IEEE Globecom 2010
Global COmmunications Conference, Miami, FL, Dec. 2010.

Dimension Reduction of Virtual Coordinate Systems in Wireless Sensor Networks*

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Abstract **– Virtual Coordinate System (VCS) based routing schemes for sensor networks characterize each node by a coordinate vector of size *M*, consisting of distances to each of a set of *M* anchors. Higher the number of anchors, the higher the coordinate generation cost as well as the communication cost. Identifying an effective set of anchors and encapsulating original VCS's information in a lower dimensional VCS will enhance the energy efficiency. Two main contributions toward this goal are presented. First is a method for evaluating the amount of novel information contained in an ordinate, i.e., in an anchor, on the coordinate space created by the rest of the anchors. This method can be used to identify unnecessary or inefficient anchors as well as good anchor locations, and thus help lower overhead and power consumption in routing. Second, a method for reducing the VCS dimensionality is presented. This Singular Value Decomposition (SVD) based method preserves the routability achieved in original coordinate space but with lower dimensions. Centralized and online realizations of the proposed algorithm are explained. Examples of different topologies with 40 anchors used in performance analysis show that coordinate length can be reduced on average by a factor of 8 without degrading the routability. Use of novelty filtering to select effective anchors prior to SVD based compression results in further improvement in routability.**

Keywords: Novelty Filter, Routing, Singular Value Decomposition, Wireless Sensor Networks, Virtual Coordinates

I. INTRODUCTION

Routing protocols for Wireless Sensor Networks (WSNs) can be broadly classified into physical coordinate based and virtual coordinate based schemes. Physical domain routing relies on the physical (geographic) position information for routing, e.g., as in Geometrical routing [1]. Virtual domain (or logical) routing is based on a set of virtual coordinates that capture the position and route information, e.g., hierarchical/clustering schemes [1], and Virtual Coordinate (VC) based routing [2],[3],[5],[6],[8-11]. The focus of this work is to reduce dimensionality of Virtual Coordinate Systems (VCSs), and thus enhance the energy efficiency without degrading the routability.

Virtual Coordinate based Routing (VCR) relies on a set of anchor nodes. The VCs of a node consists of the hop distance from the node to each of a set of *M* anchors. The cardinality of the coordinate is the number of anchors. The major advantage of VCR over physical domain routing is due to the fact that connectivity information is embedded in the VCs. Therefore, physical voids that degrade physical domain routing no longer exist in the virtual domain. Moreover high routability can be achieved without requiring physical localization or GPS.

Most of the VCR schemes [2],[3],[8-11] use Greedy Forwarding (GF) combined with a back-tracking algorithm. In GF, a packet is simply forwarded to a neighbor that is closer to the destination than the node holding the packet. VCs of nodes are used for distance evaluation between nodes as well as for node identification (ID).When a closer neighbor cannot be found, i.e., the packet is at a local minima, back-tracking is employed to climb out of it. Existing anchor placement strategies [2],[3],[6],[11] cannot guarantee unique IDs or 100% Greedy Ratio (GR). GR is defined as the percentage of routing requests that can be completed using GF alone.

Use of logical coordinates for routing has its own drawbacks. If the number of anchors is not sufficient, or if they are not properly placed, the network will suffer from identical coordinates and local minima problems [5]. As [4] and [5] explain, the anchors may cause local maxima in the distance function at their locations, and hence minima at other node locations. To avoid local minima problem in routing, most anchor placement techniques seek to select furthest apart nodes as anchors in an attempt to push those to the network boundaries. Reference [11], for example, proposes to have all the perimeter nodes as anchors. However, identification of boundary nodes is not trivial, and it also consumes a lot of energy. Beacon vector routing [6] uses a random set of nodes as anchors while GPS free coordinate assignment algorithm [2] uses the farthest apart triplet of anchors for routing. Latter results in having a large number of identical coordinates due to under deployment of anchors. Identification of farthest apart anchors also involves flooding the network several times. The anchor placement scheme in Logical Coordinate Routing [3] also follows the argument that anchors should be placed the farthest apart. Also, the number of anchors required is network topology dependent.

Finding the optimal number of anchors and the proper placement of anchors are difficult problems to solve, especially given the fact that they are interrelated. Evaluation of distance between nodes from their VCs is another challenge. L^1 and L^2 norms, typically used for distance evaluation, are accurate on orthogonal coordinate systems such as Euclidean space but not on radial VC systems. Furthermore, some of the anchors may carry redundant information for a given node pair, and others may provide

*This research is supported in part by NSF Grant CNS-0720889

incomplete information resulting in inaccurate distance values and degraded routability.

Higher number of anchors lessens the problem due to identical coordinates, yet it increases the overall energy consumption due to increased address (node ID) and packet lengths. None of the existing literature to our knowledge presents a method to reduce the dimensionality of the virtual coordinate space, to preserve the performance of the original coordinate system while decreasing the energy consumption.

