Communication-Aware Motion Planning in Fading Environments

Yasamin Mostofi
Department of Electrical and Computer Engineering
University of New Mexico, Albuquerque, NM 87113, USA

***Abstract*— In this paper we create a framework to model and characterize the impact of time-varying fading communication links on the performance of a mobile sensor network. We propose communication-aware motion-planning strategies, where each node incorporates statistical learning of communication link qualities, such as Signal to Noise Ratio (SNR) and correlation characteristics, into its motion-planning function. We show that while uncorrelated fading channels can ruin the overall performance, the introduced natural randomization can potentially help the nodes leave deep fade spots. We furthermore show that highly correlated deep fades, on the other hand, can degrade the performance drastically for a long period of time. We then propose a randomizing motion-planning strategy that can help the nodes leave highly correlated deep fades.**

I. INTRODUCTION

Mobile intelligent networks can play a key role in emergency response, surveillance and security, and battlefield operations. The vision of a multi-agent robotic network cooperatively learning and adapting in harsh unknown environments to achieve a common goal is closer than ever. A mobile network that is deployed in an outdoor environment can experience uncertainty in communication, navigation and sensing. The objects in the environment (such as buildings) will attenuate, reflect, and refract the transmitted waves, degrading the performance of wireless communication. Furthermore, the environment could be harsh and uncertain in terms of sensing and navigation due to rubble, stairs, or blocking objects. Then, high-level decision-making and control at every agent would not only affect its sensing quality but also impact the overall communication link qualities and the useful data rate exchanged through the network. This will create a multi-objective optimization problem in which optimum motion-planning decisions considering only sensing and navigation may not be the best for communication, resulting in *communication and sensing tradeoffs*.

Decentralized control of sensor motions has gotten considerable attention in recent years [1]-[3]. Most of the current research in this area, however, assumes ideal communication links, considering only sensing objectives. For instance, it is common to assume either perfect links or links that are perfect within a certain radius of a node, a significant over-simplification of communication links. Communication plays a key role in the overall performance of mobile networks as each sensor relies on improving its estimate by processing the information received from others. Considering the impact of communication channels on wireless estimation/control is an emerging area of research. The impact of distance-dependent path loss (no fading) on decentralized motion-planning has been characterized and a communication-aware decision-making strategy has been proposed [4]. In this paper, we will extend that work to embrace the effect of fading, the key performance degradation factor in mobile networks. The main challenge of motion-planning in fading environments is the introduced uncertainty. A link can change drastically by traveling a very short distance or can stay correlated for a long period of time, depending on the makeup of the environment, positions of the nodes and communication parameters. To address this, we first provide a probabilistic modeling framework for realistic characterization of mobile communication links, including uncertainties such as fading and shadowing. We then propose a probabilistic decision-making and control framework that integrates both communication and sensing objectives based on the statistical learning of link qualities. We show that for uncorrelated channels, the natural randomization can help nodes leave deep fades (locations with very low SNR). Highly correlated deep fades, on the other hand, can degrade the performance considerably for a long period of time. We then propose a randomizing motion-planning strategy to improve link qualities in such cases.

II. SYSTEM MODEL

Consider N mobile sensors that are cooperatively estimating the state of a target with the following dynamics: $x[k+1] = Ax[k] + w[k]$. We consider a target moving in a plane, with its state defined as its position.[1] Then $x[k] \in \Re^2$ is a vector representing the state of the target at time k and $w[k]$ is the process noise. $w[k]$ is assumed zero mean, Gaussian and white with Q representing its covariance matrix. Let $y_j[k]$ represent the observation of the j^{th} mobile node at time k: $y_j[k] = x[k] + v_j[k]$. The observation noise, $v_j[k]$, is zero mean Gaussian with $R_j[k]$ representing its covariance matrix: $R_j[k] = \overline{v_j[k]v_j^T[k]}$ and "superscript *T*" representing the transpose of a vector/matrix. We take $R_j[k]$ to be a function of the positions of both the sensor and the target (as opposed to the distance between the two),

