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Improving Performance of Ad Hoc and Vehicular Networks using the LCMV Beamformer

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Abstract— **Beamforming techniques can enhance both capacity and coverage in wireless networks. To be efficient, most of these techniques require accurate estimation of the destination position. In vehicular environments, standard beamforming is not suitable when continuous tracking of node location is required. To handle inaccuracies in location estimation, this work uses Linearly Constrained Minimum Variance (LCMV) beamforming to form beams in adjoining directions to facilitate tracking. The directions are selected using the last accurate destination direction and movement parameters such as direction and speed variations of the source. Performance evaluations show that the proposed approach enhances system capacity and connectivity while reducing localization overhead.**

Index Terms— **LCMV beamforming, mobile ad hoc networks, tracking, adaptive antenna arrays.**

I. INTRODUCTION

Directional antennas are receiving renewed interest worldwide as they introduce spatial reuse that leads to a variety of potential benefits for wireless communication systems. These include substantial increase in system capacity and wider coverage. By using beamforming techniques, the signals can be directed in some privileged directions. Therefore, radio interferences in unwanted directions can be reduced [1]. However, the performance of directional antennas strongly depends on the accuracy of the destination location [2]. Unfortunately, in high-mobility context, the continuous localization tracking involves significant system overhead.

Several beamforming techniques have been proposed to track mobile nodes localization in ad hoc networks. In [3] authors present a dynamic blind beamforming scheme to benefit from directional antennas while avoiding localization overhead in large mobile ad hoc networks. The technique consists in rotating the directional antenna successively in all directions; the source transmits blindly to its destination without knowing its exact position. Authors show that the probability of interfering with other destinations is lowered due to both spatial focusing and asynchronism of all communications. Nevertheless, the rotational directivity introduces significant delay when the source is not beamforming in the direction of its intended destination. Thus, a trade-off between increased delay and interference reduction is considered. In [4], authors propose a directional slotted Aloha based MAC protocol in which mobile nodes deploy a control sub channel to track the location of their intended destinations. Users are considered either to be equipped with GPS (Global Positioning System) or able to compute their own position through the calculation of the DOA (Direction of Arrival). They periodically update neighbours with their position by sending location update messages across the control sub channel. The authors make several approximations such as no velocity and movement direction changes between two consecutive location updates which limits the motion of nodes within a given area of operation and requires nodes to move with a constant velocity. Another blind beamforming algorithm to track mobile nodes is presented in [5]. Authors propose to estimate once the destination position based on existing DOA estimation techniques. During the following transmissions, the direction of nodes and the weight vector are estimated from those obtained previously. Constant Modulus Algorithm (CMA) iterations are used to overcome estimation errors induced by the extrapolation.

The main idea of this paper is to avoid the continuous tracking of node location through heavy localization methods (e.g. DOA estimation techniques [6][7]). An alternative option is the use of GPS which can provide continuous positioning and timing information. Nevertheless, the accuracy of GPS-based location may be influenced by some factors such as selective availability, atmosphere layers and multipath effects appearing in the neighbourhood of large building or other elevations. The accuracy of the computed GPS position is also affected by the number of GPS satellites visible to users and their geometric location [8]. These negative effects are even more important when the GPS antenna is mobile (e.g. within cars). Moreover, the metallic features in windshields or car window tinting films may degrade GPS signals inside vehicles, causing inaccuracy in location computing. In our work, the position determination relies on the velocity and the direction parameters of the mobile with the uncertainty on the exact position compensated by the use of appropriate wider LCMV beam.

In this paper, we propose a new dynamic beamforming technique which allows mobile users to communicate without continuously knowing the exact position of their destinations.

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In our approach, we consider the use of LCMV beamforming technique by forming a main dynamic beam pointing to a set of directions including the destination. Instead of continuously tracking the destination location, the proposed approach estimates the direction from the knowledge of the previous location, the movement direction and the velocity of the mobile nodes.

Section II presents the investigated system model. The performance criteria are the object of section III while section IV reports performance results and comparisons of the proposed approach with the MVDR technique.

