J Intell Robot Syst (2009) 56:233–256
DOI 10.1007/s10846-009-9335-9

Decentralized Communication-Aware Motion Planning in Mobile Networks: An Information-Gain Approach

Yasamin Mostofi

Received: 16 April 2008 / Accepted: 20 April 2009 / Published online: 23 May 2009

Abstract In this paper we consider decentralized motion-planning in mobile cooperative networks in the presence of realistic stochastic communication links, including path-loss, fading and shadowing effects. We propose a communication-aware motion-planning strategy, where each node considers the information gained through both its sensing and communication when deciding on its next move. More specifically, we show how each node can predict the information gained through its communications, by online learning of link quality measures such as received Signal to Noise Ratio (SNR) and correlation characteristics, and combine it with the information gained through its sensing in order to build objective functions for motion planning. We show that in the presence of path loss, our proposed strategy can improve the performance drastically. We furthermore show that while uncorrelated low-SNR fading channels can ruin the overall performance, the natural randomization of uncorrelated channels can potentially help the nodes leave deep fade spots with small movements. We finally 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.

Keywords Decentralized motion-planning · Mobile cooperative networks · Stochastic communication links

Part of this work is presented in IPSN 2005 and ICRA 2008.

Y. Mostofi (✉)
Cooperative Network Lab, Electrical and Computer Engineering Department,
University of New Mexico, Albuquerque, NM 87131, USA
e-mail: ymostofi@ece.unm.edu

1 Introduction

Unmanned Autonomous Vehicles (UAVs) can play a key role in future 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. To realize this vision, a framework that properly addresses distributed reconfigurability in the presence of environment uncertainty is needed. For instance, consider a group of UAVs in charge of cooperative target tracking, perimeter defense or obstacle mapping. The network 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. The link quality, for instance, can change drastically in a short distance due to multipath fading, making robust motion-planning challenging. Furthermore, the environment could be harsh and uncertain in terms of sensing and navigation due to rubble, stairs, or blocking objects. Since the group needs to achieve the given task in a cooperative manner, it needs to maintain good connectivity with the rest of the nodes. At the same time, each node needs to gather direct information from its environment. Therefore, motion decisions of each node should consider both the information gained through direct sensing as well as communication. 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*. In this paper, we show how the nodes can predict the quality of the links and build motion-planning functions that combine both sensing and communication objectives.

Related work: Decentralized control of sensor motions has gotten considerable attention in recent years [1–5]. In particular, active sensing for robot positioning and trajectory generation has been explored. A survey of current work on active sensing for robotics is provided in [3]. Most of the current research in this area, however, assumes ideal or non-realistic 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. Authors in [6–8] have looked at the impact of communication channels on Kalman filtering over a wireless link and the conditions required for stability. Estimation over bandwidth-limited channels have also been explored [9]. Authors in [10–15] have looked at the impact of some aspects of a communication link like noise, quantization, fading, medium access and packet loss on wireless control of a mobile sensor. In the context of motion planning, however, communication-aware motion generation in the presence of realistic link models, such as fading, shadowing and path loss, has received little attention. Our work in [16] was one of the earliest to introduce the concept of communication-aware motion-planning in non-ideal communication environments. Author in [17] used our proposed framework of [16], with small modifications, which led to similar results. In [18], we extended the work of [16] for communication-aware motion-planning in uncertain environments.

The current paper is built on our past work with the goal of establishing a foundation for communication-aware motion planning in realistic communication environments including effects such as fading and shadowing. By *communication-aware motion-planning*, we are referring to a motion-planning strategy that takes link quality predictions into account. We show that our proposed strategy can improve the performance considerably in the presence of path loss. We furthermore explore the impact of fading on the network. 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 highly 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 online 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. In summary, the contribution of the paper is threefold. First, a framework is provided for modeling and abstraction of realistic wireless links for the purpose of cooperative motion planning. Second, we show how each node can predict the information gained through its communications by online monitoring of link qualities. Third, we show how this prediction can be fused with local sensing objectives in order to build cost functions that result in the right tradeoff between information gained though sensing and communication. While the proposed framework is applicable to any UAV network, we show our results in the context of a team of UAVs in charge of cooperative target tracking. The paper is organized as follows. Section 2 describes our system model. In Section 3, we briefly summarize characterization of mobile channels including fading and path loss. Section 4 introduces our proposed

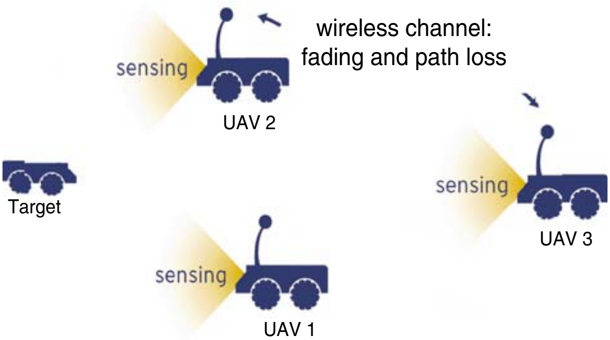


Fig. 1 Cooperative target tracking in the presence of realistic communication links

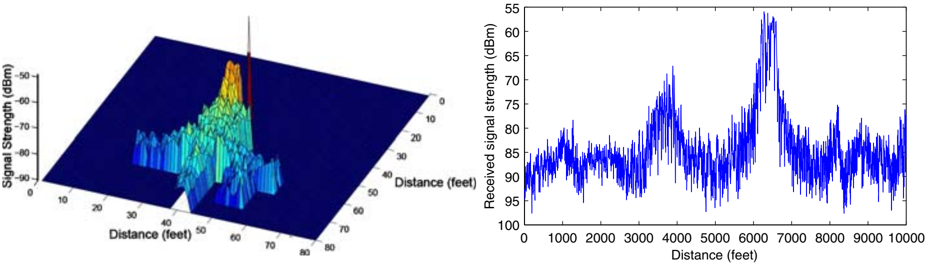


Fig. 2 (*Left*) A 2D measurement of the received signal strength in dBm—source at (40,30), courtesy of Sandia National Labs, (*right*) A measurement across a street in San Francisco, courtesy of Mark Smith [28]

communication-aware motion-planning strategy. Section 5 and 6 discuss the impact of path loss and fading respectively. We conclude in Section 7.

2 System Model

Consider N Unmanned Autonomous Vehicles that are in charge of cooperative target tracking, as is shown in Fig. 1. Each node has an estimate of the position of the target through direct local sensing. However, since its local sensing is not perfect, it also relies on getting the estimate of target position from other nodes in the network. The communication between the nodes is affected by path loss, fading and shadowing, which can impact the quality of the received information drastically. Figure 2 shows two examples of wireless channel measurements in outdoor urban environments. It can be seen that links are far from ideal and can change drastically in a short distance. Therefore, to ensure that the agents can accomplish the given task successfully and in a timely manner, realistic link models should be considered. Furthermore, link quality should be taken into account when motion-planning so that the units intelligently move to the locations that maximizes the overall information gained through both direct sensing and communication. We consider a target moving in a plane, with its state defined as its position with the following linear dynamics:

$$x[k+1] = Ax[k] + w[k]. \tag{1}$$

[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:

$$y_j[k] = x[k] + v_j[k]. \tag{2}$$

The observation noise, $v_j[k]$, is zero mean Gaussian with $R_j[k]$ representing its covariance matrix:

$$R_j[k] = \overline{v_j[k]v_j^T[k]}, \tag{3}$$

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

where "superscript T" denotes 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), as it will be the case in realistic scenarios. Table 1 contains a list of key variable used in this paper. Each node may use a local filter (such as a Kalman filter) to get a better estimate of the target position. Let $\tilde{y}_j[k]$, $e_j[k]$ and $\Pi_j[k]$ represent the local estimate of the j^{th} sensor, its corresponding error and its error covariance matrix after 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 $\tilde{y}_{j,i}[k]$ and $\Pi_{j,i}[k]$ represent the reception of the i^{th} node from the transmission of $\tilde{y}_j[k]$ and $\Pi_j[k]$ respectively. We will have,

$$\begin{aligned} \tilde{y}_{j,i}[k] &= \tilde{y}_j[k] + c_{j,i}[k] \quad c_{j,j}[k] = 0_{2\times 1} \\ \Pi_{j,i}[k] &= \Pi_j[k] + L_{j,i}[k] \quad L_{j,j}[k] = 0_{2\times 2},\ 1 \le i, j \le N, \end{aligned} \tag{4}$$