Our contributions in this paper are two-fold. First, is a method to evaluate the amount of novel information provided by a new anchor. As unnecessary anchors and poor anchor placement degrade the routability [5], this novelty parameter is useful in many ways, e.g., to determine good anchor positions and to remove redundant anchors. The second contribution is a coordinate length reduction method based on Singular Value Decomposition (SVD) [6], which replaces the original VC of each node, i.e., the M-tuple with distances to each of the M anchors, with a reduced vector (an R-tuple, with $R << M$) that contains almost all the information contained in the original coordinate set. Because of the information conservation property of SVD, we are able to achieve a similar routability with this new lower dimensional coordinates. The two steps are evaluated individually to assess their impact, and then we present results to demonstrate the net effect of the two steps combined. Using a reduced set of coordinates with minimal redundancy brings with it several benefits, including shorter message headers and less local minima, resulting in better routability and power efficiency. We also present centralized and distributed realizations of the algorithms in Section VI. The centralized implementation of the two schemes, application of novelty to eliminate redundant anchors and reducing dimensionality of the VCs, require global information while the proposed distributed, online implementation requires coordinates of the anchors only.

Section II proposes a method to evaluate novelty of an ordinate in the subspace of remaining VCs. Section III and IV discuss SVD-based method of reducing VS dimensions and dimension selection criterion respectively, while Section V explains the derivation of algorithms based on anchors' VCs. Section VI explains the centralized and distributed realizations of the algorithm and their complexities. Performance evaluation is in Section VII, with conclusions in Section VIII.

II. NOVELTY OF A NEW ANCHOR

Let the number of anchors in the network be M. Consider the selection of a node, randomly or by some scheme, to be the $(M+1)^{th}$ anchor. We are interested in finding out what is novel in $(M+1)^{th}$ dimension defined by anchor $(M+1)$. Denote the subspace formed by the initial M anchors be S_M. If we project $(M+1)^{th}$ ordinate on to S_M, it gives us the component of $(M+1)^{th}$ ordinate that resides in S_M. The other component which is perpendicular to the S_M is the novel information in the $(M+1)^{th}$ dimension. That projection is called complimentary projection or residual. We use the Novelty Filter Decomposition method to evaluate it [7].

Let the coordinate matrix of the network of N nodes, with respect to M anchors be $\underline{\boldsymbol{X}}$. Each row of the $N \times M$ matrix $\underline{\boldsymbol{X}}$ represents a coordinates of a node and each column of $\underline{\boldsymbol{X}}$ is an ordinate with respect to an anchor. The orthonormal projection matrix [8] for the subspace S_M is given by

$$\underline{\boldsymbol{P}}_{\boldsymbol{M}} = \underline{\boldsymbol{X}}\,(\underline{\boldsymbol{X}}^{\boldsymbol{T}}\underline{\boldsymbol{X}})^{-1}\underline{\boldsymbol{X}}^{\boldsymbol{T}} \tag{1}$$

By definition $\underline{\boldsymbol{P}}_{\boldsymbol{M}}$ is an orthonormal matrix and $\underline{\boldsymbol{P}}_{\boldsymbol{M}} = \underline{\boldsymbol{P}}_{\boldsymbol{M}}{}^{\boldsymbol{2}}$ [6]. Let $\underline{\boldsymbol{Y}} \in \boldsymbol{\mathcal{R}}^{\boldsymbol{N}}$, a column vector, be the ordinate of the set of nodes with respect to $(M+1)^{th}$ anchor. Projection of $\underline{\boldsymbol{Y}}$ on to the subspace formed by prior M anchors is given by

$$\underline{\boldsymbol{Y}}_{\boldsymbol{P}_{\boldsymbol{M}}} = \underline{\boldsymbol{P}}_{\boldsymbol{M}}\underline{\boldsymbol{Y}} \tag{2}$$

Norm of $\underline{\boldsymbol{Y}}_{\boldsymbol{P}_{\boldsymbol{M}}} \in \boldsymbol{\mathcal{R}}^{\boldsymbol{N}}, \|\underline{\boldsymbol{Y}}_{\boldsymbol{P}_{\boldsymbol{M}}}\|$ is the amount of information of $\underline{\boldsymbol{Y}}$, that resides in the S_M. Furthermore, complementary orthogonal projection matrix is defined as [7],

$$\underline{\boldsymbol{Q}}_{\boldsymbol{M}} = (\underline{\boldsymbol{I}} - \underline{\boldsymbol{P}}_{\boldsymbol{M}})$$

Again by definition, Q_M is an orthonormal matrix and $\underline{\boldsymbol{Q}}_{\boldsymbol{M}} = \underline{\boldsymbol{Q}}_{\boldsymbol{M}}{}^{\boldsymbol{2}}$.

$$\underline{\boldsymbol{Y}}_{\boldsymbol{Q}_{\boldsymbol{M}}} = \underline{\boldsymbol{Q}}_{\boldsymbol{M}}\underline{\boldsymbol{Y}} \tag{3}$$

