Utilizing Mobility to Minimize the Total Communication and Motion Energy Consumption of a Robotic Operation ⋆

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Abstract: It is a common assumption that motion costs more than communication and therefore it is always better to increase the transmit power of a robot, in a networked robotic operation, instead of moving to a spot that is better for communication. The goal of this paper is to see if and when this assumption is correct by considering both the communication and motion costs of a robotic operation. More specifically, we consider a scenario where a robot needs to transmit a given number of bits to a remote station under time constraint and Bit Error Rate (BER) requirement, and while minimizing the total energy consumption. The robot is allowed to move along a predefined trajectory and design its transmission rate/power and motion policy (motion speed and possible stop times) accordingly. We then address the following question: should the robot send the given information at its initial position, or spend energy on motion and move to a location with a better communication quality? By co-optimizing the communication and motion strategies of the robot, we characterize the properties of the optimum policy, which shows that under several conditions it is more beneficial for the robot to spend energy on motion in order to move to a location that is better for communication. We also discuss a special case to see how the channel parameters and motion energy model impact the motion decision of the robot. Our simulation results show that, by using our strategy, the robot can reduce its total energy cost significantly.

Keywords: Mobile robot, communication-aware motion planning, energy optimization.

1. INTRODUCTION

In recent years, considerable progress has been made in the area of mobile sensor networks and networked robotic systems Lu and Suda (2008); Jadbabaie et al. (2003); Cortes et al. (2004). In order to truly realize the full potential of these systems, an integrative approach to both communication and navigation issues is needed. Recently, such communication-aware navigation strategies have started to attract considerable attention Ghaffarkhah and Mostofi (2011); Lindhe and Johansson (2009).

In practice, energy resource of a mobile robot is typically very limited. Thus, a robot needs to efficiently plan the usage of its limited energy during the operation. Among these, motion is one of the major consumers. Communication can also be costly depending on the application. For instance, if the robot needs to send a large number of bits of information, such as high-quality images and videos, to a remote station, the communication energy cost can be significant. While individual optimization of communication and motion energy consumption has been heavily but separately explored in the communications/networking and robotics literature Goldsmith and Chua (1997); Mei et al. (2004), co-optimization of communication and motion energy consumption has received little attention so far. In Ooi and Schindelhauer (2009), the authors propose an efficient algorithm to find the path that minimizes the motion and communication energy costs. However, simplified path loss models are utilized to model the communication channels. In Yan and Mostofi (2012), a communication and motion co-optimization strategy is proposed to minimize the total energy consumption, under resource constraints, and for the case where a robot needs to move from an initial position to a given final destination.

In this paper, we are interested in answering the following question: Given a communication task, should the robot send the given information at its initial position, or spend energy on motion and move to a location with a better communication quality? More specifically, we consider a scenario where a robot needs to transmit a given number of bits of information to a remote station under time and BER constraints. The robot is allowed to move along a predefined trajectory (or equivalently move in a given area) and plan its transmission rate/power, motion speed and possible stop times accordingly, with the goal of minimizing its total energy consumption (including both communication and motion costs). Thus, the main difference between this work and Yan and Mostofi (2012) is that there is no final destination for the robot, which allows us to specifically address when motion will cost less than increasing the transmission power at the initial position. We show how the robot can co-optimize its motion and communication strategies. Furthermore, we consider a special case to see how the channel parameters and motion energy model impact the motion decision of the robot. Our

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analytical and simulation results indicate that in several scenarios, it is beneficial (results in a less total energy consumption) for the robot to spend energy to move to a better place for communication.

The rest of the paper is organized as follows. Section 2 describes the communication and motion models, and briefly discusses the probabilistic channel assessment framework of Mostofi et al. (2010); Malmirchegini and Mostofi (2012). Section 3 presents our proposed optimization framework. A special case is discussed to see when the robot should use its motion to save the total energy cost. Section 4 shows the performance of the proposed framework in a simulation environment. We conclude in Section 5.

2. PROBLEM SETUP

Consider the scenario where a robot is tasked with sending a fixed number of a priori-given bits of information (e.g. its sensing data) to a remote station, in a limited operation time and under a given BER constraint. The robot is allowed to move along a predefined trajectory $\mathcal{T}$ to find a position where the communication quality is high, in order to reduce its communication energy consumption. The predefined trajectory could, for instance, be the only feasible path due to the environmental constraints such as obstacles. The goal of the robot is to minimize its total energy cost, which includes the communication and motion energy costs. Fig. 1 shows an example of the considered scenario. The robot moves along a predefined trajectory to find a position where the communication quality is high, while transmitting the needed information to the remote station, under a given time budget and BER constraint. We are then interested in answering