[1] The results of this paper are applicable to 3D as well.

as it will be the case in realistic scenarios. Each node may use a local filter such as a Kalman filter to get a better estimate of the target position. Let $x_{KF,j}[k]$, $e_j[k]$ and $Z_j[k]$ represent the local estimate of the j^{th} sensor, its corresponding error and its error covariance matrix after Kalman filtering at time step k (in the absence of a local filter, the original measurement will be used). Each node then transmits its local measurement and measurement error covariance to other nodes. Let $\hat{x}_{KF,j,i}[k]$ and $\hat{Z}_{j,i}[k]$ represent the reception of the i^{th} node from the transmission of $x_{KF,j}[k]$ and $Z_j[k]$ respectively. We will have,

$$\begin{aligned}\hat{x}_{KF,j,i}[k] = x_{KF,j}[k] + c_{j,i}[k] \quad c_{j,j}[k] = 0_{2\times 1} \\ \hat{Z}_{j,i}[k] = Z_j[k] + L_{j,i}[k] \quad L_{j,j}[k] = 0_{2\times 2}, 1 \leq i, j \leq N,\end{aligned} \tag{1}$$

where $c_{j,i}[k] \in \Re^2$ and $L_{j,i}[k] \in \Re^{2\times 2}$ contain communication noises occurred in the transmission of each element of $x_{KF,j}[k]$ and $Z_j[k]$ respectively and $0_{2\times 1}$ and $0_{2\times 2}$ represent the zero vector and matrix respectively. Let $U_{j,i}[k]$ represent covariance matrix of $c_{j,i}[k]$:

$$U_{j,i}[k] = \overline{c_{j,i}[k] c_{j,i}^T[k]}. \tag{2}$$

Due to the impact of fading, communication noise covariance will not merely be a function of the distance between the two nodes, as we shall address in this paper.

Each sensor then fuses its own measurement with the received ones to reduce its measurement uncertainty. We assume that each sensor uses a Best Linear Unbiased Estimator (BLUE) to process local and received information. It then makes a local decision about where to move next to minimize its local fused estimation error covariance.

A. Observation Model

To characterize the observation noise of each sensor, we follow the same model used in [4] and [5]: $R_j = T(\theta_j) D_j(r_j) T^T(\theta_j)$, $T(\theta_j) = \begin{bmatrix} cos(\theta_j) & sin(\theta_j) \\ -sin(\theta_j) & cos(\theta_j) \end{bmatrix}$ and $D_j(r_j) = \begin{bmatrix} f_j(r_j) & 0 \\ 0 & \gamma f_j(r_j) \end{bmatrix}$, where r_j is the distance of the j^{th} sensor to the target and θ_j is the corresponding angle in the global reference frame with target at the origin (see Fig. 1 of [4]). The function f_j, the model for the range noise variance of the j^{th} sensor, depends on r_j and γ is a scaling constant. A common model for f is quadratic, with the minimum achieved at a particular distance from the target, i.e. the "sweet spot" radius [1].

B. Physical Layer: Mobile Communications [6]

1) Mobile Fading Channels: One of the major performance degradation factors of mobile communication is fading. Fading is a stochastic attenuation of the transmitted signal. It can be caused, for instance, by multiple paths arriving at the receiver (multipath fading) or blocking by objects such as a building (shadowing). This is in addition to the distance-dependent attenuation (path loss), and necessitates a probabilistic approach to motion-planning. Depending on the environment, communication parameters and speed of the mobile unit, fading can have different correlation properties. For instance, small changes in the transmission paths, caused by the movements of the receiver or transmitter, can introduce rapid and drastic changes in the received signal quality (small-scale fading) and affect the overall performance of cooperative target tracking considerably. On the other hand, if a mobile node's reception is blocked by a building, the attenuation caused by it can stay highly correlated for as long as the node is shadowed by the building (large-scale fading).