Equation (3) gives the residual of $\underline{\boldsymbol{Y}}$ which sits outside the S_M. Therefore, norm of $\underline{\boldsymbol{Y}}_{\boldsymbol{Q}_{\boldsymbol{M}}} \in \boldsymbol{\mathcal{R}}^{\boldsymbol{N}}, \|\underline{\boldsymbol{Y}}_{\boldsymbol{Q}_{\boldsymbol{M}}}\|$ gives us the novelty of the $(M+1)^{th}$ anchor. $\|\underline{\boldsymbol{Y}}_{\boldsymbol{Q}_{\boldsymbol{M}}}\|$ is,

$$\|\underline{\boldsymbol{Y}}_{\boldsymbol{Q}_{\boldsymbol{M}}}\| = \sqrt{\textstyle\sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{N}} \boldsymbol{y}_{\boldsymbol{i}}{}^{\boldsymbol{2}}} \tag{4}$$

Even though our description considered the introduction of a new anchor, it can be used in VCS to:

1. Identify a good subset of anchors that preserves or improves routability(Section VI - *C*),
2. Determine a terminating criterion for introducing anchors to a given network, and
3. Identify good anchor locations.

III. REDUCING DIMENSIONALITY OF VCS

Determining the optimal number of anchors and their placement for a given network is a critical problem for VCR. Different selections of M anchors typically result in different routabilities. Therefore, even if the coordinate generation is done in a central station, trying out different sets of anchors to identify the one with best routability is an exhaustive procedure. Hence, having a method to reduce the dimension in such a way that the routability is unaffected due to this reduction is pragmatic in energy limited WSN applications. If this is done at a central location, one can start with a large set of anchors and reduce dimensionality to meet the required criteria.

We begin with the Singular Value Decomposition of $\underline{\boldsymbol{X}}$ which is a $N \times M$ coordinate matrix with $N >> M$.

$$\underline{\boldsymbol{X}} = \underline{\boldsymbol{U}}.\underline{\boldsymbol{S}}.\underline{\boldsymbol{V}}^{\boldsymbol{T}} \tag{5}$$

where, $\underline{\boldsymbol{U}}, \underline{\boldsymbol{S}}$ and $\underline{\boldsymbol{V}}$ are $N \times N, N \times M$, and $M \times M$ matrices respectively. $\underline{\boldsymbol{U}}$ and $\underline{\boldsymbol{V}}$ are unitary matrices, i.e.,

$$\underline{\boldsymbol{U}}^{\boldsymbol{T}}\underline{\boldsymbol{U}} = \boldsymbol{I}_{N\times N} \text{ and } \underline{\boldsymbol{V}}^{\boldsymbol{T}}\underline{\boldsymbol{V}} = \boldsymbol{I}_{M\times M}$$

$\underline{\boldsymbol{V}}^{\boldsymbol{T}}$ is a basis of our data set $\underline{\boldsymbol{X}}$**.** Then, $\underline{\boldsymbol{U}}.\underline{\boldsymbol{S}}$ gives the coordinates of the data $\underline{\boldsymbol{X}}$ under the new basis $\underline{\boldsymbol{V}}$.

$$\underline{\widetilde{X}}_{SVD} = \underline{U}.\underline{S} \quad (6)$$

$\underline{\widetilde{X}}_{SVD}$ is the projection of $\underline{X}$ on to $\underline{V}$, i.e., $\underline{X}.\underline{V}$. Note that the dimensions of $\underline{U}.\underline{S}$ is $N \times M$. Therefore each node still has an *M*-length coordinate vector.

In order to reduce the dimensions, we use the fact that $\underline{S}$ is a diagonal matrix where diagonal elements are non-negative singular values arranged in descending order. Coordinates from SVD in (6), can be rewritten as

$$\underline{\widetilde{X}}_{SVD}{}^{(i)} = \underline{S}(i,i).\underline{U}^{(i)} \; ; i = 1, \dots, M \quad (7)$$

where $\underline{\widetilde{X}}_{SVD}{}^{(i)}$ and $\underline{U}^{(i)}$ are the i^{th} column of $\underline{\widetilde{X}}_{SVD}$ and $\underline{U}$ respectively. Basically $\underline{U}.\underline{S}$ is each column of $\underline{U}$ weighted by the corresponding diagonal element of $\underline{S}$, i.e. $\underline{S}(i,i)$, the singular values as in (7).Therefore singular elements decide which ordinate has a significant contribution. We reduce the dimensionality by ignoring the less significant singular values of $\underline{S}$

$$\underline{\widetilde{X}}_{SVD,R} = \underline{Z}_{N\times R} = \underline{U}_{N\times R}.\underline{S}_{R\times R} \quad (8)$$

$$\underline{Z}^{(i)} = \underline{S}(i,i).\underline{U}^{(i)} \; ; i = 1, \dots, R \text{ where } R \le M \quad (9)$$

where $\underline{Z}^{(i)}$ and $\underline{U}^{(i)}$ are the i^{th} column of $\underline{Z}$ and $\underline{U}$ respectively. $\underline{\widetilde{X}}_{SVD,R}$ is the new set of coordinates of the nodes and coordinate length is $R < M$.

SVD compresses the original data set in an optimal way, so it cannot improve over original values. This leads us to a new problem. What should be the new dimension *R* so that routability is not degraded? We address this issue in the next section.