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 $\tilde{y}_j[k]$ and $\Pi_j[k]$ respectively and $0_{2\times 1}$ and $0_{2\times 2}$ represent the zero vector and matrix respectively. Let $\Sigma_{j,i}[k]$ represent the covariance matrix of $c_{j,i}[k]$:

$$\Sigma_{j,i}[k] = \overline{c_{j,i}[k] c_{j,i}^T[k]} = \Psi(\mathrm{SNR}_{j,i}[k]). \tag{5}$$

Table 1 List of key variables

$x[k]$	State of the network (target position) at time k	$n_{p,j,i}[k]$	Path loss exponent on the link from node j to node i at time k
$w[k]$	Process noise at time k	$\Psi(.)$	Function relating communication noise variance to SNR
Q	Process noise covariance	$\hat{x}_j[k]$	Estimate of node j after fusion at time k
$y_j[k]$	Local sensing of j^{th} node at time k	$\mathcal{I}_j[k]$	Information gain of node j at time k
$v_j[k]$	Local sensing noise of j^{th} node at time k	$\mathcal{I}_j^s[k]$	Info gain through local sensing of node j at time k
$R_j[k]$	Sensing noise covariance of j^{th} node at time k	$\mathcal{I}_{i,j}^c[k]$	Info gain of node j by communication with node i at time k
$\tilde{y}_j[k]$	Local estimate of j^{th} node (before fusion) at time k	$\mathcal{I}_{i,j}^l[k]$	Info loss from node i to node j at time k due to non-ideal link
$e_j[k]$	Local estimation error of j^{th} node at time k	$\mathcal{M}_j[k]$	Motion decision vector of node j at time k
$\Pi_j[k]$	Local estimation error covariance of j^{th} node at time k	$\sigma^2_{\mathrm{comm},i,j}[k]$	Comm. noise variance from node i to node j at time k
$\tilde{y}_{j,i}[k]$	Reception of i^{th} node of transmission of $\tilde{y}_j[k]$ at time k	$\mathrm{SNR}_{j,i}[k]$	SNR on the link from node j to node i at time k
$c_{j,i}[k]$	Comm. noise in transmission from node j to node i at time k	$\alpha_{j,i}[k]$	Path-loss parameter at time k
$\Sigma_{j,i}[k]$	Covariance matrix of $c_{j,i}[k]$ at time k	$d_{j,i}[k]$	Distance between nodes i and j at time k
$\Pi_{j,i}[k]$	Reception of i^{th} node of transmission of $\Pi_j[k]$ at time k		

$\Sigma_{j,i}[k]$ is a function of instantaneous received Signal to Noise Ratio (SNR) from node j to node i, as indicated by function $\Psi(.)$. Depending on the receiver design, the receiver may then drop all the erroneous packets or keep some of them (see [19] for more details). Independent of the receiver strategy, however, Eq. 5 is a measure of reception quality. If we only consider the impact of path loss, reception quality will be a function of the distance between two nodes. In fading environments, however, received SNR and the resulting reception quality will not merely be a function of the distance between the two nodes. We shall address both cases and their impact on motion-planning in this paper. Each sensor fuses its own measurement with the received ones to reduce its measurement uncertainty. It then makes a local decision about where to move next in order to maximize the overall information it gains through both direct sensing as well as communication.

2.1 Observation Model

To characterize the observation noise of each sensor, we follow the same model used in [20, 21]:

$$R_j = T(\theta_j) D_j(r_j) T^T(\theta_j), \tag{6}$$

where $T(\theta_j)$ is the rotation matrix:

$$T(\theta_j) = \begin{bmatrix} cos(\theta_j) & sin(\theta_j) \\ -sin(\theta_j) & cos(\theta_j) \end{bmatrix} \tag{7}$$

and

$$D_j(r_j) = \begin{bmatrix} f_j(r_j) & 0 \\ 0 & \gamma f_j(r_j) \end{bmatrix}, \tag{8}$$

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, as illustrated in Fig. 3. 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]. This means that, in the absence of communication constraints, the optimum position of the robot is at a distance from the target and not necessarily at the target. The reason for this is twofold. First, most

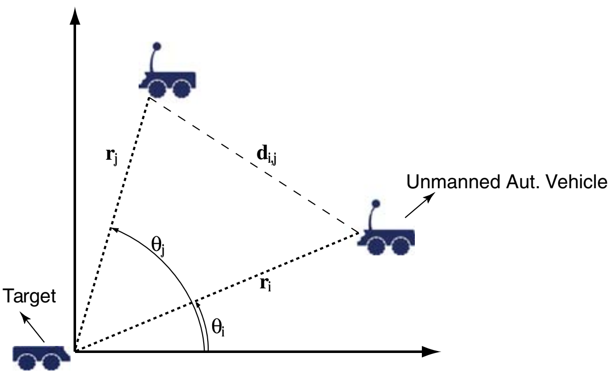


Fig. 3 Illustration of sensor and target positions

sensors do not work well if they are too far or too close to the object of interest (see [20, 21] for more details). Second, in the context of target tracking, the nodes may not want to get too close to the target. Instead, a distance that allows for good tracking without getting too close is optimum.

3 Physical Layer: Mobile Communications [27]

A wireless transmission is degraded by several factors, among which distance-dependent path loss, fading and receiver thermal noise are the most critical ones. As a result, some of the transmitted bits can be flipped which will manifest itself as noisy reception, as indicated by Eq. 4. Most literature on motion-planning, however, do not consider these factors. As a result, communication-aware motion-planning strategies that can operate robustly in harsh uncertain outdoor environments are lacking, an issue that this paper addresses. In this section, we briefly review characteristics of realistic mobile communication links necessary for motion-planning. Readers are referred to [26, 29] for more details.

3.1 Distance-Dependent Path Loss

In the absence of fading (for instance if a strong line of sight component exists), channel attenuation can be modeled as a distance-dependent path loss. This means that the received signal power is only attenuated as a function of the distance between the two nodes. While this can not be the case all the time, due to the blocking and scattering objects, it can be the appropriate model from time to time, and is therefore worth exploring. In such cases, received Signal to Noise Ratio is the main parameter for channel characterization, as discussed next.