2) Channel Signal to Noise Ratio: A fundamental parameter that characterizes the performance of a communication channel is the received Signal to Noise Ratio, which is defined as the ratio of the instantaneous received signal power divided by the receiver thermal noise power. Let $\Upsilon_{j,i}[k]$ represent the instantaneous received Signal to Noise Ratio at k^{th} transmission from node j to node i. We will have

$$\Upsilon_{j,i}[k] = \frac{|h_{j,i}[k]|^2 \sigma_s^2}{\sigma_T^2}, \tag{3}$$

where $\sigma_s^2 = \mathbb{E}(|s|^2)$ is the transmitted signal power, $\sigma_T^2 = \mathbb{E}(|n_{\text{thermal}}|^2)$ is the power of the receiver thermal noise and $h_{j,i}[k] \in \mathbb{C}$ represents time-varying fading coefficient of the baseband equivalent channel during the k^{th} transmission from node j to node i. $\Upsilon_{j,i}[k]$ determines how well the transmitted bits of the k^{th} transmission can be retrieved. As a node moves, it will experience different channels and therefore different received Signal to Noise Ratios. Therefore, we model $\Upsilon_{j,i}[k]$ as a stochastic process whose average, $\Upsilon_{j,i,ave}[k]$, changes as a function of the distance between the transmitter and receiver ($\Upsilon_{j,i}[k]$ is a non-stationary process in general). The distribution of $\Upsilon_{j,i}[k]$ is a function of the transmission environment and the level of mobility. A common model for outdoor environments (with no Line-of-Sight path) is to take $\Upsilon_{j,i}$ to be exponentially distributed, which is the model we will adopt (without loss of generality) in order to generate fading channels.

3) Channel Correlation Characteristics: As was discussed earlier, correlation properties of the channel play a key role in the overall performance. In this paper, we are interested in learning channel correlation characteristics in order to move to locations that are better for communication. For instance, if a node has measured a highly correlated but poor quality channel for the past few receptions, it may need to change its direction. In rich scattering environments, channel can change drastically due to multipath small-scale fading and can get uncorrelated rapidly. In such cases, a small movement of the node can result in a better channel (or a worse one). When the received signal is attenuated due to a blocking object or is experiencing a small angle of arrival spread, on the other hand, it can take longer for the channel to get uncorrelated. *Deep fades* refer to the instants of a severe drop in channel quality. For highly correlated channels, experiencing deep fades can pose a challenge as the channel can have a poor quality over an extended period of time with high probability. To address this, we characterize the impact of channel correlation on the overall performance. We furthermore propose to learn the correlation characteristics of the channel statistically for the purpose of motion-planning. As channel correlation increases, we can learn and predict the channel and design better motion-planning algorithms that are aware of their impact on link qualities, as we shall explore in the next section.

4) Communication Noise Variance: Poor link quality can result in some of the transmitted bits to be flipped. This will then result in the noisy reception of the transmitted positions and covariances (see Eq. 1). Let $c_{j,i}^{(1)}[k]$ and $U_{j,i}^{(1,1)}[k]$ represent the communication noise in the reception of the position along x-axis and its corresponding variance respectively. We have $U_{j,i}^{(1,1)}[k] = \mathbb{E}(|c_{j,i}^{(1)}[k]|^2|h_{j,i}[k])$, which will be a function of $\Upsilon_{j,i}[k]$: $U_{j,i}^{(1,1)}[k] = \Xi(\Upsilon_{j,i}[k])$, where $\Upsilon_{j,i}[k]$ is the instantaneous received Signal to Noise Ratio (see Section II-B-2) in the transmission from the j^{th} agent to the i^{th} one. Ξ is a non-increasing function that depends on the transmitter and receiver design principles as well as the transmission environment. $\Upsilon_{j,i}[k]$ is a random process whose average changes with distance:

$$\Upsilon_{j,i,ave}[k] = \frac{\alpha_{j,i}[k]}{d_{j,i}^{n_{p,j,i}[k]}[k]}, \tag{4}$$

where $d_{j,i}[k]$ is the distance between the i^{th} and j^{th} agents at time k and $n_{p,i,j}[k] > 0$ is the path loss exponent which depends on the environment. $\alpha_{j,i}[k] \geq 0$ is a function of the transmitted signal power, receiver noise, frequency of operation and the communication environment [6].