II. SYSTEM MODEL

We consider wireless networks as shown in Figure 1. Some nodes are fixed while others are mobile. The fixed nodes (i.e. access points APs) use omni-directional antennas and the mobile nodes (i.e. cars) are equipped with multiple antennas capable of both transmit and receive beamforming. In our investigation, we focus on the uplink. Cars access (directionally) public hotspots or mesh networks.

We assume that within a given road, nodes can move with known minimum and maximum speeds. Source nodes estimate their locations, relative to destination nodes, from the knowledge of the movement direction and the velocity. When an important deviation in the movement direction is detected (for instance, through the variation of the SINR gradient, see section II.B), source nodes update their location using existing techniques [6][7]. Due to the velocity variation, the transmitting nodes may have imprecise location information of their intended destination. We propose to compensate this uncertainty by the use of the LCMV adaptive beamformer technique by forming wide beams pointing to a set of directions that include the destination direction.

A. Adaptive Beamforming

The adaptive beamforming consists in steering beams toward desired users and nulls toward interfering signals. Thus, it requires the knowledge of the direction of arrival of the desired signal [2]. Adaptive beamformers such as Minimum Mean Square Error (MMSE) [9] and Minimum Variance Distortionless Response (MVDR) [10] derive the weight vectors w as the solution to:

$$\begin{aligned} &\min imize\ w^H R\ w \\ &subject\ to\ w^H a(\theta) = 1 \end{aligned} \tag{1}$$

where
R is the data covariance matrix
w is then given by:

$$w = \frac{1}{a(\theta)^H \hat{R}\, a(\theta)} \tag{2}$$

These techniques form a beam toward a single direction θ, which can lead to significant performance degradation when this direction is not accurate. Imprecise direction information might cause mobile nodes to form antenna beams in directions that deviate from the desired ones.

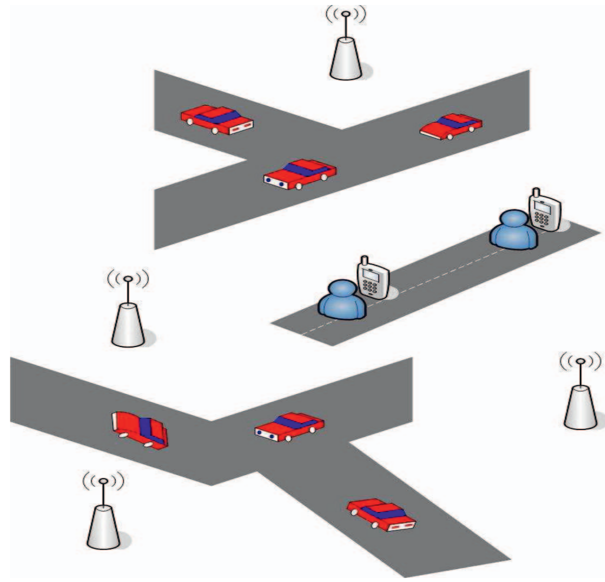


Fig.1. Example of Ad hoc network with fixed and mobile nodes

Traditional approaches for increasing robustness to DOA uncertainty include Linearly Constrained Minimum Variance (LCMV)[11], diagonal loading and quadratically constrained beamforming [12][13]. These techniques allow pointing the beam to a set of L Directions of Arrival around the nominal look direction rather than just to one direction. In [14], LCMV provides better performance with less complexity compared to the other techniques.

The weight vector according to LCMV beamformer is chosen as the optimal solution to:

$$\begin{aligned} &\min imize\ w^H R\ w \\ &subject\ to\ B^H w = f \end{aligned} \tag{3}$$

The analytical solution of the above equation is given by:

$$w = R^{-1} B (B^H R^{-1} B)^{-1} f \tag{4}$$

where
R is the data covariance matrix.
B is the matrix of array responses in the L constrained directions.
f is a vector of length L specifying the desired response in each constrained direction.

B. Directional Constraints' Estimation

The objective of our investigation is to derive the weight vector that allows mobile nodes to form LCMV beams toward the stationary nodes, in order to maximize the connectivity and the spectral efficiency.