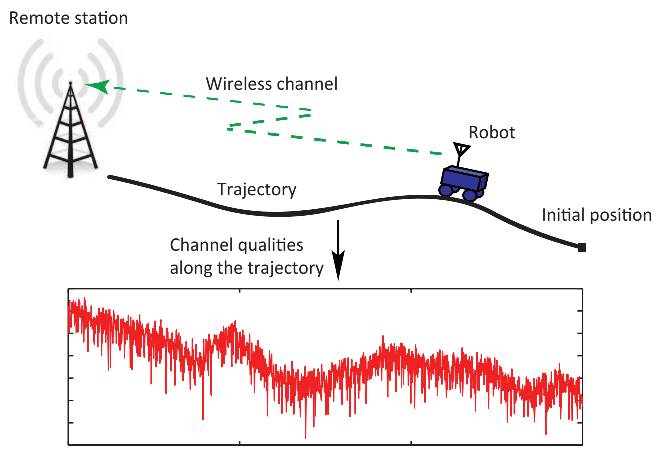

Fig. 1. The robot needs to transmit a number of given bits to the remote station, under a given time budget and BER constraint. It is allowed to move along a predefined trajectory to find a position where the channel quality is high. The goal of the robot is to minimize its total energy cost, including both communication and motion energy costs.

the following questions: *Should the robot just stay at its initial position, increase its transmission power as needed and transmit its data, or spend some motion energy to find a position where the communication quality is better?* For instance, in Fig. 1, it can be seen that the channel qualities are low around the initial position. So, under what condition is it worth to move along the given route, find a better communication spot, and then send the information? Also, if the robot should move, where should it move to? Finally, given the position where the robot should move to, what is the optimum communication and motion strategy? As can be seen, such assessments require the robot to evaluate the link quality along the trajectory before moving. In this section, we first discuss the existing models for the probabilistic modeling and prediction of a wireless channel. We then introduce the communication and motion cost models that are used in the paper.

2.1 Probabilistic Modeling of a Wireless Channel

As shown in the communication literature Goldsmith (2005), received CNR can be modeled as a multi-scale random process with three components: path loss, shadow fading (shadowing) and multipath fading. Let $\gamma(q)$ denote the received CNR in the transmission from a robot at position q to the remote station. By using a 2D non-stationary random field model, we have the following characterization for $\gamma(q)$ (in dB): $\gamma_{\mathrm{dB}}(q) = \alpha_{\mathrm{dB}} - 10\, n \log_{10}\left(\|q - q_b\|\right) + \gamma_{\mathrm{SH}}(q) + \gamma_{\mathrm{MP}}(q)$, where $\gamma_{\mathrm{dB}}(q) = 10 \log_{10}\left(\gamma(q)\right)$, q_b is the position of the remote station, α_{dB} and n are the path loss parameters, and $\gamma_{\mathrm{SH}}(q)$ and $\gamma_{\mathrm{MP}}(q)$ are independent random variables representing the effects of shadowing and multipath fading in dB. Consider the case where the robot has a small number of a priori-collected CNR measurements in the same operation environment. It can then probabilistically assess the CNR quality at an unvisited location based on these measurements. More specifically, a Gaussian random variable (in the dB domain), $\Upsilon_{\mathrm{dB}}(q)$, with the mean of $\overline{\Upsilon}_{\mathrm{dB}}(q)$, and the variance of $\sigma^2_{\mathrm{dB}}(q)$ can best characterize the CNR at an unvisited location $q \in \mathcal{T}$, where $\overline{\Upsilon}_{\mathrm{dB}}(q)$ and $\sigma^2_{\mathrm{dB}}(q)$ are functions of q and the a priori CNR measures. See Mostofi et al. (2010); Malmirchegini and Mostofi (2012) for more details and the performance of this framework with real data and in different environments.

In this paper, we discretize the predefined trajectory $\mathcal{T}$ into N sub-trajectories, $\mathcal{T}_i$s, for $i \in \{1, \cdots, N\}$, each with length l_i. Initially, the robot is located at the beginning of $\mathcal{T}_1$, and is able to move to $\mathcal{T}_i$ (traveling through $\mathcal{T}_2, \mathcal{T}_3, \cdots, \mathcal{T}_{i-1}$), for $i \in \{2, \cdots, N\}$, if needed. We assume that l_i is small enough, such that the channel along $\mathcal{T}_i$ can be considered stationary. To consider the most general case, we further allow l_is to be different from each other in order to account for the cases where the trajectory spans over a large area with changing environmental features (such as from indoor to outdoor), resulting in different stationary lengths in different parts of the trajectory. Then a Gaussian random variable, $\Upsilon_{\mathrm{dB}}(q_i) = \Upsilon_{\mathrm{dB},i}$, with the mean $\overline{\Upsilon}_{\mathrm{dB}}(q_i) = \overline{\Upsilon}_{\mathrm{dB},i}$ and variance $\sigma^2_{\mathrm{dB}}(q_i) = \sigma^2_{\mathrm{dB},i}$ can best characterize the distribution of CNR at $\mathcal{T}_i$, where $q_i \in \mathcal{T}_i$ Mostofi et al. (2010); Malmirchegini and Mostofi (2012). Note that the channel is still space-varying over each $\mathcal{T}_i$ due to multipath fading. The robot can adapt its strategy online after it moves to each $\mathcal{T}_i$ and measures the true value of the CNR. We do not discuss the online adaption strategy in this paper. See Yan and Mostofi (2012) for an example of such a strategy. [1]

[1] The formulation of this paper clearly holds if the full knowledge of the channel is available (as opposed to an estimation).