3.1.1 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 $\mathrm{SNR}_{j,i}[k]$ represent the instantaneous received Signal to Noise Ratio at k^{th} transmission from node j to node i. We will have

$$\mathrm{SNR}_{j,i}[k] = \frac{|h_{j,i}[k]|^2 \sigma_s^2}{\sigma_T^2}, \tag{9}$$

where $\sigma_s^2 = \mathbb{E}(|s|^2)$ is the transmitted signal power, $\sigma_T^2 = \mathbb{E}(|n_{\mathrm{thermal}}|^2)$ is the power of the receiver thermal noise and $h_{j,i}[k] \in \mathbb{C}$ represents the time-varying fading coefficient of the baseband equivalent channel during the k^{th} transmission from node j to node i. $\mathrm{SNR}_{j,i}[k]$ 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. For a distance-dependent path loss, we will have

$$\mathrm{SNR}_{j,i,\mathrm{path\ loss}}[k] = \frac{\alpha_{j,i}[k]}{d_{j,i}^{n_{p,j,i}[k]}[k]}, \tag{10}$$

where $d_{j,i}[k]$ is the distance between the i^{th} and j^{th} agents at time k and $n_{p,j,i}[k] > 0$ 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 [26].

3.2 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 channel modeling and as a result to motion-planning.

3.2.1 Channel Signal to Noise Ratio in Fading Environments

In the presence of fading, the instantaneous Signal to Noise Ratio, $\mathrm{SNR}_{j,i}[k]$, is not merely a function of the distance between the nodes, as was the case in the previous part. Instead, it becomes a non-stationary stochastic process whose average (averaged over both small-scale and large-scale fading), $\mathrm{SNR}_{j,i,\mathrm{ave}}[k]$, changes as a function of the distance between the transmitter and receiver. The average of fading is then dictated by the distance-dependent path loss. We will have,

$$\mathrm{SNR}_{j,i,\mathrm{fading}}[k] \sim \text{random process with}$$

$$\mathrm{SNR}_{j,i,\mathrm{ave}}[k] = \mathbb{E}(\mathrm{SNR}_{j,i,\mathrm{fading}}[k]) = \frac{\alpha_{j,i}[k]}{d_{j,i}^{n_{p,j,i}[k]}[k]}. \tag{11}$$

The distribution of $\mathrm{SNR}_{j,i}[k]$ 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 $\mathrm{SNR}_{j,i}$ to be exponentially distributed, which is the model we will adopt (without loss of generality) in order to generate fading channels. For other distributions as well as models for large-scale fading, see [23] and [29].

3.2.2 Channel Correlation Characteristics

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 or shadowing). 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.

3.3 Communication Noise Variance

Poor link quality can result in some of the transmitted bits to be flipped, resulting in the noisy reception of the transmitted positions and covariances (see Eq. 4). Let $c_{j,i}^{(1)}[k]$ and $\Sigma_{j,i}^{(1,1)}[k]$ represent the communication noise in the reception of the position along the x-axis and its corresponding variance respectively. We have

$$\Sigma_{j,i}^{(1,1)}[k] = \mathbb{E}\big(|c_{j,i}^{(1)}[k]|^2 | h_{j,i}[k]\big), \tag{12}$$

which will be a function of $\mathrm{SNR}_{j,i}[k]$:

$$\Sigma_{j,i}^{(1,1)}[k] = \Psi^{(1,1)}(\mathrm{SNR}_{j,i}[k]), \tag{13}$$

where $\mathrm{SNR}_{j,i}[k]$ is the instantaneous received Signal to Noise Ratio in the transmission from the j^{th} agent to the i^{th} one, and $\Psi(.)$ is defined for Eq. 5. More specifically, if the channel is only experiencing path loss, we will have $\mathrm{SNR}_{j,i}[k] = \mathrm{SNR}_{j,i,\text{path loss}}[k]$ and if it also experiences fading, we will have $\mathrm{SNR}_{j,i}[k] = \mathrm{SNR}_{j,i,\text{fading}}[k]$. In the latter, communication noise variance will become a random process through its dependency on $\mathrm{SNR}_{j,i}[k]$. Ψ is a non-increasing function that depends on the transmitter and receiver design principles as well as the transmission environment.

3.3.1 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 [26]. Let q and N_b represent the quantization step size and the number of quantization bits respectively. Then we have shown that the communication noise variance will be [10]:

$$\Sigma_{j,i}^{(1,1)}[k] = \frac{q^2}{12} + \frac{4^{N_b} - 1}{3} q^2 \times \Omega(\sqrt{\mathrm{SNR}_{j,i}[k]}), \tag{14}$$

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. 4.

3.4 Packet Drop

We saw in the previous parts that poor link quality can result in noisy reception. The receiver can then decide to either keep the received packet or drop it. The criteria for making this decision vary depending on the application. Data networks, for example, are not as sensitive to delays since the application is not real time. The receiver, therefore, can afford to drop erroneous packets and wait for retransmission. The amount of tolerable bit error rate is therefore set on the order of 10^{-8}, which is considerably low [23]. Voice applications such as cellular networks, on the other hand, are sensitive to delays. In every transmitted bit stream, there are key bits embedded for synchronization and other crucial tasks. If these bits get corrupted, the receiver drops the transmitted stream. However, once these bits are received accurately, the rest of the bit error rate is either corrected through channel coding or tolerated [22] since there is no time for retransmission. The level of tolerable bit error rate is therefore set considerably higher, on the order of 10^{-3} [23]. Estimation and control of dynamical systems over wireless links is an emerging application for which new communication design paradigms should be developed. Control applications are typically delay sensitive as we may be racing against the dynamics of the system under observation (such as a moving target in our case). While optimization of packet drop design is out of the scope of this paper (readers are referred to [19, 24] for more details), reception quality before dropping the packets is a good measure for communication-aware motion-planning independent of packet drop decision, as we shall use it in this paper. Reception quality, i.e. communication noise and its variance, translates Signal to Noise Ratio to a noise-like metric, which could then be compared with the sensing error.

4 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 online learning of channel characteristics. Figure 4 shows our envisioned approach for integrating local sensing and communication objectives in fading environments. Every transmitted packet contains training bits, which every node will utilize to estimate received SNR (this is done in all communication receivers [23]). 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. Finally each agent builds a cost function that reflects both sensing and communication costs and chooses a motion decision that minimizes it. The main challenge in building an appropriate cost function is for each node to predict the information it will gain through direct sensing and communication as a function of the next move. Furthermore, 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

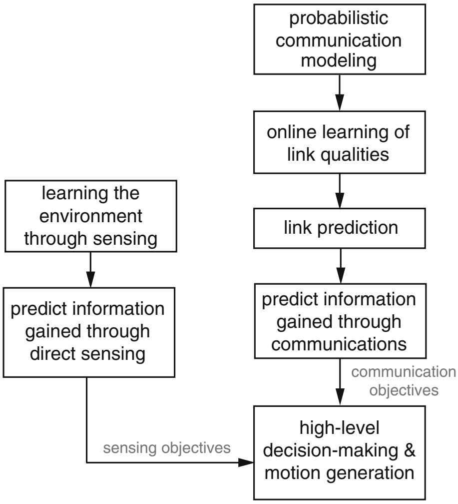


Fig. 4 Integration of communication & local sensing objectives in motion planning

solutions, where every agent makes a local decision on where to go next, without having any knowledge of where others would go. These issues make achieving optimal solutions challenging. In the next few subsections, we discuss our proposed strategies to address these challenges.