Example: Consider a scenario where the observation is quantized using a uniform quantizer. The quantized bits are then transmitted using binary modulation and Gray coding [6]. Let Δ and N_b represent the quantization step size and number of quantization bits respectively. Then we have shown that the communication noise variance will be [7]:

$$U_{j,i}^{(1,1)}[k] = \frac{\Delta^2}{12} + \frac{4^{N_b}-1}{3}\Delta^2 \times \Omega(\sqrt{\Upsilon_{j,i}[k]}), \tag{5}$$

where $\Omega(\eta) = \frac{1}{\sqrt{2\pi}}\int_{\eta}^{\infty} e^{-z^2/2}dz$. Similar expressions can be written for the transmission of the position along y-axis and other elements of the error covariance matrix of Eq. 1. The models of this section provide the abstraction necessary to characterize mobile fading channels for the purpose of motion-planning, and will be adopted in this paper.

C. Cross-Layer Information Path

Since motion-planning affects communication link qualities, the impact of motion-planning on link qualities should be taken into account when each agent plans where to move next. While knowledge of the link qualities is available in the physical layer, the application layer is in charge of estimation and control. In order to optimize the performance of the network in outdoor environments that are harsh in terms of sensing and communication, a cross-layer information path is needed, i.e. a path from the physical layer (which is the layer in charge of communication) to the application layer that carries information on the quality of the link (Signal to Noise Ratio or communication noise variance in this case). In other words, the physical layer can let the application layer know, using a cross-layer path, how much it trusts the accuracy of each received packet. Using such information in motion-planning can improve the performance considerably. In order to do so, however, a proper abstraction of the physical layer is required for the purpose of motion planning. Since physical layer is represented by several parameters, a proper abstraction is a compression of the physical layer that only keeps the most relevant information. In Section II-B, our aim was to provide such abstraction in the form of stochastic communication noise variance and Signal to Noise Ratio, which we will use for motion-planning and control.

III. Communication-Aware Motion-planning

In order to maximize the probability of robust behavior in harsh uncertain environments, we propose communication-aware decision-making strategies that utilize statistical learning of channel characteristics. Fig. 1 shows our envisioned approach for integrating communication and sensing objectives in fading environments. Every transmitted packet contains training bits, which every node will utilize to estimate channel power and correlation function statistically. Probabilistic models of wireless channels (if available) could also be used to improve channel prediction. This information will then be used in high-level motion planning, as is shown in the figure. For instance, each node can use this information to predict the impact of its possible motion movements on link qualities, as we will explore in more details in this section.

On the sensing side, each agent improves its learning of the environment through sensing and exploration. This allows an agent to build a map of the environment, which could also be used for further enhancing channel prediction, as is shown in Fig. 1 (if such a map is available). For instance, this allows an agent to predict the impact of an already sensed obstacle on its link qualities and plan its motion accordingly. In a similar manner, learning channel characteristics can also provide useful information for building the map of the environment, as is shown in the figure. Finally each agent builds a cost function that embraces both sensing and communication costs and chooses a motion decision that minimizes it. The main challenge in building an appropriate cost function is the multi-objective nature of the problem. Each agent's motion affects the quality of its communication to all the other agents as well as its sensing quality, resulting in a multi-objective optimization problem. We are also interested in decentralized solutions, where every agent makes a local decision on where to go next, without having any knowledge of where others would go. This, along with the uncertainty in channel prediction,