2.2 Communication Energy Model

In this paper, we assume MQAM modulation for the communication between the robot and the remote station. Then, we have the following approximated expression for BER Goldsmith (2005): $p_b(\gamma) \approx 0.2\exp\big(-1.5/(M-1) P_{\mathrm{C}}\gamma\big) = 0.2\exp\big(-1.5/(2^R-1)P_{\mathrm{C}}\gamma\big)$, where $p_b(\gamma)$ is the BER, P_{C} denotes the communication transmit power, M represents the modulation constellation size and $R = \log_2(M)$ is the spectral efficiency. This approximation is tight (within 1 dB) when 0 dB $< 10\log_{10}(P_{\mathrm{C}}\gamma) <$ 30 dB Goldsmith (2005).

In practice, R is subject to an integer constraint. Hence, in this paper, we assume that the robot can only choose R from a finite set of integers $\mathcal{R} = \{R_0, R_1, \cdots, R_{|\mathcal{R}|}\}$, where $0 = R_0 < R_1 < \cdots < R_{|\mathcal{R}|}$. Note that if $R = R_0 = 0$, the robot does not send any bits. Then, given a target BER, $p_{b,\mathrm{th}}$, and a spectral efficiency, $R_j \in \mathcal{R}$, the minimum required average transmit power along $\mathcal{T}_i$ is $P_{\mathrm{C},i,j} = ((2^{R_j}-1)/K)\,\mathbb{E}\{1/\Upsilon_i\}$, where $K = -1.5/\ln(5p_{b,\mathrm{th}})$ and $\Upsilon_i = 10^{\Upsilon_{\mathrm{dB},i}/10}$. The total average communication energy cost of the robot along $\mathcal{T}_i$ can then be found as follows:

$$E_{\mathrm{C},i} = \sum_{j=0}^{|\mathcal{R}|} P_{\mathrm{C},i,j} t_{\mathrm{tr},i,j} = \sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},i,j} t_{\mathrm{tr},i,j}, \tag{1}$$

where $t_{\mathrm{tr},i,j}$ denotes the transmission time of using the spectral efficiency R_j along $\mathcal{T}_i$. Note that the robot can adapt the average spectral efficiency along $\mathcal{T}_i$ based on choosing the corresponding $t_{\mathrm{tr},i,j}$s.

In this paper, we say that $\mathcal{T}_i$ has a better estimated channel quality if $\mathbb{E}\{1/\Upsilon_i\}$ is smaller. From Section 2.1, Υ_i is a lognormal random variable. Then, it is straightforward to show that $\mathbb{E}\{1/\Upsilon_i\} = \exp\big((\ln 10/10)^2\,\sigma^2_{\mathrm{dB},i}/2\big)/\overline{\Upsilon}_i$, where $\overline{\Upsilon}_i = 10^{\overline{\Upsilon}_{\mathrm{dB},i}/10}$. Hence, the average assigned communication energy cost decreases, as the estimated mean value of the channel increases and/or the estimation variance decreases (i.e. as the estimated channel quality improves).

2.3 Motion Energy Model

We assume that the robot uses a DC motor for its motion. Experimental studies show that the motion power cost of a mobile robot can be approximated by a polynomial of its velocity. In this paper, we use the following linear model to characterize the motion power cost of the robot Mei et al. (2006): $P_{\mathrm{M}} = \kappa_1 u + \kappa_2$, for $0 < u \le u_{\max}$, where P_{M} is the motion power, u denotes the velocity of the robot, κ_1 and κ_2 are positive constants, and $u_{\max}$ is the maximum velocity of the robot. This model is a very good fit to the Pioneer 3DX robot, when the velocity is smaller than 0.9 m/s Mei et al. (2006). The motion power model above does not consider the impact of acceleration since it is negligible for many DC motors Mei et al. (2004).

Then, the motion energy consumption for traveling $\mathcal{T}_i$ with length l_i can be found as follows:

$$E_{\mathrm{M},i} = \kappa_1 l_i + \kappa_2 \frac{l_i}{u_i} = \kappa_1 l_i + \kappa_2 t_{\mathrm{mo},i}, \tag{2}$$

where $t_{\mathrm{mo},i} = l_i/u_i \ge l_i/u_{\max}$ is the motion time. It can be seen that the motion energy cost of the robot is linearly increasing with respect to the distance it traveled. Also, it is minimized only if $u_i = u_{\max}$.