4.1 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 (see Eq. 4). We will have the following for the reception of the j^{th} node from the transmission of the i^{th} one,

$$\tilde{y}_{i,j}[k] = x[k] + \underbrace{e_i[k]}_{\text{function of local sensing quality}} + \underbrace{c_{i,j}[k]}_{\text{function of comm. link qualities}}, \tag{15}$$

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. Note that considering reception quality before potential dropping allows us to quantify the impact of communication links (in the form of the communication noise covariance) in such a way that can be compared with sensing quality. Let $\hat{x}_j[k]$ represent the estimate of the j^{th} node of the position of the target after fusing the received and local information at time step k. Then the following represents the Best Linear Unbiased Estimator (BLUE) of target position based on the received information [25]:

$$\hat{x}_j[k] = \sum_{i=1}^{N} \rho_{i,j}[k]\tilde{y}_{i,j}[k] \tag{16}$$

$$\text{where } \rho_{i,j}[k] = \arg\min \mathbb{E}|\hat{x}_j[k] - x[k]|^2 \tag{17}$$

$$\text{such that } \mathbb{E}\hat{x}_j[k] = x[k]. \tag{18}$$

We will have

$$\hat{x}_j[k] = \left(\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k]\right)^{-1} \sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k]\tilde{y}_{i,j}[k], \tag{19}$$

where

$$P_{i,j}[k] = \Pi_i[k] + \Sigma_{i,j}[k]. \tag{20}$$

Then $\hat{P}_{i,j}[k]$ represents the estimate of $P_{i,j}[k]$ based on the received information, i.e. by replacing $\Pi_i[k]$ by $\Pi_{i,j}[k]$ and estimating $\Sigma_{i,j}[k]$ 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 $\Pi_i[k]$ by the communication noise, the overall fusion performance differs from a typical BLUE estimator and can be proved to be as follows:

$$\mathbb{E}\{(\hat{x}_j[k] - x[k])(\hat{x}_j[k] - x[k])^T\} = \left(\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k]\right)^{-1} \times \sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k] P_{i,j}[k] \hat{P}_{i,j}^{-1}[k] \times \left(\sum_{i=1}^{N} \hat{P}_{i,j}^{-1}[k]\right)^{-1}. \tag{21}$$

4.2 Decentralized Communication-Aware Motion-Planning

Consider the overall estimation error covariance of the j^{th} node, as indicated by Eq. 21. Consider the case that the j^{th} node could perfectly estimate $P_{i,j}$ of Eq. 21, i.e. $\hat{P}_{i,j} = P_{i,j}$ (we will relax this assumption). Then the information gain matrix can be defined as follows for the j^{th} node:

$$\mathcal{I}_j[k] = \underbrace{\mathcal{I}_j^s[k]}_{\text{information gained through local sensing}} + \sum_{i \neq j} \underbrace{\mathcal{I}_{i,j}^c[k]}_{\text{information gained through communication from node } i}, \tag{22}$$

where $\mathcal{I}_j[k] = [\mathbb{E}\{(\hat{x}_j[k] - x[k])(\hat{x}_j[k] - x[k])^T\}]^{-1}$ represents the overall information gain (through its relationship with Fisher information),

$$\mathcal{I}_j^s[k] = \Pi_j^{-1}[k] \tag{23}$$

represents the information gained through direct local sensing and

$$\mathcal{I}_{i,j}^c[k] = \left[(\mathcal{I}_i^s[k])^{-1} + \Sigma_{i,j}[k]\right]^{-1} \tag{24}$$

denotes the information gained through communication from the i^{th} node. By assuming that the communication noises in the transmissions of different elements of vector $y_{i,j}$ are i.i.d (this will be the case for several communication environments/parameters [26]), we will have $\Sigma_{i,j}[k] = \sigma^2_{\text{comm},i,j}[k]I$, where I denotes the identity matrix and

$\sigma^2_{\mathrm{comm},i,j}[k]$ represents communication noise variance per element (or per reception from node i to node j). We have,

$$\begin{aligned}\mathcal{I}^c_{i,j}[k] &= \left[(\mathcal{I}^s_i[k])^{-1} + \sigma^2_{\mathrm{comm},i,j}[k]I\right]^{-1} \\ &= \mathcal{I}^s_i[k] - \sigma^2_{\mathrm{comm},i,j}[k]\mathcal{I}^s_i[k]\left(I + \sigma^2_{\mathrm{comm},i,j}[k]\mathcal{I}^s_i[k]\right)^{-1}\mathcal{I}^s_i[k] \\ &= \underbrace{\mathcal{I}^s_i[k]}_{\text{information gained by node } i \text{ through local sensing}} \\ &\quad \underbrace{- U^s_i[k]\begin{bmatrix}\frac{(\lambda^s_{i,1}[k]\sigma_{\mathrm{comm},i,j}[k])^2}{1+(\lambda^s_{i,1}[k]\sigma_{\mathrm{comm},i,j}[k])^2} & 0 \\ 0 & \frac{(\lambda^s_{i,2}[k]\sigma_{\mathrm{comm},i,j}[k])^2}{1+(\lambda^s_{i,2}[k]\sigma_{\mathrm{comm},i,j}[k])^2}\end{bmatrix}(U^s_i[k])^T}_{\mathcal{I}^l_{i,j}[k]:\ \text{information loss due to non-ideal link from node } i \text{ to node } j} \end{aligned} \tag{25}$$

where $U^s_i[k]$ is a matrix whose columns are the eigenvectors of $\mathcal{I}^s_i[k]$ with $\lambda^s_{i,1}[k]$ and $\lambda^s_{i,2}[k]$ representing the corresponding eigenvalues. $\mathcal{I}^l_{i,j}[k]$ of Eq. 25 quantifies the loss of information incurred due to non-ideal communication links. Therefore, the overall information is reduced compared to the case of ideal communication, as expected, and is lower bounded by the local information gain:

$$\mathcal{I}^s_j[k] \preceq \mathcal{I}_j[k] \preceq \sum_i \mathcal{I}^s_i[k], \tag{26}$$

where $\preceq$ denotes matrix inequality. Figure 5 shows the overall information gained by the j^{th} node and its components, i.e. the information gained through its local sensing as well as through its communications with other nodes. Let $\mathcal{M}_j[k]$ denote the motion vector of the j^{th} node at time step k. Then $\mathcal{M}_j[k]$ should be chosen such that $\mathcal{I}_j[k+1]$ is minimized. Since the j^{th} node can not exactly calculate $\mathcal{I}_j[k+1]$ for

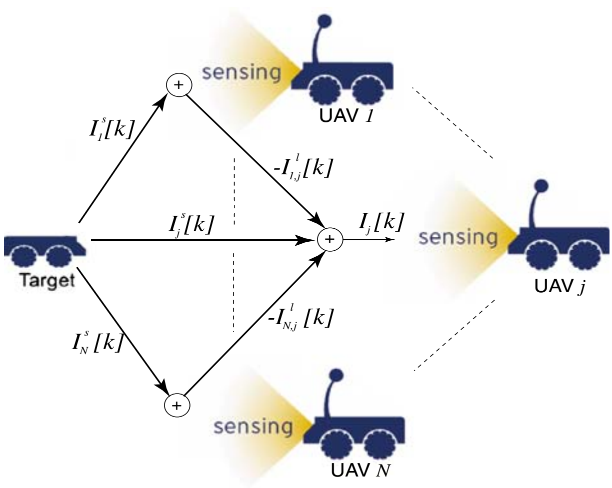


Fig. 5 An illustration of the information gained through direct sensing and communications for node j—transfer of information over wireless links results in an information loss

the possible set of motions, it will predict it based on online learning of link qualities. Then the j^{th} node will form the following optimization problem:

$$\mathcal{M}_j^*[k] = \arg\max \quad \Gamma\left(\hat{\mathcal{I}}_j\big[k+1, \mathcal{M}_j[k]\big]\right), \tag{27}$$

where $\hat{\mathcal{I}}_j\big[k+1, \mathcal{M}_j[k]\big]$ represents the prediction of the j^{th} node of its information gain at time step $k+1$, as a result of motion decision $\mathcal{M}_j[k]$. Function Γ maps the predicted information gain matrix to a scalar value. Possible choices are determinant, spectral norm, Frobenius norm and trace, as discussed in [3]. $\mathcal{M}_j[k]$ belongs to a finite set of possible motion vectors at time step k. For instance, in the absence of obstacles, possible motion set could consist of a number of vectors with constant amplitude but different phases that are equally distributed between 0 and 2π. We have the following information gain prediction:

$$\begin{aligned}\hat{\mathcal{I}}_j\big[k+1, \mathcal{M}_j[k]\big] &= \hat{\mathcal{I}}_j^s\big[k+1, \mathcal{M}_j[k]\big] + \sum_{i\neq j} \hat{\mathcal{I}}_{i,j}^c\big[k+1, \mathcal{M}_j[k]\big] \\ &= \hat{\mathcal{I}}_j^s\big[k+1, \mathcal{M}_j[k]\big] + \sum_{i\neq j}\left(\hat{\mathcal{I}}_i^s\big[k+1, \mathcal{M}_j[k]\big] - \hat{\mathcal{I}}_{i,j}^l\big[k+1, \mathcal{M}_j[k]\big]\right),\end{aligned} \tag{28}$$

where $\hat{\mathcal{I}}_j^s\big[k+1, \mathcal{M}_j[k]\big]$ and $\hat{\mathcal{I}}_i^s\big[k+1, \mathcal{M}_j[k]\big]$ for $i \neq j$ represent the prediction of the j^{th} node of its own local error covariance and the local error covariance of the i^{th} node respectively and can be obtained by propagating the corresponding Kalman filters one step ahead. Furthermore, the j^{th} node can use $\hat{x}_j[k]$ as well as any information available on the dynamics of target movement (such as Eq. 1) to predict the next state of the target. $\hat{\mathcal{I}}_{i,j}^l\big[k+1, \mathcal{M}_j[k]\big]$ denotes prediction of the j^{th} node of the information loss that will occur in communication from the i^{th} node and will be formed by predicting $\sigma_{\text{comm},i,j}\big[k+1, \mathcal{M}_j[k]\big]$. The j^{th} node can predict $\sigma_{\text{comm},i,j}\big[k+1, \mathcal{M}_j[k]\big]$ using the estimates available on the positions of other nodes, channel correlation and SNR properties. By incorporating a measure of link qualities in the overall cost function, we build a communication-aware motion-planning strategy that constantly guides the nodes to positions that will maximize the overall information gain. We will show the performance of the proposed strategy with an emphasis on the impact of communication imperfections such as path loss and fading.

5 Impact of Distance-Dependent Path Loss

In this section, we first consider the impact of path loss (no fading) on decentralized motion-planning and show the performance of the proposed communication-aware motion-planning strategy. Before doing so, it would be of interest to characterize the optimum network configuration from a global perspective for the sake of comparison. In [1], it was shown that for the case of perfect communication, in the absence of a local Kalman filter and for a fixed target position, the optimum configuration of the nodes is on the sweet spot radius (assuming that the nodes have the same f function) and with the angle difference of $\frac{k\pi}{N}$ for $k = 1, \ldots, N-1$. In the presence of imperfect communication links, however, finding the optimum configuration analytically is not

Table 2 System parameters

Sensing parameters	
f	$0.0008(r-15.625)^2+0.1528$
γ	5
Q	$.01I_2$
Communication parameters	
q	0.0018
N_b	15
n_p	2

feasible. In [16], we characterized the optimum configuration in the presence of path-loss and for two UAVs with $n_p = 2$, through a brute-force search. For the system parameters of Table 2, Table 3 summarizes the results, where Δ_{opt} represents the angle difference between the two UAVs and α is as defined in Section 3.1 (note that the optimum radius will still be the sweet spot radius). The table shows the angle for different link qualities, i.e. different αs. We will use this result as a benchmark to compare the performance of a decentralized network.

5.1 Performance without a Communication-Aware Motion-Planning Approach

To see the performance without having a communication-aware motion-planning strategy, Fig. 6 shows sensor trajectories for $N = 2$, system parameters of Table 2, $\alpha = 5700$ and for 50 time steps (target is almost stationary). In this case, the motion planner of each UAV assumes that the links are perfect, while they are not. As can be seen, the algorithm does not converge to the corresponding angle indicated in Table 2. The sensors are acting independently as if $N = 1$, which means that they will traverse the sweet spot radius, without finding the optimum angle [16].

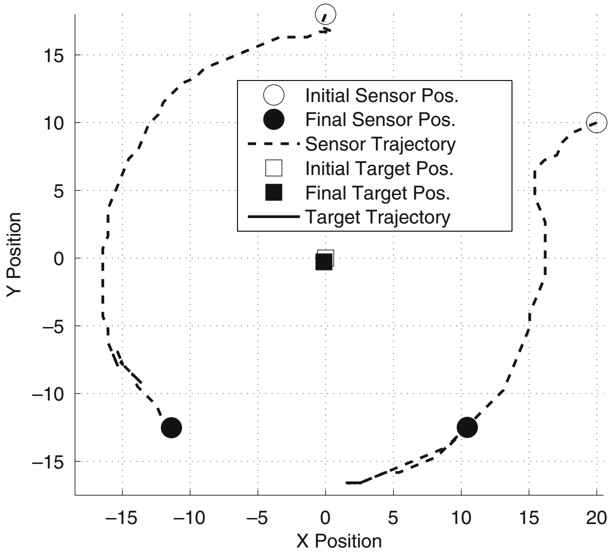
5.2 Performance of the Proposed Communication-Aware Motion-Planning Strategy

Next we consider the performance of the proposed communication-aware motion-planning approach of Section 4 in path-loss (no fading) environments in order to motivate motion planning in fading environments (see [16] for more details on performance in path-loss environments). In this case, link qualities are taken into account when predicting the overall information gain of Eq. 28. Figures 7, 8 show the performance of the proposed algorithm in the presence of path loss but with no fading and for the parameters of Table 2 (almost stationary target). Figure 7 shows sensor trajectories for 50 time steps, $N = 2$ and $\alpha = 570$. After 50 time steps, we have $\Delta[50] = 13.5°$, $r_1[50] = 16$ and $r_2[50] = 16.1$. Comparing these values with the corresponding optimal ones in Table 3 shows convergence of the decentralized algorithm to the optimal locations. It should be noted that the optimum distance from the target is defined by function f in Table 2 and is not zero. The sweet spot

Table 3 Optimal angle for the case of two UAVs experiencing path-loss (no fading) [16]

