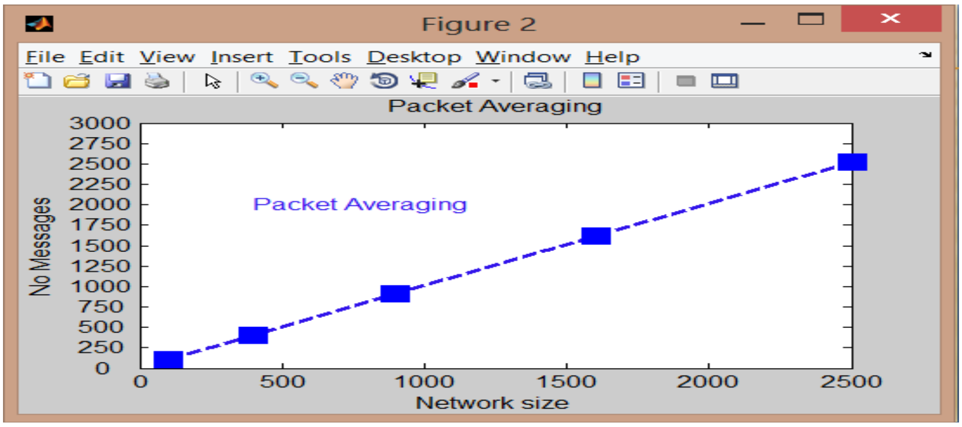



Fig 9 is compared with the fig. 7 and concluded that hierarchical algorithm Simulation results are better.

*PERFORMANCE METRICS:* Message complexity, Accuracy, Congestion, Resource usage, Energy efficiency, robustness, scalability, self-configuration etc. In this paper the result is discussed for the 3, 4, and 5 gossiping level and compared with each other as shown in the above graphs.

## IV. CONCLUSION

Compare multiscale gossip against path averaging which is in theory the fastest algorithm for gossiping on random geometric graphs. It is worth emphasizing that both algorithms operate under the same two assumptions. First, each nodes know the coordinates of itself and its neighborhood the unit square. Second, each node know the size of the network n. In path averaging this is implicit since each message needs to be routed back to the source through the same path. It is thus necessary that nodes have global unique Ids which are equivalent to knowing the maximum id and thus the size of the network. In multiscale gossip, network size is used for each node to determine its role in the logical hierarchy and also decide the number of hierarchy levels. Advantages are like Message size constant and independent of network size. Nodes update their estimate at each iteration. Less congestion and resource usage, Energy efficient and robustness. In this paper the individual and compared results, graphs is described and analyzed for the gossiping level 3, 4, and 5.

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