3. CO-PLANNING THE COMMUNICATION AND MOTION STRATEGY TO MINIMIZE THE TOTAL ENERGY COST

In this section, we address the main questions of this paper: Should the robot spend its energy on motion to move to a better spot for communication or should it stay at its initial position and increase its transmission power? If it should move, where the robot should move to? Given the position where the robot should move to, what is the optimum communication and motion strategy (transmission power/rate, motion speed and stop times) along the trajectory? We start by formulating the general optimization problem in Section 3.1. Then a simplified framework is proposed in Section 3.2, based on the properties we prove for the main optimization problem. Finally, in Section 3.3, we discuss a special case to see when the motion can help save the total energy cost.

3.1 Optimization Framework

Consider the case that the robot moves from $\mathcal{T}_1$ to $\mathcal{T}_k$ and stops there (assume a given $\mathcal{T}_k$ for now). Based on the communication and motion energy models that are discussed previously, we can then formulate the following optimization problem to minimize the total energy cost:

$$\begin{aligned}
\min \quad & \widetilde{J}_k = \sum_{i=1}^{k} \underbrace{\sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},i,j} t_{\mathrm{tr},k,i,j}}_{E_{\mathrm{C},k,i}} + \sum_{i=1}^{k-1} \underbrace{\kappa_1 l_i + \kappa_2 t_{\mathrm{mo},k,i}}_{E_{\mathrm{M},k,i}} \\
\text{s.t.} \quad & \sum_{i=1}^{k-1} t_{\mathrm{mo},k,i} + \sum_{i=1}^{k} t_{\mathrm{st},k,i} \le T, \\
& \sum_{i=1}^{k}\sum_{j=1}^{|\mathcal{R}|} R_j t_{\mathrm{tr},k,i,j} \ge Q/B, \quad \sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,k,j} \le t_{\mathrm{st},k,k}, \\
& \sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,i,j} \le t_{\mathrm{mo},k,i} + t_{\mathrm{st},k,i}, \quad i \in \{1, \cdots, k-1\}, \\
& t_{\mathrm{st},k,i},\ t_{\mathrm{tr},k,i,j} \ge 0,\ t_{\mathrm{mo},k,i} \ge l_i/u_{\max}, \quad \forall\, i, j,
\end{aligned} \tag{3}$$

where the unknown variables to solve for are $t_{\mathrm{tr},k,i,j}$s, $t_{\mathrm{mo},k,i}$s and $t_{\mathrm{st},k,i}$s, for $t_{\mathrm{st},k,i}$ representing the time that the robot stops along $\mathcal{T}_i$. The subscript k denotes that the variables are for the case that the robot moves from $\mathcal{T}_1$ to $\mathcal{T}_k$. Furthermore, $T > 0$ is the given operation time budget, $Q > 0$ is the total number of bits that needs to be sent, and B is the given fixed bandwidth. Note that (3) is a linear program, which can be solved with high efficiency.

Our optimization framework of (3) plans the motion speed/stop time of the robot (available time budget) and schedules the transmission of the given bits along each sub-trajectory (by adapting the rate), while minimizing the total energy cost and satisfying the time budget and target BER. Note that, as mentioned in Section 2.3, the motion energy is minimized when $t_{\mathrm{mo},k,i} = l_i/u_{\max}$. Thus, we introduced the stop time variables $t_{\mathrm{st},k,i}$s in (3), in order to allow the robot to stop during the operation if needed. Then, the total time that the robot can spend along $\mathcal{T}_i$ is $t_{\mathrm{mo},k,i} + t_{\mathrm{st},k,i}$, which includes both the motion and stop time durations. Hence, the transmit time $\sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,i,j}$ along $\mathcal{T}_i$ should always satisfy $\sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,i,j} \le t_{\mathrm{mo},k,i} + t_{\mathrm{st},k,i}$, for $i \in \{1, \cdots, k-1\}$, and $\sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,k,j} \le t_{\mathrm{st},k,k}$.

Note that if $k = 1$, then the robot just stays at its initial position and sends its information. Hence, there is no motion energy cost. If $k \in \{2, \cdots, N\}$, the robot spends some motion energy (depending on how long it travels) in order to find a place where the communication quality is better. The optimum $\mathcal{T}_k$ can then be found as follows:

$$k^\star = \arg \min_{k \in \{1, \cdots, N\}} \{\widetilde{J}_k^\star\}, \tag{4}$$

where the superscript $\star$ represents the optimum solution of the corresponding optimization problem. Then, the optimum strategy of the robot is to use the optimum solution of (3), for $k = k^\star$.

3.2 Simplification of the Optimization Framework

Clearly, N linear programs need to be solved in order to find the optimum strategy and the final sub-trajectory based on the framework in the previous section. Next, we prove some properties of the optimum solution, which allows for a considerably more simplified framework.