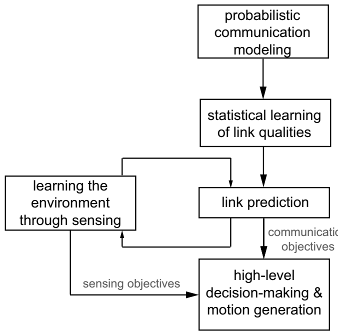

Fig. 1. Integration of comm. & sensing objectives in decision-making

makes achieving optimal solutions even more challenging. In the next few subsections, we characterize the impact of fading channels on the performance of cooperative target tracking and further discuss our proposed strategy to address the corresponding challenges.

A. Communication-Aware Data Fusion

Each node constantly receives local estimation information of others. The received data is corrupted by process noise, observation noise and communication noise. We will have the following for the reception of the j^{th} node from the transmission of the i^{th} one,

$$\hat{x}_{KF,i,j}[k] = x[k] + e_i[k] + c_{i,j}[k], \tag{6}$$

where the position of the target is corrupted by both the Kalman Filter error (which reflects the impact of both observation and process noises) and the communication noise. Each node, therefore, should devise the best possible strategy to combine the received information by taking into account link and observation qualities. A Best Linear Unbiased Estimator (BLUE) is the appropriate candidate since it accounts for noises. We will have,

$$\hat{x}_j[k] = (\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k])^{-1} \sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k]\hat{x}_{KF,i,j}[k], \tag{7}$$

with $P_{i,j}[k] = Z_i[k] + U_{i,j}[k]$. Then $\hat{P}_{i,j}[k]$ represents the estimate of $P_{i,j}[k]$ based on the received information, i.e. by replacing $Z_i[k]$ by $\hat{Z}_{i,j}[k]$ and estimating $U_{i,j}[k]$ based on the measurement of the received SNR. Since the exact knowledge of $P_{i,j}[k]$ is not available at the j^{th} node, due to the corruption of $Z_i[k]$ by the communication noise, the overall fusion performance differs from a typical BLUE estimator and can be proved to be as follows:

$$\mathbb{E}\{(\hat{x}_j[k] - x[k])(\hat{x}_j[k] - x[k])^T\} = (\textstyle\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k])^{-1} \times \\ \textstyle\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k] P_{i,j}[k] \hat{P}_{i,j}^{-1}[k] \times (\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k])^{-1}. \tag{8}$$

It should be noted that the aforementioned fusion process naturally takes care of information that travels over poor quality links by giving it less weight. Therefore, there is no need to assume that a number of links are non-existing as they will be treated in this manner naturally.

B. Decentralized Motion-planning

We extend the decentralized motion-planning algorithm that was originally developed in [1], assuming perfect communication links, to embrace the impact of fading links. Incorporating the proposed communication-aware fusion method of the previous section into the algorithm will result in the j^{th} sensor taking the following steps to decide on its next move at time instant k:

- The j^{th} node uses $\hat{x}_j[k]$ as well as any information available on the dynamics of target movement to predict the next state of the target.
- The j^{th} node has a finite set of possible motion vectors to choose from. These vectors all have the same amplitude but different phases equally distributed between 0 and 2π. For every possible motion vector, m, the j^{th} node predicts its performance, i.e. its fused estimation error covariance of Eq. 8. However, since it does not have access to $P_{i,j}$s, it uses $\hat{P}_{i,j}$s instead. It will then have the following cost function,

$$\text{Cost}_j[k,m] = \Gamma\left[Z_{\text{predicted},j}^{-1}[k+1,m] + \\ \textstyle\sum_{i\neq j}(Z_{\text{predicted},i,j}[k+1] + U_{\text{predicted},i,j}[k+1,m])^{-1}\right]^{-1}, \tag{9}$$