Since the continuous localization tracking may increase the system overhead, we propose that mobile nodes only update their locations to stationary nodes when they detect an important deviation in the movement direction. This deviation can be deduced from the SINR gradient degradation which can be used as a trigger to update localization whenever the movement direction changes. When the slope of the SINR gradient curve achieves a defined threshold, mobile nodes must update their location by using existing localization methods [6][7]. Figure 2 illustrates an example of SINR gradient variation and its use to trigger localization update. The two negatives peaks in the curve correspond to an important SINR degradation caused by a change in the mobile node direction. The first negative peak at t=13 is followed by a positive peak. This explains that a change in node movement direction happened for a short time and that the node quickly recovered its initial direction. The second negative peak at t=35 achieves the threshold and it is not followed immediately by a positive peak. This can trigger a location update procedure. The second positive peak shown in figure 2 corresponds to a localization update by existing techniques. In the following, we denote by T_L the location update interval. We also assume that between two consecutive location updates, a mobile node does not change its movement direction; however its velocity V can vary within an interval $[V_{min}, V_{max}]$.

From the knowledge of its movement direction, velocity and its previous location, a mobile node may deduce the destination direction and thus derive the weight vector of the LCMV beamformer forming a large beam around this estimated look direction. This allows to overcome the uncertainty in the estimated direction caused by the mobile node velocity variation.

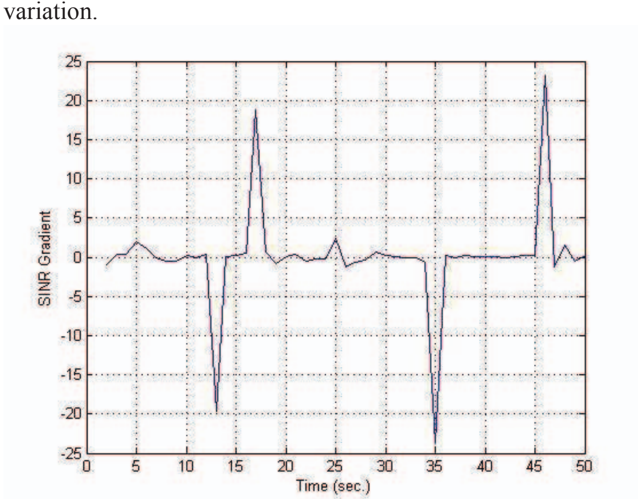


Fig.2. Scenario illustrating the update localization

C. DOA Estimation

Consider the communicating pair $\{S_i\ D_j\}$, with S_i the transmitter mobile node and D_j the receiver stationary node. θ_i represents the AOD (Angle of Departure) estimated by S_i at time t_i ($0 \le t_i \le T_L$) to beamform in the direction of D_j (see Figure 3).

We assume that at time t_i, mobile node S_i has moved by a mean distance d_i=V. t_i.

Thus, we can derive θ_i as:

$$\theta_i = arctg\left(\frac{\left|A-(V.\ t_i)\right|}{r}\right) \tag{5}$$

where

r denotes the distance between the antenna axis of D_j and the line of movement of S_i.

A is the distance between the last estimated location of S_i and its orthogonal projection into the antenna axis of D_j.

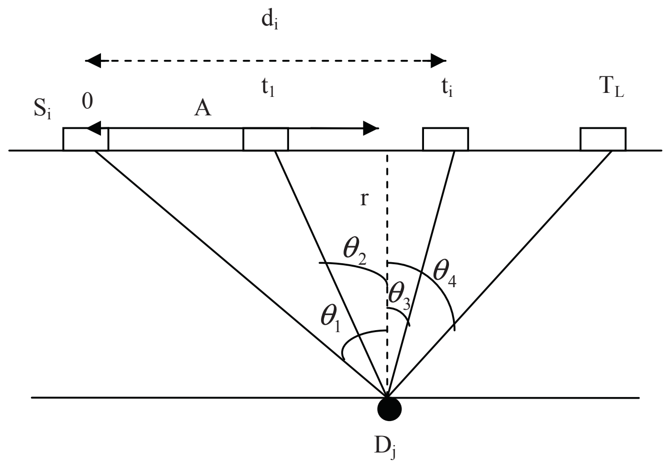


Fig.3. Scenario illustrating direction calculation

The matrix B required in equation (4) can be expressed as:

$$B=[a(\theta_i-\Delta\theta)\ \cdots\ a(\theta_i-2)\ \ a(\theta_i-1)\ \ a(\theta_i)\ \ a(\theta_i+1)\ \ a(\theta_i+2)\ \cdots\ a(\theta_i+\Delta\theta)]$$

$\Delta\theta$ describes the uncertainty in direction caused by the velocity variation. Since, in urban area, mobile users' velocity may change over time, $\Delta\theta$ is given by:

$$\Delta\theta = \frac{\left|\theta_{max} - \theta_{min}\right|}{2} \tag{6}$$

where

$$\theta_{max} = arctg\left(\frac{\left|A-(V_{max}\ .\ t_i)\right|}{r}\right) \tag{7}$$

$$\theta_{min} = arctg\left(\frac{\left|A-(V_{min}\ .\ t_i)\right|}{r}\right) \tag{8}$$

III. Performance Evaluation

The performance evaluation of the proposed technique is conducted through the measurement of different indicators including the SINR, the network connectivity and the spectral efficiency.

A. SINR model

The signal transmitted from the M-antenna array of a source node S_i is given by:

$$x_i = b\, w_i^{\;H} \tag{9}$$

Where w_i is the (M –dimensional) transmit beamforming weight vector used by S_i to transmit to node D_j and b is the data sequence.

The signal received by destination node D_j can be expressed as:

$$y_j = h_{ji}\, b\, w_i^{\;H} + n_j \tag{10}$$

where

h_{ji} denotes the spatial channel response vector between S_i and D_j. It includes the path loss factor depending on the distance between the source and the destination.

n_j represents the additive white Gaussian noise with mean zero and variance σ^2.

The received SINR at node D_j can be formulated as follows:

$$SINR = \frac{w_i^{\;H} R\, w_i}{\sum_{\substack{k=1\\k\neq i}}^{K} w_k^{\;H} R\, w_k + \sum_{\substack{l=1\\l\neq i}}^{L_I} w_l^{\;H} R_I\, w_l + \sigma^2} \tag{11}$$

where

w_k is the transmitting beamforming weight vector used by S_i to transmit to another node D_k.

R is the covariance matrix (between S_i and D_j), it is given by:

$$R = E\left\{h_{ji} h_{ji}^{\;H}\right\} \tag{12}$$

The second term of the denominator refers to transmissions from any other source node S_l ($l=1...L_I$) to any destination node D_p neighbour of node D_j. These are all the transmissions whose beam is covering D_j when it is receiving a signal from S_i.

w_l is the transmitting beamforming weight vector used by source S_l to transmit to destination D_p

R_I is the interference covariance matrix, it has the form:

$$R_I = \sum_{l=1}^{L_I} E\left\{h_{jl} h_{jl}^{\;H}\right\} \tag{13}$$

B. Connectivity

Several definitions of connectivity exist in the literature [3] [15]. Most of them consider that two nodes are connected if a given criterion is above a determined threshold. Used criteria may be received power level or the SINR. In our work, the connectivity is defined with respect to the level of the received SINR. Thus, a pair node is connected if the SINR at the destination is above the threshold SINR-thresh.

SINR > SINR_thresh

C. Spectral efficiency

The spectral efficiency in (b/s/Hz) is given by [16]:

$$C = \frac{1}{T}\sum_{i=1}^{N} \log_2\left(1 + SINR_i\right) \tag{14}$$

T is the total transmission time for all the N signals.

IV. Simulation Results

In this section, we present numerical results and performance comparison between the LCMV beamformer using directional constraints and the MVDR beamformer pointed to a single direction.