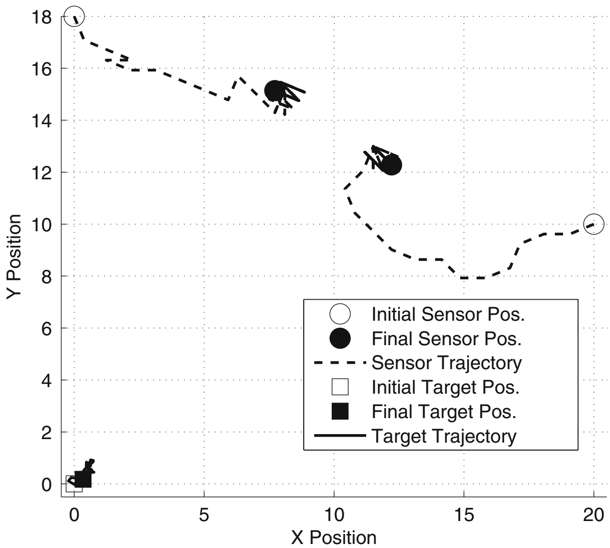
	Perfect comm	Distance-dependent path loss		
		$\alpha = 570$	$\alpha = 5700$	$\alpha = 57000$
Δ_{opt}	90°	18°	70.56°	90°

Fig. 6 Performance of motion planning in a path-loss environment when link qualities are not taken into account, UAVS move on the sweet spot radius without finding the optimum angle—$N = 2$ and $\alpha = 5700$ [16]



radius is 15.625 in this case, which is the distance the nodes have from the target in Fig. 7. We can see that by learning and accounting for communication links in the decision-making process, we improve the performance considerably. Figure 8 shows the determinant of the error covariance of one of the sensors (after fusion) as a function of time, for two different channels and for $N = 5$. For comparison, performance with perfect communication links is also plotted. We can see that for $\alpha = 5700$, the error stays very close to that of the ideal communication from the beginning. For $\alpha = 570$, the sensors start out acting individually but can find the

Fig. 7 Performance of the proposed communication-aware motion-planning algorithm in the presence of path-loss, $N = 2$, $\alpha = 570$; the nodes achieve the optimum configuration which is on the sweet spot radius with an angle of 18° (see [16] for more details)



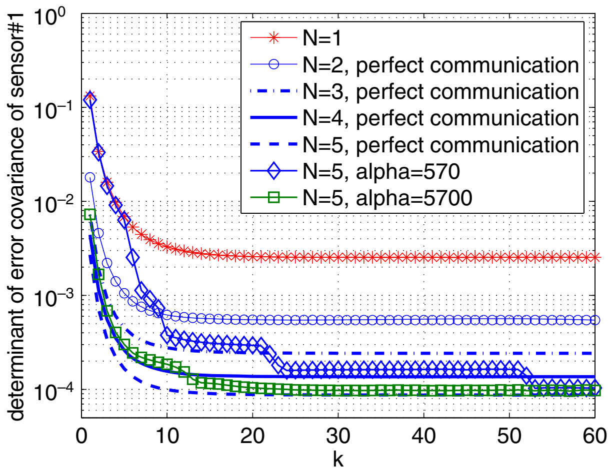


Fig. 8 Performance of the proposed communication-aware motion-planning algorithm in the presence of path-loss, $N = 5$

optimum configuration quickly resulting in the error reaching very close to that of the ideal communication case after a few time steps. The convergence gets faster as the quality of the link improves. Convergence time is also a function of the initial positions of the UAVs and may be different for different nodes of the network. The error is always bounded by that of a single sensor case, independent of the quality of the links, since the proposed strategy properly weigh the communicated data based on estimating link qualities.

To see the performance of the proposed algorithm when the target is moving faster, consider the performance for $A = .7I$, $Q = .1I$ (I denotes the identity matrix)

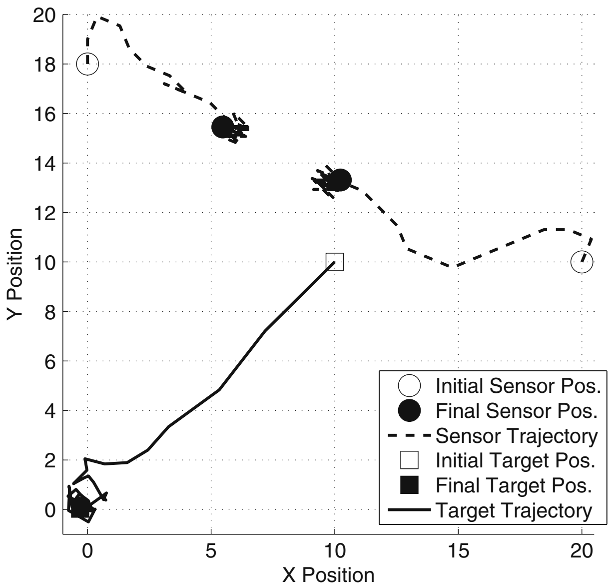


Fig. 9 Performance of the proposed communication-aware motion-planning algorithm in the presence of path-loss—case of a fast moving target, $N = 2$

and with the rest of the parameters as summarized in Table 2 (target is initialized far from the origin). Figure 9 shows how the UAVs track the target for $N = 2$, $\alpha = 570$ and 50 time steps. Performance curve of this case is similar to Fig. 8.

6 Communication-Aware Motion Planning in Fading Environments

In the previous section we showed that the proposed communication-aware motion planning approach works robustly in the presence of path loss. In fading environments, channels can behave more sporadically which makes designing robust decentralized cooperative networks more challenging. In particular, prediction of link qualities and as a result the information loss terms of Eq. 28 becomes more challenging. In this section we consider decentralized motion-planning in fading environments using the proposed communication-aware information-gain approach of the previous section. We furthermore propose to utilize channel correlation properties in order to predict link qualities and as a result the overall information gain of Eq. 28 more accurately. We emphasize the importance of channel correlation properties and discuss two cases of uncorrelated and highly-correlated channels. It was shown in Section 5.1 that the already existing motion-planning strategies (with no communication-aware approach) perform considerably poorly in the presence of path loss. It should be noted that they perform even worse with fading.

6.1 Uncorrelated Fading

By uncorrelated fading channels, we refer to channels that get uncorrelated from one transmission to the next. Consider Eq. 25. $\sigma^2_{\mathrm{comm},i,j}[k]$ is a function of $\mathrm{SNR}_{i,j}[k]$: $\sigma^2_{\mathrm{comm},i,j}[k] = \psi(\mathrm{SNR}_{i,j}[k])$, where function $\psi(.)$ denotes the dependency of $\sigma^2_{\mathrm{comm},i,j}[k]$ on $\mathrm{SNR}_{i,j}[k]$. In fading environments, $\mathrm{SNR}_{i,j}[k]$ is a random process with $\mathrm{SNR}_{i,j,\mathrm{ave}}[k]$ denoting its average, as described in Section 3.2. Then $\sigma^2_{\mathrm{comm},i,j}[k]$ and as a result $\mathcal{I}^c_{i,j}[k]$ become random processes. To see the impact of fading on cooperative target tracking of a team of UAVs, consider a network of three UAVs that are tracking a target. Figure 10 shows the performance of the proposed communication-aware motion-planning algorithm when the channels change rapidly and get uncorrelated from one transmission to the next. The figure shows the overall average norm (Frobenius norm[2]) of the estimation error covariance matrix for 60 time steps for $N = 3$, system parameters of Table 2 and for different αs (see Section 3.2 for details of fading channels). The target is almost stationary in 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 3.2. The best channel has $\alpha = 57000$ (see Eq. 10), which corresponds to a fading channel with the average SNR of 27 dB at a distance of 10 m, whereas $\alpha = 5700$ corresponds to an average SNR of 17 dB at the same distance (all realistic scenarios). For comparison, the performance for perfect communication is also plotted.