IV. Dimension Size Selecting Criteria

Before evaluating the error due to reduction of the dimension from *M* to *R,* let's zero-pad $\underline{Z}_{N\times R}$ so that it is of the same size as $\underline{\widetilde{X}}_{SVD}$. Let us call zero-padded $\underline{Z}$, $\underline{Z}_P$. Then the distance between $\underline{\widetilde{X}}_{SVD}$ and $\underline{Z}_P$ will be same as the distance between $\underline{\widetilde{X}}_{SVD}$ and $\underline{Z}$, which is evaluated using Frobenius norm [12] as:

$$\left\|\underline{\widetilde{X}}_{SVD} - \underline{Z}_P\right\|_F^2 = \sum_{\forall i,j} (\underline{\widetilde{X}}_{SVD}(i,j) - \underline{Z}_P(i,j))^2$$

$$= \left\|\underline{U}.\underline{S} - (\underline{U}_{N\times R}.\underline{S}_{R\times R})_P\right\|_F^2 = \left\|\underline{U}.\underline{S} - (\underline{U}.\underline{S}_P)\right\|_F^2$$

where, $\underline{S}_P$ is zero-padded $\underline{S}.\underline{U}$ is an orthonormal matrix. Orthonormal matrices induce rotations. Since Frobenius norm [12] is invariant for rotations;

$$\left\|\underline{\widetilde{X}}_{SVD} - \underline{Z}_P\right\|_F^2 = \left\| \begin{bmatrix} 0 & & \cdots & & 0 \\ & \ddots & & & \\ \vdots & & 0 & & \vdots \\ & & & \sigma_{R+1} & \\ & & & & \ddots \\ 0 & & \cdots & & \sigma_M \end{bmatrix} \right\|_F^2 \quad (10)$$

The difference between the full SVD coordinates and dimension reduced coordinates are simply given by,

$$\left\|\underline{\widetilde{X}}_{SVD} - \underline{Z}_P\right\|_F = \sqrt{\sum_{i=R+1}^{M} \sigma_i{}^2} \quad (11)$$

By defining a threshold value for the information loss in the transformation, we can get a value for the dimension R of the new coordinate system.

V. Reducing Dimensionality Based on Anchors' VC

$\underline{V}$ in (5) is evaluated based on $\underline{X}$, which is a $N \times M$ matrix that consists of VCs of the entire network. With sensor networks, it is crucial to reduce communication and computation overheads involved. This section presents a process to generate the transformation matrix $\underline{V}$ with a much smaller subset of data of $\underline{X}$, $\underline{X}_A$, the $M \times M$ matrix corresponding to the coordinate set of only the *M* anchors. As *M* <<*N,* computation overhead is reduced significantly.

Let the SVD of $\underline{X}_A$ be,

$$\underline{X}_A = \underline{U}_A \cdot \underline{S}_A \cdot \underline{V}_A{}^T \quad (12)$$

$\underline{V}_A$ is a basis for $\mathcal{R}^M$. Note that $\underline{V}_A$ has the same size as $\underline{V}$ in (5). Following the same procedure as earlier

$$\underline{\acute{X}}_{SVD,(i)} = (\underline{X})_{(i)}.\underline{V}_A \quad (13)$$

$\underline{\acute{X}}_{SVD,(i)}$ is the SVD based coordinate of the i^{th} node, and $(\underline{X})_{(i)}$ is the i^{th} row of $\underline{X}$, i.e., VC of i^{th} node. Each node can evaluate its SVD coordinate locally with the knowledge of $\underline{V}_A$. In order to reduce the dimension, each node can estimate *R* following the same procedure explained in Section IV, based on $\underline{S}_A$.

$$\underline{\acute{X}}_{SVD,R(i)} = (\underline{X})_{(i)}.(\underline{V}_A)_{M\times R} \quad (14)$$

Moreover novelty analysis explained in Section II can be used to identify novelty of each anchor just using anchors' VC set $\underline{X}_A$.Let us define $(\underline{X}_A)_{(i)} (\in \mathcal{R}^M)$ as the coordinate vector of i^{th} anchor. Then projection matrix for the i^{th} anchor can be written as,

$$\underline{P}_{M,A_i} = \underline{B}\,(\underline{B}^T\underline{B})^{-1}\underline{B}^T \quad (15)$$

where, $\underline{B}$ is $\underline{X}_A \backslash (\underline{X}_A)_{(i)}$. Hence complementary orthogonal projection matrix is $\underline{Q}_{M,A_i} = (\underline{I} - \underline{P}_{M,A_i})$. Projection of $(\underline{X}_A)_{(i)}$ on to the subspace *M-1* and complementary projection of $(\underline{X}_A)_{(i)}$ can be found following the same procedure explained in Section II. Hence the novelty of each anchor on the remaining subspace can be estimated.

VI. Implementation In Sensor Networks

A. *Offline Realization*

As the following examples indicate, a centralized implementation does not diminish the value of the proposed methods for sensor networks.

Ex. 1: For manual sensor node deployment, e.g., when a sensor network is deployed in a building, the reduced VCs can be pre-computed and each node preconfigured with its VCs. VCR will simplify routing and achieve very high routability in spite of geographical voids.