We evaluate the performance in terms of SINR of the desired signal, the average network connectivity and spectral efficiency. Results are averaged with respect to 50 different random topologies. The power budgets for all source nodes are the same with SNR of 15 dB. The antenna array of each mobile node is a uniform linear array (ULA) with half-wavelength spacing and M=10 elements.

Figures 6 and 7 illustrate the SINR variation as a function of the number of interferers, for different values of $\Delta\theta$.

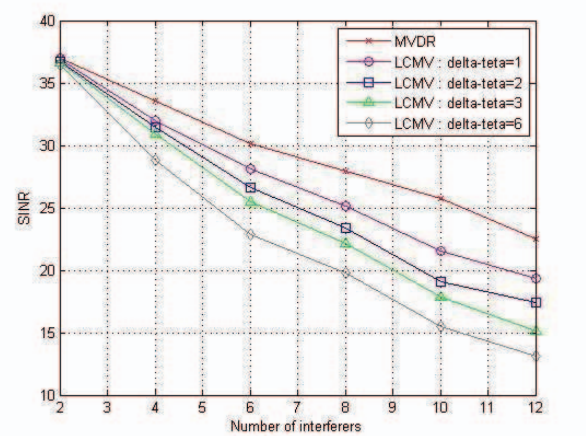


Fig. 6. SINR versus number of interference users, for perfect knowledge of the destination direction

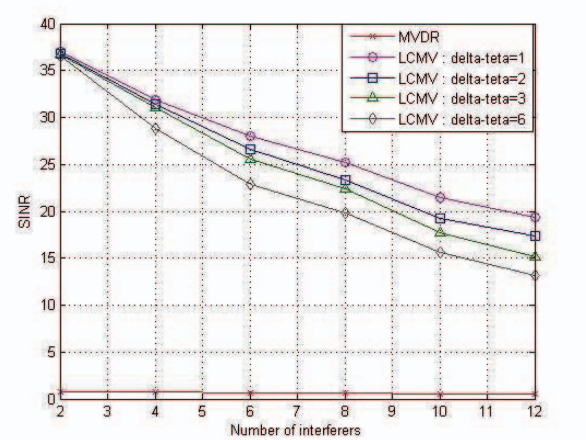


Fig. 7. SINR versus number of interference users, under imperfect pointing to the destination

The case of good knowledge of the destination direction is depicted in Figure 6 where we observe performance degradations for all the SINR curves as the number of interferers increases. We can also notice that the MVDR is less sensitive to interference compared to LCMV for all $\Delta\theta$ values. For LCMV, higher $\Delta\theta$ values lead to lower SINR at the receiver.

The case of imperfect pointing to the destination is depicted in Figure 7. As expected the performance of the MVDR is very sensitive to direction errors and can suffer great loss in signal quality when orientation errors exceed few degrees (>2°).

Figure 8 plots the SINR versus the difference between the estimated direction and the actual direction, for different values of $\Delta\theta$. We observe that the SINR curve for MVDR quickly decrease since the beamformer can not adapt to errors in the direction estimation. LCMV with $\Delta\theta = 3$ (i.e. L=7) is the most tolerant to the direction estimation errors compared to the others curves. Nevertheless, its SINR value is lower than the SINR of LCMV with $\Delta\theta = 2$ (i.e. L=5) for estimation direction errors lower than 7. The signal power received for $\Delta\theta = 2$ is better thanks to the spatial focusing effect of the transmit beam.