Lemma 1. The optimum strategy satisfies the following properties: 1) $\mathbb{E}\{1/\Upsilon_{k^\star}\} < \mathbb{E}\{1/\Upsilon_i\}$, for $\forall\, i \in \{1, \cdots, k^\star - 1\}$; 2) $t^\star_{\mathrm{mo},k^\star,i} = l_i/u_{\max}$, for $\forall\, i \in \{1, \cdots, k^\star - 1\}$; 3) $t^\star_{\mathrm{st},k^\star,i} = 0$, for $\forall\, i \in \{1, \cdots, k^\star - 1\}$, and $t^\star_{\mathrm{st},k^\star,k^\star} = T - \sum_{i=1}^{k^\star-1} l_i/u_{\max}$.

Proof. We prove Lemma 1 by contradiction.

1) Suppose that $\mathcal{T}_{k^\star}$ is the optimum sub-trajectory that the robot should move to, and $\mathbb{E}\{1/\Upsilon_{k^\star}\} \geq \mathbb{E}\{1/\Upsilon_i\}$, for some $i \in \{1, \cdots, k^\star - 1\}$. Then, there exists an $\ell < k^\star$ such that $\mathbb{E}\{1/\Upsilon_\ell\} = \min_{i \in \{1, \cdots, k^\star\}}\{\mathbb{E}\{1/\Upsilon_i\}\}$. Let $t^\star_{\mathrm{mo},k^\star,i}$, $t^\star_{\mathrm{st},k^\star,i}$ and $t^\star_{\mathrm{tr},k^\star,i,j}$ denote the optimum solution of (3) for $k = k^\star$. We can always choose a feasible point of (3) for $k = \ell$ as follows: $t_{\mathrm{mo},\ell,i} = t^\star_{\mathrm{mo},k^\star,i}$, $t_{\mathrm{st},\ell,i} = t^\star_{\mathrm{st},k^\star,i}$, $t_{\mathrm{tr},\ell,i,j} = t^\star_{\mathrm{tr},k^\star,i,j}$, for $i \in \{1, \cdots, \ell - 1\}$, $t_{\mathrm{st},\ell,\ell} = \sum_{i=\ell}^{k^\star-1} t^\star_{\mathrm{mo},k^\star,i} + \sum_{i=\ell}^{k^\star} t^\star_{\mathrm{st},k^\star,i}$ and $t_{\mathrm{tr},\ell,\ell,j} = \sum_{i=\ell}^{k^\star} t^\star_{\mathrm{tr},k^\star,i,j}$. Clearly, by using this feasible point we have the following: $E_{\mathrm{C},\ell,i} = \sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},i,j} t_{\mathrm{tr},\ell,i,j} = \sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},i,j} t^\star_{\mathrm{tr},k^\star,i,j} = E^\star_{\mathrm{C},k^\star,i}$, $E_{\mathrm{M},\ell,i} = \kappa_1 l_i + \kappa_2 t_{\mathrm{mo},\ell,i} = \kappa_1 l_i + \kappa_2 t^\star_{\mathrm{mo},k^\star,i} = E^\star_{\mathrm{M},k^\star,i}$, for $i \in \{1, \cdots, \ell - 1\}$, and $E_{\mathrm{C},\ell,\ell} = \sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},\ell,j} t_{\mathrm{tr},\ell,\ell,j} = \sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},\ell,j} \sum_{i=\ell}^{k^\star} t^\star_{\mathrm{tr},k^\star,i,j} \leq \sum_{i=\ell}^{k^\star} E^\star_{\mathrm{C},k^\star,i}$. Hence, $\widetilde{J}_\ell = \sum_{i=1}^{\ell-1} E_{\mathrm{C},\ell,i} + \sum_{i=1}^{\ell-1} E_{\mathrm{M},\ell,i} + E_{\mathrm{C},\ell,\ell} \leq \sum_{i=1}^{\ell-1} E^\star_{\mathrm{C},k^\star,i} + \sum_{i=1}^{\ell-1} E^\star_{\mathrm{M},k^\star,i} + \sum_{i=\ell}^{k^\star} E^\star_{\mathrm{C},k^\star,i} < \widetilde{J}^\star_{k^\star}$. This contradicts the assumption that $\mathcal{T}_{k^\star}$ is the optimum sub-trajectory that the robot should move to. Hence, $\mathbb{E}\{1/\Upsilon_{k^\star}\} < \mathbb{E}\{1/\Upsilon_i\}$, for $\forall\, i \in \{1, \cdots, k^\star - 1\}$.