Ex. 2: Consider a sensor network where the nodes are deployed randomly. Each node sends its neighbors information to a central station or a mobile base that traverses the region so that the adjacency matrix [13] of the network can be formed at the central station with the complexity of $O(N^2)$. Reduced coordinates are computed using the algorithms in Section II - IV implemented at the base station. Since adjacency matrix is available, reduced coordinates of cardinality *R* can be sent back to each node with an operation of complexity of $O(N^2)$. Alternatively, the mobile station traverses the region distributing the coordinates to the nodes. Centralized implementation avoids multiple flooding in the network involved in traditional anchor generation phase [2],[3].

B. *Online Realization*

A distributed implementation of the above may be achieved as follows. The anchor based VC generation is first carried out the traditional way, i.e., via flooding [1]. One of the anchors collects the set of anchors' coordinates and generate $\underline{V_A}$. It estimates R and sends first R columns of $\underline{V_A}$ to the rest of the nodes in the network with organized flooding mechanism, which requires $O(N)$ messages. Each node i can now generate $\underline{\boldsymbol{\acute{X}}}_{\boldsymbol{SVD,R(i)}}$ (14) locally by simply multiplying its own coordinate by $(\underline{\boldsymbol{V_A}})_{M\times R}$.

VII. Performance Analysis

The performance of the proposed methods is evaluated next for three network topologies representative of a variety of networks: Fig. 1 a) is a 496-node circular shaped network with three holes in the middle of the network, Fig. 1 b) is a uniformly distributed 30 by 30 node grid with 100 missing nodes, and Fig. 1 c) is an odd shaped network with 550 nodes. Communication range of a node in all three networks is unity. MATLAB® 2008b is used for our simulations. VCSs are generated purely based on the adjacency matrix [13]. We used random anchor placement but the same methodology is valid for any other anchor selection method. For consistency, we use pure GF for routing; hence the results can be expected to hold for other routing algorithms, e.g., an improved GF scheme with backtracking. Routing is considered successful if the packet is routed to the exact destination, identified by a unique node ID. GR is evaluated using Monte Carlo simulation. GR is evaluated considering random source destination pairs. If a packet is routed to the destination using GF, then that packet is counted as routed. Average of all those routed packets to total packets is defined as the Greedy Ratio, i.e.,

$$\text{Greedy Ratio\%} = \frac{\text{\# timespacketsreach thedestination}}{\text{Total \# packetsoriginated}} \times 100\% \qquad (16)$$

A. *Novelty Value in Anchor Placement*

Novelty of anchors was evaluated using(4) by introducing one anchor at a time. In all three networks (See Fig. 1), anchors introduced after about 15th anchor, do not contain significantly novel information. Furthermore this method can be used to select a better anchor location for $(M+1)^{th}$ anchor by defining a novelty threshold for an anchor. If the novelty of $(M+1)^{th}$ anchor is less than the threshold, we can change the position of the anchor till we find a 'good' anchor.

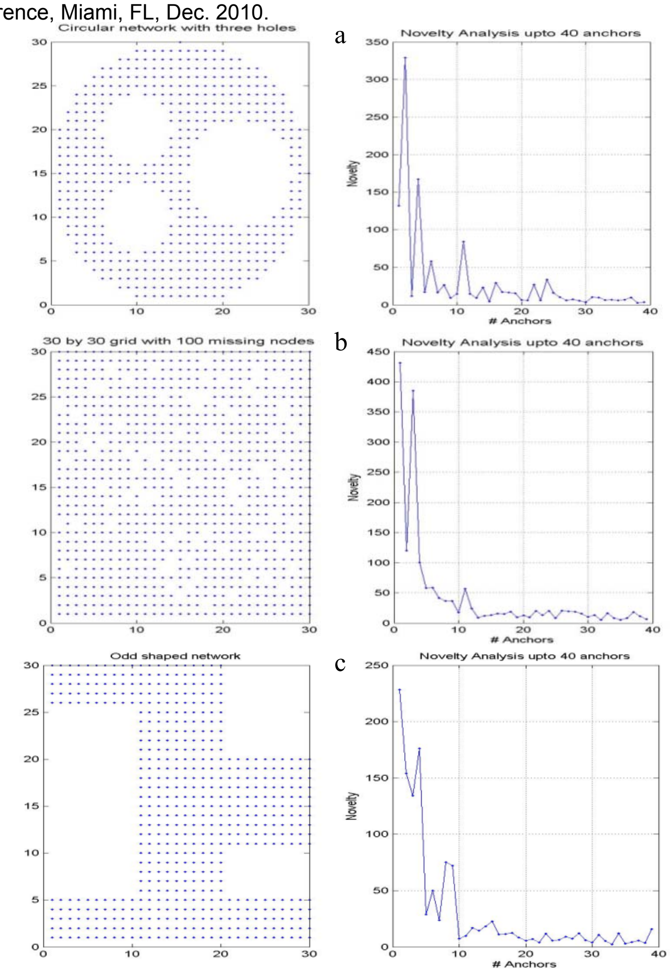

Fig. 1. Novelty measurement as # anchors increases up to 40 for a)Circular shaped network with three holes in the middle b) Grid based network with 100 random missing nodes c) Odd shaped network.