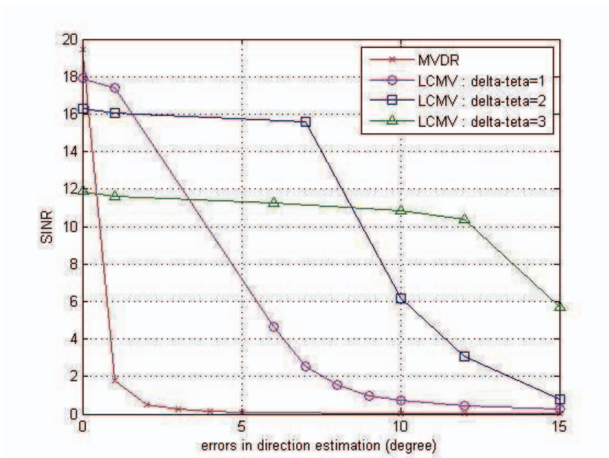


Fig. 8. SINR versus errors in direction estimation

Figure 9 illustrates the average network connectivity which is defined by the number of connected pairs (whose SINR > SINR_thresh, as defined in section III.B) divided by the number of communicating pairs in the network, in the case of good pointing of source nodes' beams toward their destinations. A similar decreasing behaviour is observed for all the curves when the number of communicating pairs increases because the number of interferer increases. The MVDR beamformer results even if equally affected in degradation remain better than those obtained for the three examples of LCMV beams.

Figure 10 shows the average connectivity variation versus the number of communicating node pairs in the network. We observe that in the case of imperfect direction knowledge, LCMV curves are above MVDR. With LCMV, we can select the optimum $\Delta\theta$ according to the uncertainty on the destination direction induced by user mobility. The LCMV beamformer can thus improve robustness in the presence of destination location uncertainty.

The performance of LCMV compared to MVDR in the case of imperfect pointing is illustrated in figures 11(a), 11(b) and 11(c) depicting the spectral efficiency versus the number of communicating node pairs, for three levels of velocity variation: low, medium and high. There exists an optimal *L* (number of constrained directions) which maximizes the spectral efficiency for each interval of velocity variation ($\Delta\theta$), illustrating the trade-off between covering the interval of uncertainty and increasing the received power at the destination as well as the uncertainty interval versus interference reduction. The greater L is, the larger is the beam thus the better robustness to DOA uncertainty but also the lower is the received power and the greater is the number of interferers.

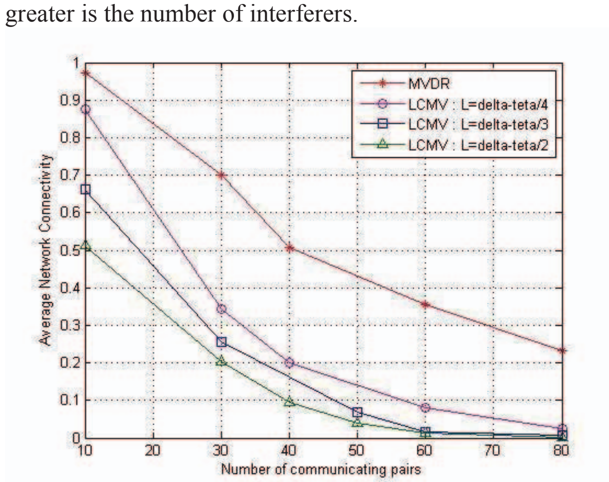


Fig. 9. Network Connectivity versus number of communicating pairs of nodes, under good pointing of source nodes' beams, $\Delta\theta$ =6, SINR_thresh=10 dB

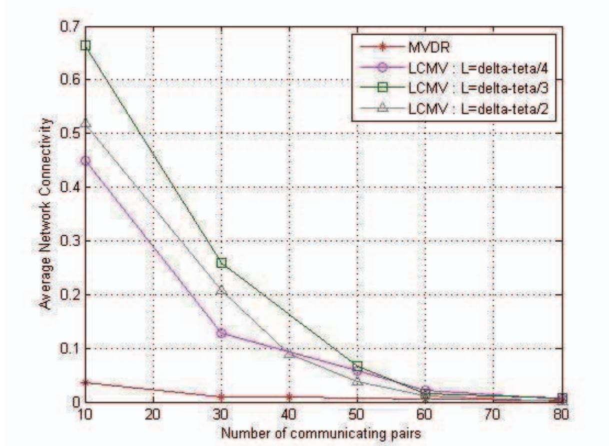
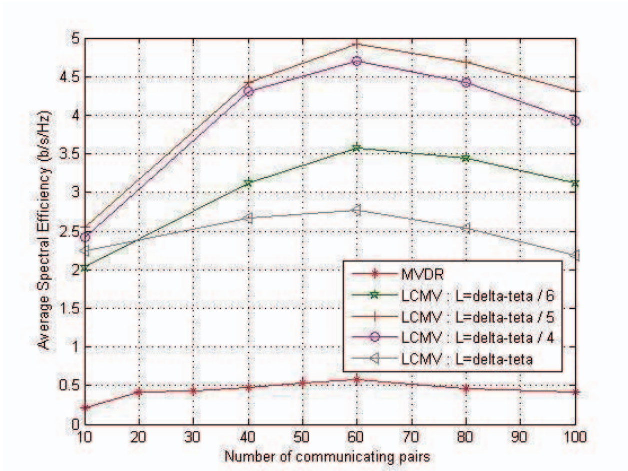