2) Let $t^\star_{\mathrm{mo},k^\star,i} > l_i/u_{\max}$, for some $i \in \{1, \cdots, k^\star - 1\}$, be the optimum motion time along $\mathcal{T}_i$. Then, by choosing the following feasible point: $t_{\mathrm{mo},k^\star,i} = l_i/u_{\max}$, $t_{\mathrm{st},k^\star,i} = t^\star_{\mathrm{st},k^\star,i} + t^\star_{\mathrm{mo},k^\star,i} - l_i/u_{\max}$ and $t_{\mathrm{tr},k^\star,i,j} = t^\star_{\mathrm{tr},k^\star,i,j}$, we have $E_{\mathrm{C},k^\star,i} = E^\star_{\mathrm{C},k^\star,i}$ and $E_{\mathrm{M},k^\star,i} < E^\star_{\mathrm{M},k^\star,i}$. This means that the robot spends the same amount of communication energy, but saves some motion energy along $\mathcal{T}_i$. This contradicts the assumption that $t^\star_{\mathrm{mo},k^\star,i}$ is the optimum solution. Hence, $t^\star_{\mathrm{mo},k^\star,i} = l_i/u_{\max}$, for $\forall\, i \in \{1, \cdots, k^\star - 1\}$.

3) Let $t^\star_{\mathrm{st},k^\star,i} > 0$, for some $i \in \{1, \cdots, k^\star - 1\}$, be the optimum stop time along $\mathcal{T}_i$. We can always choose the following feasible point: $t_{\mathrm{st},k^\star,i} = 0$, $t_{\mathrm{tr},k^\star,i,j} = t^\star_{\mathrm{tr},k^\star,i,j}\big(t^\star_{\mathrm{mo},k^\star,i}/(t^\star_{\mathrm{st},k^\star,i} + t^\star_{\mathrm{mo},k^\star,i})\big)$, $t_{\mathrm{st},k^\star,k^\star} = t^\star_{\mathrm{st},k^\star,k^\star} + t^\star_{\mathrm{st},k^\star,i}$, and $t_{\mathrm{tr},k^\star,k^\star,j} = t^\star_{\mathrm{tr},k^\star,k^\star,j} + t^\star_{\mathrm{tr},k^\star,i,j}\big(t^\star_{\mathrm{st},k^\star,i}/(t^\star_{\mathrm{st},k^\star,i} + t^\star_{\mathrm{mo},k^\star,i})\big)$. This feasible point means that the robot can choose to send less information along $\mathcal{T}_i$, while sending more information along $\mathcal{T}_{k^\star}$. Based on Part 1, it can be seen that $\widetilde{J}_{k^\star} < \widetilde{J}^\star_{k^\star}$, since the estimated channel quality is the best along $\mathcal{T}_{k^\star}$. This contradicts the assumption that $t^\star_{\mathrm{st},k^\star,i}$ is the optimum solution. Hence, we have $t^\star_{\mathrm{st},k^\star,i} = 0$, for $\forall\, i \in \{1, \cdots, k^\star - 1\}$, and $t^\star_{\mathrm{st},k^\star,k^\star} = T - \sum_{i=1}^{k^\star-1} l_i/u_{\max}$.

Remark 1. Part 1 of Lemma 1 says that if the robot chooses to move to a new position, then that position should have the property that its estimated channel quality is better than that of all the sub-trajectories before it. This is intuitive since it is not optimum for the robot to spend more motion energy (travel longer distance) to go to some places that have worse estimated channel qualities. Part 2 of Lemma 1 shows that the robot will always travel with its maximum speed to save motion energy. If it needs to spend more time at some positions where the estimated channel qualities are high, it chooses to stop rather than reducing its speed. Part 3 of Lemma 1 says that the robot only stops once and at the destination position, where the estimated channel quality is the best (Part 1 of the lemma). Note that if $k^\star = 1$, then it is the best if the robot simply stays at its initial position.

Based on Parts 2 and 3 of Lemma 1, we can simplify (3) as follows:

$$\begin{aligned} \min \quad & J_k = \sum_{i=1}^{k} \sum_{j=1}^{|\mathcal{R}|} P_{\mathrm{C},i,j} t_{\mathrm{tr},k,i,j} + \sum_{i=1}^{k-1} \left(\kappa_1 l_i + \kappa_2 \frac{l_i}{u_{\max}}\right) \\ \text{s.t.} \quad & \sum_{i=1}^{k} \sum_{j=1}^{|\mathcal{R}|} R_j t_{\mathrm{tr},k,i,j} \geq Q/B, \quad \sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,i,j} \leq \frac{l_i}{u_{\max}}, \\ & i \in \{1, \cdots, k-1\}, \quad \sum_{j=1}^{|\mathcal{R}|} t_{\mathrm{tr},k,k,j} \leq T - \sum_{i=1}^{k-1} \frac{l_i}{u_{\max}}, \\ & t_{\mathrm{tr},k,i,j} \geq 0, \quad \forall\, i, j, \end{aligned} \tag{5}$$

where the variables to solve for are only $t_{\mathrm{tr},k,i,j}$s, as compared with (3). Moreover, based on Part 1 of Lemma 1, the robot only needs to solve (5) at $\mathcal{T}_k$, where $\mathbb{E}\{1/\Upsilon_k\} < \mathbb{E}\{1/\Upsilon_i\}$, for $\forall\, i \in \{1, \cdots, k - 1\}$. This can also reduce the computational complexity significantly. Algorithm 1 summarizes how to find the optimum position where the robot should move to, and its corresponding optimum communication and motion strategy. [2]

3.3 Discussions on a Special Case

So far, we have proposed an algorithm to find the optimum sub-trajectory where the robot should move to, and its corresponding optimum communication and motion strategy. The solution is found by solving a series of linear programs. In this section, we discuss a special (sub-optimum) case where the robot does not adapt its transmission rate along the trajectory.