B. *Dimensionality Selection Criteria and Performance of Reduced Coordinate System*

Performance of new coordinates with reduced dimension given by SVD was evaluated and compared with the performance of original coordinate set. A good estimate for R in (8) was obtained using (11) for centralized implementation without using a Brute-force approach. Moreover, R for online implementation was obtained as explained in Section VI. GR of the new coordinate system should be the same as or within a bearable margin compared to the original coordinate system for both implementations. Hence ultimate selection criterion of R is the GR difference, where GRs were obtained by Monte Carlo simulation.

We did the simulation on the three networks in Fig. 1 a), b) and c). In Fig. 2 a), b) and c), we have plotted, as the dimensionality of the new coordinate system varies, the following:

1. Amount of information remaining after dimension reduction given by the dimension criteria in (11) using entire VC information,
2. Singular value corresponding to each dimension using entire VC information,

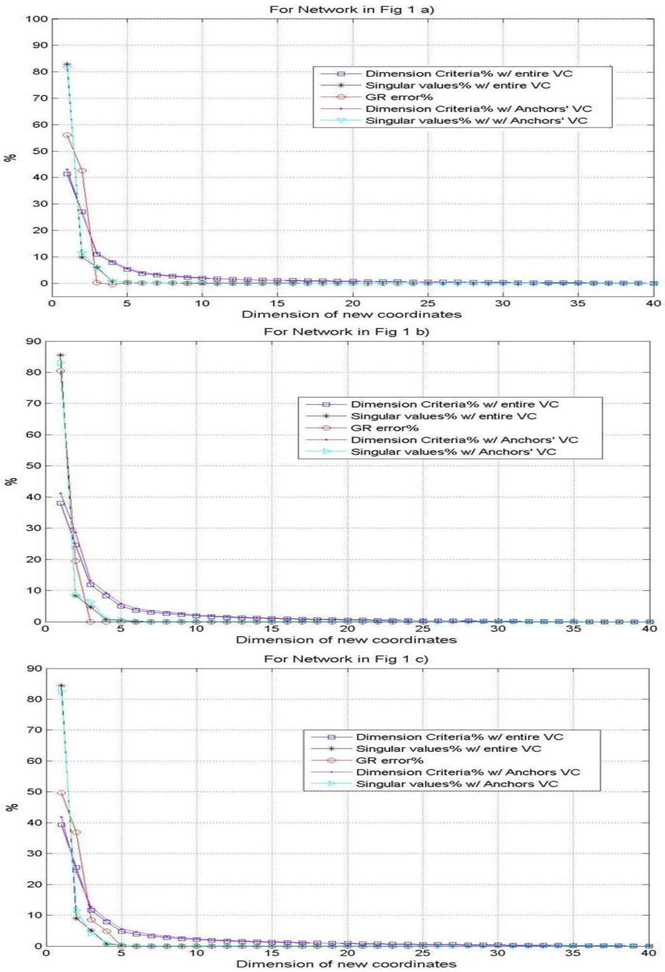

Fig. 2. Selection of R for network a) Fig. 1 a) b)Fig. 1 b) c) Fig. 1 c).

3. GR difference between original coordinate system and new coordinate system with corresponding dimension,
4. Amount of information remaining after dimension reduction given by the dimension criteria in (11) using anchors' VC information, and
5. Singular value corresponding to each dimension using anchors' VC information.

It can be clearly seen from Fig. 2 that the singular values are approximately the same as the GR difference so we can avoid having a Monte Carlo approach to get GR difference. Moreover centralized implementation and online implementation criteria curves are almost the same. For implementations, R is 10, 5 and 5, for the three networks respectively, based on Fig. 2.

As shown in Fig. 3, in all 10 configurations with different random anchor placements, GR were almost the same for the original coordinate system with 40 anchors as well as reduced coordinate system for R: 10, 5 and 5 respectively for both centralized and distributed applications.

C. *Novelty Based Anchor Selection Followed by SVD Based Compression*

Novelty values of anchors were used to select a good set of anchors out of the original anchor set and that coordinate set