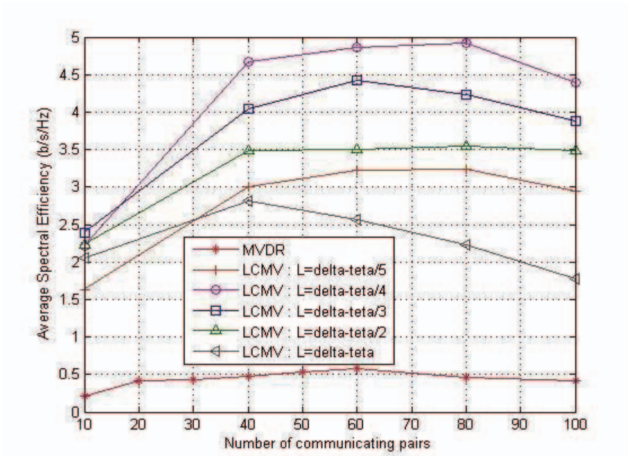
Fig. 10. Network Connectivity versus number of communicating pairs of nodes, under imperfect pointing of sources toward their destinations, $\Delta\theta$ =6, SINR_thresh=10 dB

V. Conclusion

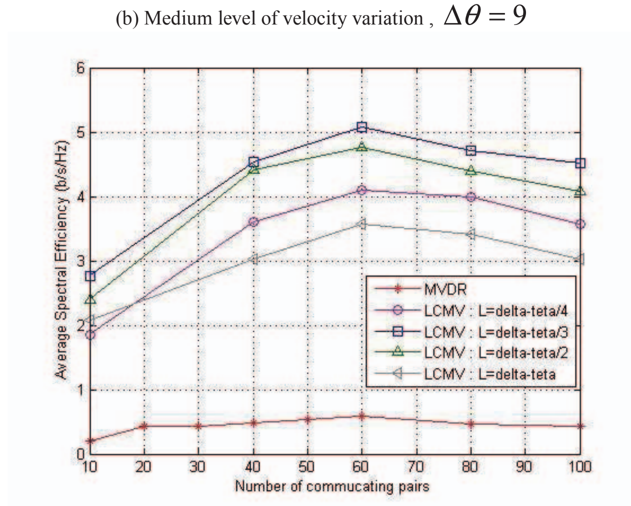
In this work, we proposed a dynamic and adaptive beamforming technique for mobile ad hoc networks, based on the LCMV beamformer. The mobile source nodes derive their weight vector and form dynamic beams taking into account their mobility in terms of movement directions and velocity.
Beam dynamicity includes beam direction and beam width. These dynamic beams overcome the uncertainty due to mobility and the induced imprecision in destination location.



(a) High level of velocity variation , $\Delta\theta = 15$



(b) Medium level of velocity variation , $\Delta\theta = 9$



(c) Low level of velocity variation : $\Delta\theta = 5$

Fig. 11. Spectral efficiency versus number of communicating pairs of nodes for different values of $\Delta\theta$

Simulation results show that when using LCMV beamformer with appropriate parameters, we can achieve enhanced performance compared to the MVDR solution, in the case of imprecise knowledge of the destination position. With LCMV beamformer, an optimally selected number of constrained directions maximize the spectral efficiency. This optimum results from a trade-off between covering the interval of uncertainty and increasing the received power at the destination. Future work will include analysis of localization overhead reduction when using a dynamic LCMV beamformer.

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