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

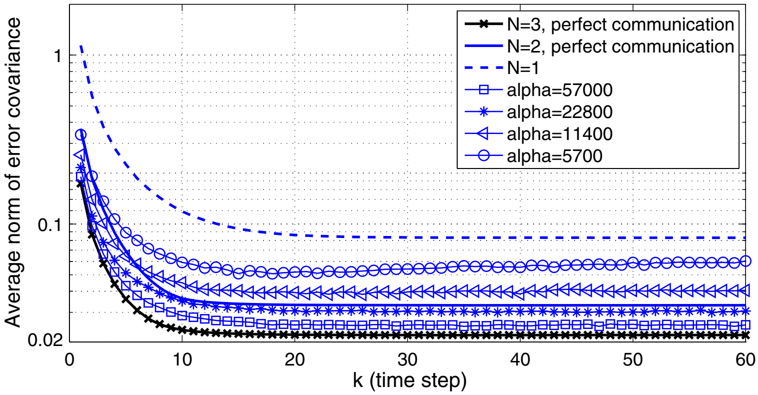


Fig. 10 Performance of the proposed communication-aware motion-planning approach for uncorrelated fading channels, $N = 3$

It can be seen that the higher average SNR is, the closer the performance is to the perfect case. As the channel quality gets worse, however, the performance degrades. For instance, for $\alpha = 5700$, the performance gets closer to the $N = 1$ case, which means that the nodes can not benefit from cooperation. It should, however, be noted that any already-existing motion-planning strategy that is not aware of its impact on link qualities would have performed considerably worse. Compared to the case with only path loss, the network will perform considerably better for channels with no fading but the same distance-dependent path-loss, as expected. 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 with little effort (small movement).

6.2 Highly-Correlated Fading

By a highly-correlated channel, we refer to a channel that stays correlated over several transmissions. Highly correlated fading 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 (see Section 3.2) can pose serious challenges as the information flow in the network can be interrupted for a long period of time (high information loss terms in Eq. 25). To see this, Fig. 11 shows one run of the norm of the average estimation error covariance of all the three nodes. The channels have different qualities but each channel stays highly correlated in the duration of simulation. In particular, channels from node 2 and 3 to node 1 are experiencing highly correlated deep fades (note that wireless channels are not necessarily symmetric as transmissions occur in different

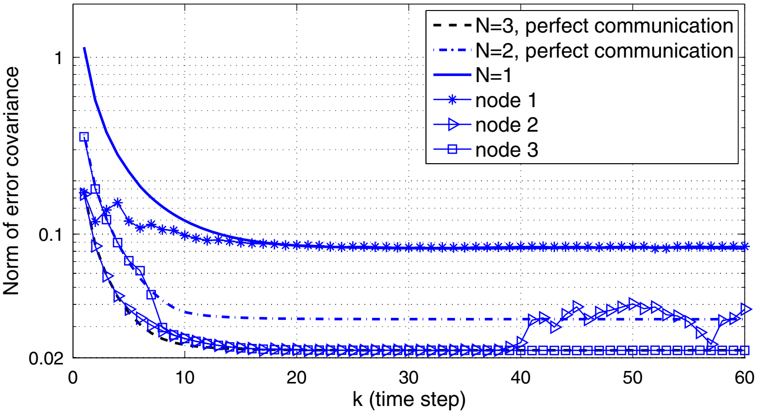


Fig. 11 Impact of highly correlated channels on motion planning—node 1 is experiencing highly-correlated low-SNR channels from nodes 2 and 3, which degrades its performance

frequencies). 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.

6.3 Randomization through Adaptive Motion-Planning

In Fig. 11, 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 a deep fade for several steps (for instance when a node's communication is blocked by a building for several movements). In such cases, we propose to introduce randomization by taking larger steps. Increasing the step size (i.e. increasing the amplitude of vector $\mathcal{M}_j[k]$ of Section 4.2), 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 UAV experiences low SNR links from majority of the UAVs 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. But it will increase the probability of it. The idea of

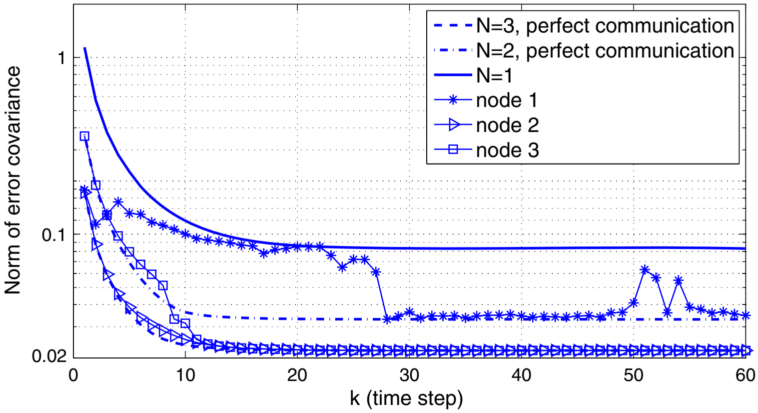


Fig. 12 Performance of the proposed adaptive communication-aware motion-planning strategy for highly correlated low SNR channels of Fig. 11, step size is doubled in the event of correlated deep fade

enforcing time-variations in link qualities has also been used in the context of Digital Audio Broadcasting [27] when encountering stop signs that are in deep fade.

To see the performance of our proposed communication-aware adaptive motion-planning, Fig. 12 shows the performance improvement gained through adaptation for the system parameters and channel initial conditions of Fig. 11 (at the beginning, node 1 is experiencing highly correlated poor-quality links from nodes 2 and 3). For this result, if a node experiences SNR below a threshold (10dB here) for three consecutive receptions from the other two nodes, then it will double its step size (it will go back to normal step size once this condition is not met anymore). It can be seen that proper adaptation to link qualities can enhance the performance considerably (compare the performance of node 1 with that of Fig. 11). Figure 13 shows similar results when adapting the step size by tripling it. To see the performance for a case

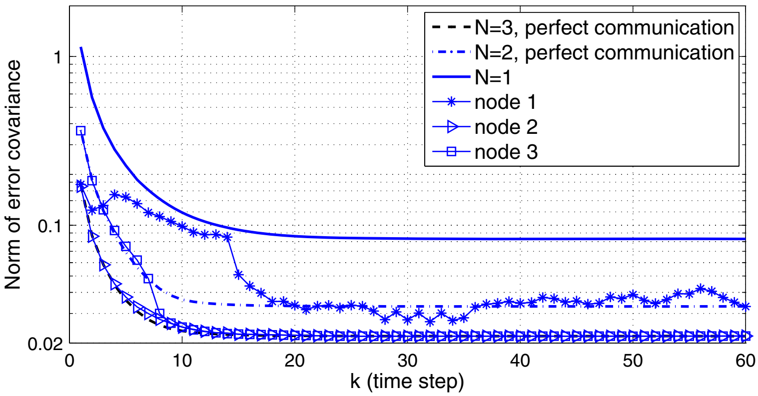


Fig. 13 Performance of the proposed adaptive communication-aware motion-planning strategy for highly correlated low SNR channels of Fig. 11, step size is tripled in the event of correlated deep fade

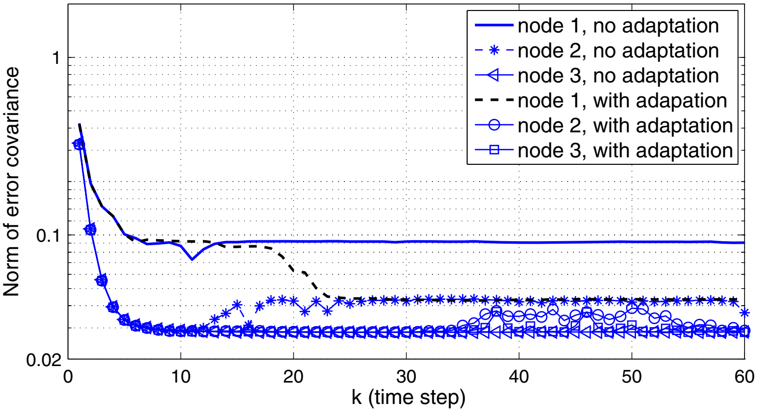


Fig. 14 Case of a fast moving target—Performance of both non-adaptive and adaptive algorithms for highly correlated low SNR channels—for the adaptive case, step size is tripled in the event of correlated deep fade

of a mobile target, Fig. 14 shows the performance for $A = \begin{bmatrix} 0.7 & 0 \\ 0 & 0.7 \end{bmatrix}$ and $Q = 0.05I$ (target is initialized far from the origin and the UAVs). 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.