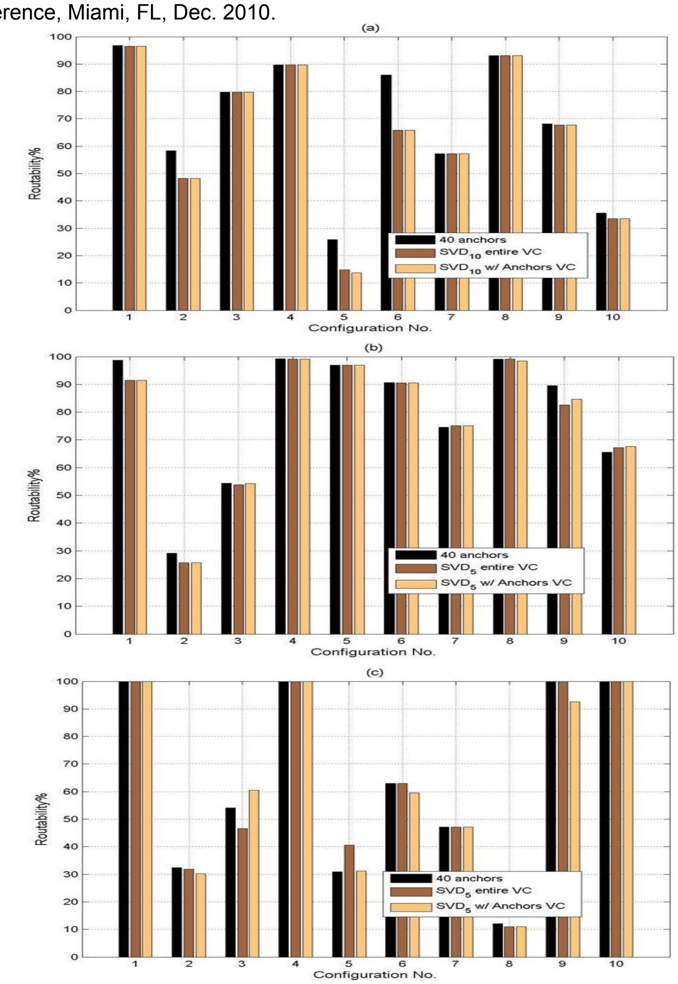

Fig.3.GF with entire anchor set (40 anchors) SVD based reduction with dim. 5 (SVD_5 w/ entire VC), anchor coordinate set based SVD reduction with dim. 5(SVD_5 w/ Anchors VC) a) Fig. 1 a) b)Fig. 1 b) c) Fig. 1 c).

from good anchors was further compressed using (8). First, 40 random anchors were placed in the networks in Fig. 1 a) b) and c). Novelty thresholds were defined based on the novelty value of i^{th} anchor on the 39-anchor subspace. In the simulation, the subset of anchors with a novelty higher than 75% of the mean novelties of anchors was selected to define the 'good' anchor set. Proposed methods for offline and online implementations resulted in the same decision values. Number of anchors selected by novelty method based on entire coordinate set and just the anchors' coordinate set, for the three topologies in 15 simulation turns with random anchor placements are tabulated in Table I. Then the coordinates based on these selected anchors was further compressed as in (8).

Average size of coordinate sets selected by novelty method for networks in Fig. 1 a) b) and c) for both the implementations discussed were 28, 26 and 28 out of 40 respectively. Using SVD compression the numbers were further reduced to R= 10, 5 and 5 respectively in online as well as in offline realizations. We have selected a general threshold for novelty just for illustrating purpose of using the novelty information to filter good anchors. Threshold should be selected appropriately by observing the novelty plot of the anchors in each network individually. Even with the mean novelty threshold, in some of the cases selecting a subset of anchors improves the routability (See Fig. 4). This can be explained by the fact that redundant anchors degrade the routability [5]. Online and offline realizations give more or less the same performance.

TABLE I
MAXIMUM, MINIMUM AND AVERAGE NOVELTY BASED COORDINATE SET SIZE WITH 40 INITIAL ANCHORS, IN 15 CONFIGURATIONS OF NETWORKS IN FIG. 1. a), b)AND c)

Network	Maximum dimension selected	Minimum dimension selected	Average dimension selected
a	32	22	28
b	35	18	26
c	36	21	28