  where $Z_{\text{predicted},j}[k+1,m]$ and $Z_{\text{predicted},i,j}[k+1]$ represent the prediction of the j^{th} sensor of its own local error covariance and the local error covariance of the i^{th} node respectively and are obtained by propagating the corresponding Kalman filters one step ahead. $U_{\text{predicted},i,j}[k+1,m]$ is the j^{th} sensor's prediction of the communication noise covariance of the i^{th} sensor's transmission, given motion vector m, and is produced based on the estimates available on the positions of other nodes, channel correlation and SNR properties. Function Γ maps the predicted fused error covariance to a scalar value. Possible choices are determinant, norm, and trace.
- It chooses the motion vector that minimizes the cost: $m^* = \text{arg min} \quad \text{Cost}_j[k,m]$.

C. Impact of Fading on Cooperative Target Tracking

To see the impact of fading on mobile cooperative networks, consider a network of three mobile agents that are tracking a target. In this part, we will explore the impact of channel correlation and SNR on the performance.

Uncorrelated Fading: Fig. 2 shows the performance of the communication-aware motion-planning algorithm when the channels change rapidly and get uncorrelated from one transmission to the next. The figure shows the average norm (Frobenius norm[2]) of the fused error covariance matrix for 60 time steps for $N = 3$ and for different αs. The following system parameters are used: $f(r) = 0.0008(r-15.625)^2 + 0.1528$, $\gamma = 5$, $Q = .01I_2$, $A = I_{2\times 2}$, $q = .0018$, $N_b = 15$ and $n_p = 2$. The target is almost stationary in

[2]similar results are seen with other measures such as determinant or trace.

this case. We consider faster target motions later in this section. The channel is an exponentially distributed random process (a common distribution in outdoor environments) whose average is time-varying and distance-dependent as modeled in Section II-B. The best channel has $\alpha = 57000$ (see Eq. 4), which corresponds to a fading channel with the average SNR of 27dB at a distance of 10m, whereas $\alpha = 5700$ corresponds to an average SNR of 17dB at the same distance (all realistic scenarios). For comparison, the performance for perfect communication is also plotted. It can be seen that the performance is close to the perfect case for the high average SNR cases. As the channel quality gets worse, however, the performance degrades considerably. For instance, for $\alpha = 5700$, the performance gets closer to the $N = 1$ case, which means that the nodes can not benefit from networked estimation. It should, however, be noted that any traditional motion-planning strategy that is not aware of its impact on link qualities would have performed considerably worse. Compared to the no fading case, the network will perform considerably better for channels with no fading but the same distance-dependent path-loss (see [4]). It should also be noted that these curves are averaged over several random sequences of channel realizations. For one sequence, the performance will lie between the curves for $N = 1$ and the perfect $N = 3$. This is due to the fact that an uncorrelated channel can change drastically from one transmission to the next. However, since the channel gets uncorrelated in the next transmission, there is always a chance of recovery from deep fades by having a better channel. This is what we refer to as the natural randomization introduced by an uncorrelated channel, which can help the nodes leave low SNR spots.