[2] The third line of Algorithm 1 is to ensure that the algorithm terminates immediately if the robot incurs too much motion energy (larger than the minimum total energy cost that has been found so far), since the optimum point cannot be at any point along the remaining part of the trajectory in this case. The fourth line of the algorithm is to guarantee the feasibility of (5).

Algorithm 1 Find the optimum position and its corresponding optimum communication and motion strategy

$k \leftarrow 1$
minimum energy $\leftarrow \infty$, smallest found $\mathbb{E}\{1/\Upsilon_i\} \leftarrow \infty$
while $k <= N$
  if $\sum_{i=1}^{k-1}(\kappa_1 l_i + \kappa_2 l_i/u_{\max}) >=$ minimum energy
  or $\sum_{i=1}^{k-1} l_i/u_{\max} > T$
    break
  end if
  if $\mathbb{E}\{1/\Upsilon_k\} <$ smallest found $\mathbb{E}\{1/\Upsilon_i\}$
    solve (5), smallest found $\mathbb{E}\{1/\Upsilon_i\} \leftarrow \mathbb{E}\{1/\Upsilon_k\}$
    if $J_k^\star <$ minimum energy
      minimum energy $\leftarrow J_k^\star$
      optimum strategy $\leftarrow$ solution of (5)
    end if
  end if
  $k \leftarrow k+1$
end while

To be more specific, consider the case where $k = 1$, i.e. the robot chooses to send all its data at the initial position. By solving (5), we have $t^\star_{\mathrm{tr},1,1,j}$ and $J_1^\star$, which represent the optimum communication strategy and its corresponding energy cost respectively. We then choose the same transmission rate for the other sub-trajectories. Thus, for some $\mathcal{T}_k$ that satisfies the condition in Part 1 of Lemma 1, the following feasible solution is used: $t_{\mathrm{tr},k,i,j} = t^\star_{\mathrm{tr},1,1,j}((l_i/u_{\max})/T)$, for $i \in \{1, \cdots, k-1\}$, and $t_{\mathrm{tr},k,k,j} = t^\star_{\mathrm{tr},1,1,j}((T - \sum_{i=1}^{k-1} l_i/u_{\max})/T)$.

Let $\mathcal{T}_\ell$ and $\mathcal{T}_k$ be the sub-trajectories that satisfy the condition in Part 1 of Lemma 1 with $\ell > k$. Then, the robot will choose $\mathcal{T}_\ell$ as the optimum sub-trajectory to move to, if the following equation is negative:

$$
\begin{aligned}
J_\ell - J_k = &\sum_{i=k+1}^{\ell-1}\sum_{j=1}^{|\mathcal{R}|}(P_{\mathrm{C},i,j} - P_{\mathrm{C},k,j})\frac{l_i/u_{\max}}{T} t^\star_{\mathrm{tr},1,i,j} \\
&+ \sum_{j=1}^{|\mathcal{R}|}(P_{\mathrm{C},\ell,j} - P_{\mathrm{C},k,j})\frac{T - \sum_{i=1}^{\ell-1} l_i/u_{\max}}{T} t^\star_{\mathrm{tr},1,i,j} \\
&+ \sum_{i=k}^{\ell-1}(\kappa_1 l_i + \kappa_2 l_i/u_{\max}), \qquad (6)
\end{aligned}
$$

where the first and second terms of the right hand side of (6) represent the difference of the average communication energy cost, and the third term represents the extra motion energy cost for moving to $\mathcal{T}_\ell$. Note that the difference of the average communication energy cost not only depends on the estimated channel quality along $\mathcal{T}_\ell$, but also on the estimated channel qualities along $\mathcal{T}_i$, for $i \in \{k+1, \cdots, \ell-1\}$. Clearly, equation (6) decreases if $P_{\mathrm{C},\ell,j}$s, or equivalently $\mathbb{E}\{1/\Upsilon_\ell\}$, decrease. This means that the robot is more likely to move to $\mathcal{T}_\ell$ if the estimated channel quality along $\mathcal{T}_\ell$ is very high. Also, equation (6) is a monotonically decreasing function of T. This says that the robot is more likely to move farther if it has sufficiently large time budget. Finally, equation (6) decreases if κ_1 and/or κ_2 decreases, which implies that the robot is more likely to move farther if the motion energy cost is smaller.