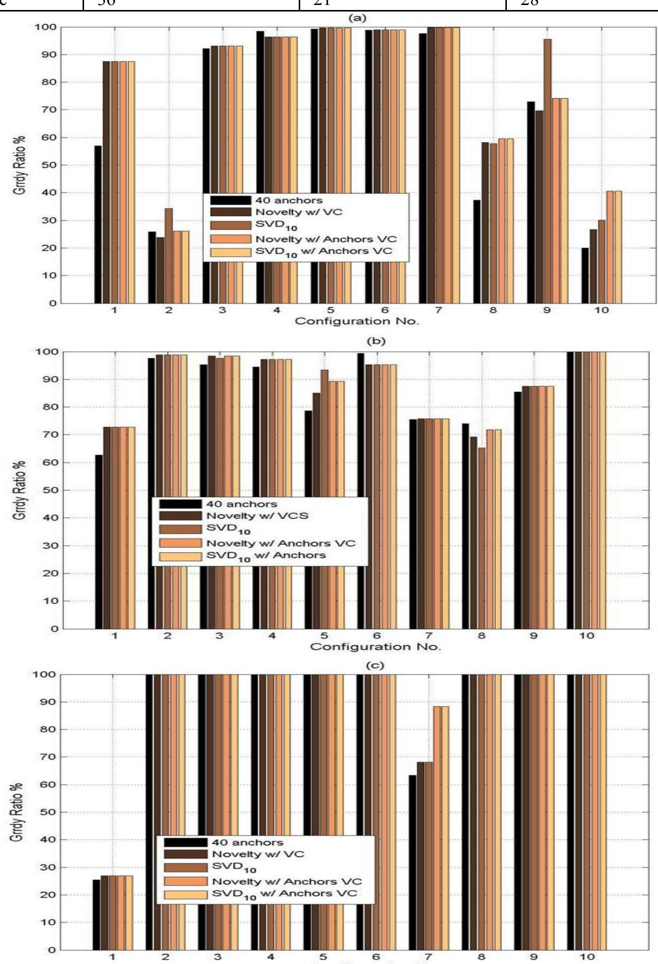

Fig. 4. GR with original coordinates (40 anchors), coordinates selected by novelty (Novelty w/ VCS), SVD-based reduction on selected coordinate set by novelty(SVD_{10}), coordinates selected by novelty based on Anchors VC (Novelty w/ Anchors VC), and SVD-based reduction on selected coordinate set by novelty based on Anchors VC(SVD_{10} Anchors VC); in network a) Fig. 1 a) b)Fig. 1 b) c) Fig. 1 c)

VIII. CONCLUSIONS

In virtual coordinate based routing in sensor networks, higher the number of anchors, higher is the communication overhead. Although higher number of anchors reduces the probability of having identical coordinate, it does not necessarily increase the routability. Therefore a method of identifying 'good' anchors or anchor locations and coordinate size reduction is essential to improve routability and energy efficiency. First contribution of this paper, novelty estimation, can be effectively used to find the novel information content of anchor. Different 40-anchor configurations indicate that most of the routing information can be captured by about 15 anchors. Based on the novelty value of anchors in the network, an effective set of anchors can be selected. Our results for different configurations show that the coordinate length can be reduced from 40 to 28 on average, while maintaining Greedy Routability within a narrow margin. Moreover proposed novelty method can be used as a tool for network partitioning based on the effectiveness of anchors in each region. The next contribution is dimension reduction based on SVD. In the example networks, it reduced the cardinality of the virtual coordinates from 40 to 5, a change by a factor 8, resulting in significant efficiencies in packet length, and implicitly in energy consumption. Basically, SVD extracts prominent features and information in the original coordinates while removing the linear dependency in the original coordinate set resulting in reduced dimensionality. Centralized and distributed implementations of the algorithms are discussed.

REFERENCES

[1] J.N. Al-Karaki, and A.E. Kamal, "Routing techniques in wireless sensor networks: a survey," IEEE Wireless Communications, Vol. 11, pp.6-28, Dec. 2004.
[2] A. Caruso, S. Chessa, S. De, and A. Urpi, "GPS free coordinate assignment and routing in wireless sensor networks," Proc. 24th IEEE Joint Conf. of Computer and Communications Societies, Vol. 1, pp. 150-160, Mar. 2005.
[3] Q. Cao and T. Abdelzaher, "Scalable logical coordinates framework for routing in wireless sensor networks," ACM Transactions on Sensor Networks, Vol. 2,pp. 557-593, Nov 2006.
[4] D. C. Dhanapala, "On Performance of Random Routing and Virtual Coordinate Based Routing in WSNs", M.S. Thesis, Colorado State University, Fort Collins, CO, USA, 2009.
[5] D. C. Dhanapala and A. P. Jayasumana, "CSR: Convex Subspace Routing Protocol for WSNs," Proc. 33rd IEEE Conf. on Local Computer Networks,Oct. 2009.
[6] R. Fonseca, S. Ratnasamy, J. Zhao, C. T. Ee, D. Culler and S. Shenker,and I. Stoica, "Beacon vector routing: Scalable point-to-point routing in wireless sensor networks," Proc. 2nd Symposium on Networked Systems Design and Implementation, pp. 329–342, 2005.
[7] M. Kirby," Geometric data analysis- An empirical approach to dimensionality reduction and the study of patterns," John Wiley & Sons, 2001.
[8] C-H Lin, B-H Liu, H-Y Yang, C-Y Kao, and M-J Tsai, "Virtual-coordinate-based delivery-guaranteed routing protocol in wireless sensor networks with unidirectional links", Proc. IEEE INFOCOM 2008,pp: 351-355 , 13-18 April 2008.
[9] K. Liu and N. Abu-Ghazaleh, "Aligned virtual coordinates for greedy routing in WSNs," Proc. IEEE Int. Conf. on Mobile Ad-hoc and Sensor Systems, pp.377–386, Oct. 2006.
[10] K. Liu and N. Abu-Ghazaleh, " Virtual coordinate backtracking for void traversal in geographic routing," Proc. 5th Int. Conf. on Ad-Hoc Networks & Wireless, Aug. 2006.
[11] A. Rao, S. Ratnasamy, C. Papadimitriou, S. Shenker, and I. Stoica , "Geographic routing without location information," ,Proc. 9th Int. conf. on Mobile computing and networking, pp.96 - 108, 2003.
[12] E.W. Weisstein, "Frobenius norm." From Math World--A Wolfram Web Resource. http://mathworld.wolfram.com/FrobeniusNorm.html
[13] E.W. Weisstein, "Adjacency Matrix." From Math World--A Wolfram Web Resource. http://mathworld.wolfram.com/AdjacencyMatrix.html