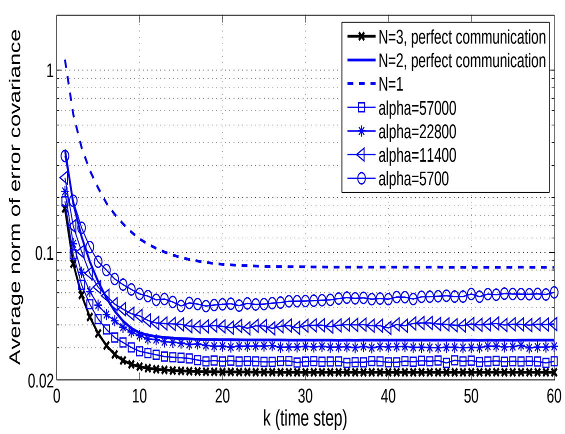

Fig. 2. Average performance for uncorrelated fading channels for $N = 3$

Highly Correlated Fading: Highly correlated fading, on the other hand, has a different impact on the overall performance. A highly correlated good quality channel will pose no problem for a cooperative mobile network. However, a highly correlated channel in deep fade can pose serious challenges as the information flow in the network can be delayed for a long period of time. To see this, Fig. 3 shows one run of the norm of the average estimation error covariance of all the three nodes. The channels are highly correlated with different qualities. In particular, channels from node 2 and 3 to node 1 are experiencing highly correlated deep fades. It can be seen that the overall performance is degraded considerably as node 1 can not reduce its error beyond $N = 1$ case and has to rely on itself. Such scenarios can be catastrophic to the robustness of cooperative mobile networks. To address this, we next propose an adaptive motion-planning algorithm to mitigate effects of highly correlated deep fades.

D. Randomization Through Adaptive Motion-planning

In Fig. 3, we showed how correlated deep fading can ruin the performance of a cooperative network considerably. If a channel gets uncorrelated from one transmission to the next, it naturally creates a randomization in the channel quality. This can be taken advantage of if the link is currently in a deep fade. However, for highly correlated channels, this can be more challenging as the channel can stay in deep fade for several steps. In such cases, we propose to introduce a randomization by taking larger steps. Increasing the step size (i.e. increasing the amplitude of vector m of Section III-B), in general, has its advantages (potential higher speed of convergence) and disadvantages (potential lower search resolution and higher energy cost). *Adapting* the step size, on the other hand, can keep the benefits of both smaller and larger step sizes as it only increases the step size if needed. In fading environments, adapting the step size can potentially help mitigate the impact of highly correlated deep fades. We propose to adapt the step size when highly correlated deep fades are experienced. If a node experiences low SNR links from all the other nodes (or from the majority of them) for a longer than a predefined period of time, it will then try to enforce randomization of link qualities by increasing its step size. Increasing its step size can decrease channel correlation, which can help leave deep fade spots. It should be noted, however, that due to the random and complex nature of wave propagation, there is no guarantee that a considerable performance improvement will be achieved all the time. The idea of enforcing time-variations in link qualities has also been used in the context of Digital Audio Broadcasting when encountering stop signs that are in deep fade.

To see the performance of our proposed communication-aware adaptive motion-planning, Fig. 4 shows the performance improvement gained through adaptation for the system parameters and channel initial conditions of Fig. 3. In this result, if a node experiences SNR below a threshold (10dB here) for three consecutive receptions from all the other nodes, then it will double its step size. It can be seen that proper adaptation to link qualities can enhance the performance considerably. Fig. 5 shows similar results when adapting the step size by tripling it. To see the performance for a case of a mobile target, Fig. 6 shows the performance for $A = \begin{bmatrix} 0.7 & 0 \\ 0 & 0.7 \end{bmatrix}$ and $Q = 0.05 I_2$ (target is initialized far from the origin and the sensors). The figure shows a case where node 1 is experiencing highly correlated low SNR channels from nodes 2 and 3 and can not improve its performance beyond $N = 1$ case (without adaptation). It also shows the performance gained through adaptation.