7 Summary and Further Extensions

In this paper we considered decentralized motion planning and decision making for a team of Unmanned Autonomous Vehicles that are in charge of cooperative target tracking in realistic communication environments. We proposed a communication-aware motion-planning strategy, where each node considers the information gained through both its sensing and communication when deciding on its next move. More specifically, we showed how each node can predict the information gained through its communications, by online learning of link quality measures such as received Signal to Noise Ratio (SNR) and correlation characteristics, and combine it with the information gained through its local sensing in order to assess its overall information gain. We then showed the impact of path loss and fading on the performance of cooperative target tracking. We furthermore showed that as channel correlation decreases from one transmission to the next in fading environments, the network can potentially benefit from the natural randomization of 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. Our simulation results showed the superior performance of the proposed approach in realistic communication environments. While we did not explicitly discuss large-size networks, the proposed framework can be applied in a network of an arbitrary size in order to ensure that each UAV is connected to a minimum number of nodes or in order to maintain connectivity with neighbors.

References

1. Chung, T.H., Gupta, V., Burdick, J.W., Murray, R.M.: On a decentralized active sensing strategy using mobile sensor platforms in a network. In: 43rd IEEE Conf. on Decision and Control (2004)
2. Yang, P., Freeman, R.A., Lynch, K.M.: Distributed cooperative active sensing using consensus filters. In: IEEE International Conference on Robotics and Automation (2007)
3. Mihaylova, L., Lefebvre, T., Bruyninckx, H., Gadeyne, K., Schutter, J.D.: Active sensing for robotics—a survey. In: Proc. of the 5th Intl. Conf. on Numerical Methods and Applications, pp. 316–324 (2002)
4. Yeung, D., Bekey, G.A.: A decentralized approach to the motion planning problem for multiple mobile robots. In: Proc. of Intl. Conf. on Robotics and Automation, vol. 4, pp. 1779–1784 (1987)
5. Guo, Y., Parker, L.E.: A distributed and optimal motion planning approach for multiple mobile robots. In: Proc. of Intl. Conf. on Robotics and Automation, vol. 3, pp. 2612–2619 (2002)
6. Sinopoli, B., Schenato, L., Franceschetti, M., Poolla, K., Jordan, M., Sastry, S.: Kalman filtering with intermittent observations. IEEE Trans. Autom. Contr. **49**(9), 1453–1464 (2004)
7. Liu, X., Goldsmith, A.J.: Kalman filtering with partial observation losses. In: 43rd IEEE Conference on Decision and Control (2004)
8. Mostofi, Y., Murray, R.: On dropping noisy packets in Kalman filtering over a wireless fading channel. In: Proceedings of the 24th American Control Conference (ACC) (2004)
9. Ribeiro, A., Giannakis, G.B., Roumeliotis, S.I.: SOI-KF: distributed Kalman filtering with low-cost communications using the sign of innovations. IEEE Trans. Signal Process. **54**(12), 4782–4795 (2006)
10. Mostofi, Y., Murray, R.: Effect of time-varying fading channels on the control performance of a mobile sensor node. In: Proceedings of 1st IEEE International Conference on Sensor and Adhoc Communications and Networks (2004)
11. Xiao, L., Johansson, M., Hindi, H., Boyd, S., Goldsmith, A.: Joint optimization of communication rates and linear systems. IEEE Trans. Autom. Contr. **48**(1), 148–153 (2003)
12. Liu, X., Goldsmith, A.: Wireless communication tradeoffs in distributed control. In: 42nd IEEE Conference on Decision and Control, vol. 1, pp. 688–694 (2003)
13. Liu, X., Goldsmith, A.J.: Wireless medium access control in distributed control systems. In: Allerton Conference on Communication, Control and Computing (2003)
14. Tatikonda, S., Sahai, A., Mitter, S.: Control of LQG systems under communication constraints. In: IEEE 37th Conference on Decision and Control, vol. 1, pp. 1165–1170 (1998)
15. Spanos, D.P., Murray, R.M.: Robust connectivity of networked vehicles. In: 43rd IEEE Conf. on Decision and Control (2004)
16. Mostofi, Y., Chung, T., Murray, R., and Burdick, J.: Communication and sensing trade offs in decentralized mobile sensor networks: a cross-layer design approach. In: 4th International Conference on Information Processing in Sensor Networks (IPSN), Los Angeles, April 2005
17. Frew, E.: Information-theoretic integration of sensing and communication for active robot networks. ACM/Springer Mobile Networks and Applications Journal, Oct. 2008
18. Mostofi, Y.: Communication-aware motion planning in fading environments. In: IEEE International Conference on Robotics and Automation (ICRA), May 2008
19. Mostofi, Y., Murray, R.: To drop or not to drop: design principles for Kalman filtering over wireless fading channels. IEEE Trans. Autom. Contr. **54**(2), 376–381 (2009)
20. Ramachandra, K.V.: Kalman filtering techniques for radar tracking. Marcel Dekker, New York (2000)
21. Umeda, K., Ota, J., Kimura, H.: Fusion of multiple ultrasonic sensor data and imagery data for measuring moving obstacle's motion. In: Intl. Conf. on Multisensor Fusion and Integration for Intelligent Systems, pp. 742–748, December 1996
22. Goodman, D.: Wireless Personal Communications Systems. The Addison-Wesley Wireless Communications Series. Addison-Wesley, Reading (1997)
23. Goldsmith, A.: Wireless Communications. Cambridge University Press, Cambridge (2005)
24. Mostofi, Y., Murray, R.: Kalman filtering over wireless fading channels—how to handle packet drop. Int. J. Robust Nonlinear Control (Special Issue on Control with Limited Information) (2009, in press)

25. Kay, S.M.: Fundamentals of Statistical Signal Processing: Estimation Theory. Prentice Hall, Englewood Cliffs (1993)
26. Jakes, W.: Microwave Mobile Communications. IEEE, New York (1974)
27. Le Floch, B., Hallbert-Lasalle, R., Castellain, D.: Digital audio broadcasting to mobile receivers. IEEE Trans. Consum. Electron. **35**(3), 493–503 (1989)
28. Smith, W.M.: Urban propagation modeling for wireless systems. Ph.D. Thesis, Stanford University (2004)
29. Ghaffarkhah, A., Mostofi, Y.: Communication-aware navigation functions for robotic networks. Am. Control Conf. (ACC) (2009, to appear)