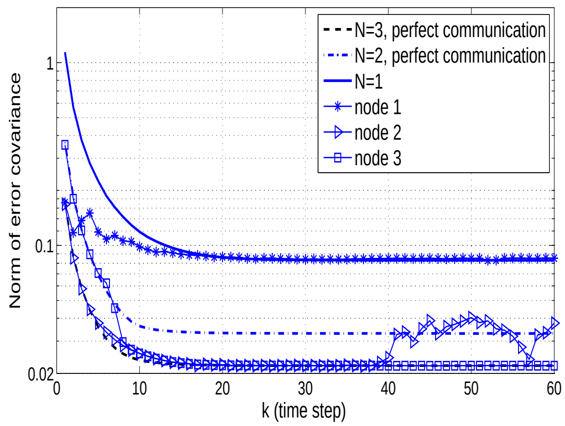

Fig. 3. Performance for highly correlated low SNR channels

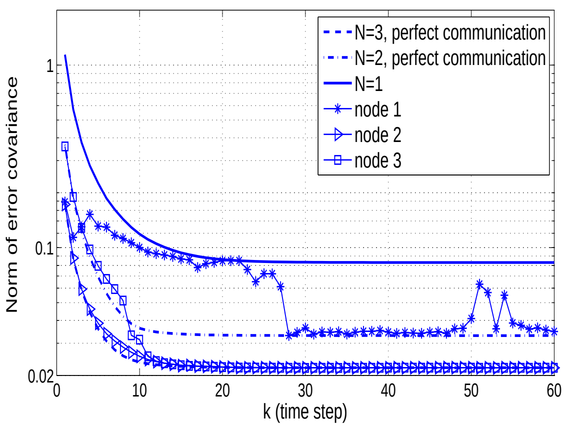

Fig. 4. Performance of the adaptive algorithm for highly correlated low SNR channels – step size is doubled in the event of correlated deep fade

IV. Summary

In this paper we considered the impact of mobile fading channels on decentralized mobile networks. We provided an abstraction of the physical layer for the purpose of motion-planning by characterizing communication noise and its variance as a function of the stochastic Signal to Noise Ratio. We showed how to incorporate mobile link quality measures such as SNR and correlation properties in the estimation and control process. We showed that as channel correlation decreases from one transmission to the next, the network can potentially benefit from the natural randomization of the link qualities to leave low SNR spots. On the other hand, for highly correlated channels, a node can be in a deep fade for a long period of time, which can ruin the performance considerably. To address this, we proposed a motion-planning strategy that adapts the step size according to channel correlation properties in order to enforce randomization of link qualities.

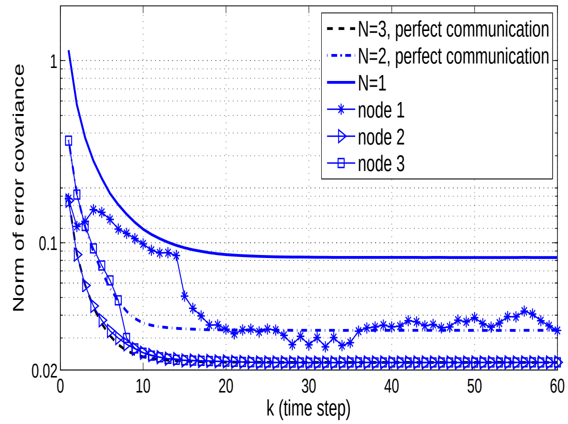

Fig. 5. Performance of the proposed algorithm for highly correlated low SNR channels – step size is tripled in the event of correlated deep fade

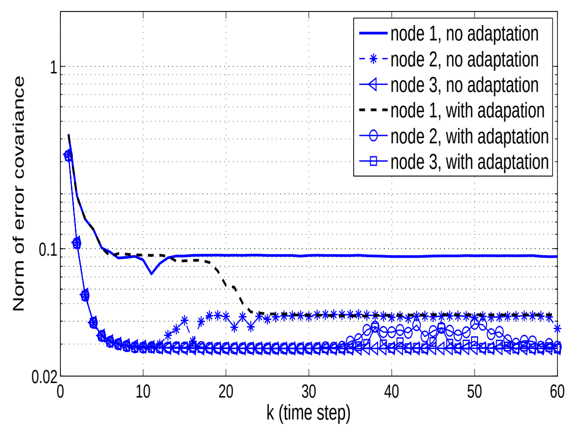

Fig. 6. Case of fast moving target – Performance of both non-adaptive and adaptive algorithms for highly correlated low SNR channels – for the adaptive case, step size is tripled in the event of correlated deep fade

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