Next, consider a simplified case where the channel only has the path loss component, and the predefined trajectory is a straight line from the initial position towards the remote station. Then, $P_{\mathrm{C},k,j} = (2^{R_j} - 1)/(K\alpha)(D - \sum_{i=1}^{k-1} l_i)^n$, where $\alpha = 10^{\alpha_{\mathrm{dB}}/10}$ and D denotes the distance between the initial position of the robot and the remote station. Let $\ell = k+1$. Equation (6) can then be simplified as follows: $J_{k+1} - J_k = (\kappa_1 l_k + \kappa_2 l_k/u_{\max}) + (C/\alpha)((D - \sum_{i=1}^{k} l_i)^n - (D - \sum_{i=1}^{k-1} l_i)^n) \approx (\kappa_1 l_k + \kappa_2 l_k/u_{\max}) - (C/\alpha)(D - \sum_{i=1}^{k-1} l_i)^{n-1} n l_k$, where $C = \sum_{j=1}^{|\mathcal{R}|}((2^{R_j} - 1)/K)((T - \sum_{i=1}^{k} l_i/u_{\max})/T)t^\star_{\mathrm{tr},1,1,j}$, and the approximation is based on the assumption that $D - \sum_{i=1}^{k-1} l_i \gg l_k$. Hence, $J_{k+1} < J_k$ only if

$$
(\kappa_1 + \kappa_2/u_{\max})l_k < \frac{C}{\alpha}\left(D - \sum_{i=1}^{k-1} l_i\right)^{n-1} n l_k. \qquad (7)
$$

From (7), it can be seen that the robot has an incentive to move towards the remote station if $D - \sum_{i=1}^{k-1} l_i$, i.e. the distance between the robot and the remote station is sufficiently large, and/or n, i.e. the path loss exponent, is large. It is also straightforward to see that the robot is more likely to move if Q/B, or equivalently C, is sufficiently large (clearly, C increases as Q/B increases, i.e. the robot has to consume more communication energy if it needs to send more bits). Moreover, the left hand side of (7) is the rate of increase of motion energy cost (with respect to an increase in l_k) while the right hand side is the rate of decrease of average communication energy cost (with respect to moving closer to the remote station by l_k). Then the robot has an incentive to move towards the remote station only if the rate of decrease of average communication energy cost is larger than the rate of increase of the motion energy cost.

4. SIMULATION RESULTS

Consider the case where the remote station is at $(0,0)$ and the predefined trajectory is a line from $(1000,0)$ to $(800,0)$, i.e. the robot is located at $(1000,0)$ initially, so the distance between the robot and the remote station is 1000 m. The channel is generated by our probabilistic channel simulator Gonzalez-Ruiz et al. (2011) with the following parameters: path loss exponent = 4, shadowing decorrelation distance = 10 m, and standard deviation of shadowing (in dB) = 8. Furthermore, the multipath fading is taken to be uncorrelated Rician fading with parameter $K_{\mathrm{ric}} = 5$. We use 2000 discrete values to represent the entire channel and the channel is assumed to be constant along each 0.1 meter interval. Furthermore, we assume that the robot has 10% a priori channel samples gathered in the same environment (200 samples). The robot then utilizes the channel assessment framework of Section 2.1 to predict the channel quality along the whole trajectory, based on these a priori channel samples.

Since the planning strategy and the performance depend on each realization of the channel, we average the performance over 100 runs of independent channel samples (but with the same underlying parameters). We compare our strategy with the case where the robot sends all the data at its initial position. We also use two different sets of real motion parameters of the Pioneer 3DX robot Mei et al. (2006) to see how the motion model impacts the overall performance. Fig. 2 shows the simulation results of our strategy as a function of Q/B. We have $p_{b,\mathrm{th}} = 10^{-6}$,

$B = 2$ MHz, $\mathcal{R} = \{0, 2, 4, 6\}$ bits/Hz/s, $T = 100$ s and $u_{\max} = 1$ m/s in this case. Clearly, the total energy costs of all cases increase as Q/B increases. Also, when Q/B is small, i.e. there is only a few bits to be sent, the robot cannot benefit a lot from the motion. However, when Q/B is large, i.e. the robot needs to send a large amount of data, motion can save the total energy considerably. Fig. 3 shows the simulation results of our strategy as a function of total time budget. We have $p_{b,\text{th}} = 10^{-6}$, $B = 2$ MHz, $Q/B = 200$ bits/Hz, $\mathcal{R} = \{0, 2, 4, 6\}$ bits/Hz/s and $u_{\max} = 1$ m/s in this example. It can be seen that the total energy costs of all the cases decrease as T increases. Moreover, both Fig. 2 and 3 show that the robot can save more energy if it has less motion cost (case of $\kappa_1 = 7.4$, $\kappa_2 = 0.29$). Overall, the observed behaviors of Fig. 2 and 3 are consistent with what we proved for the special case of Section 3.3.

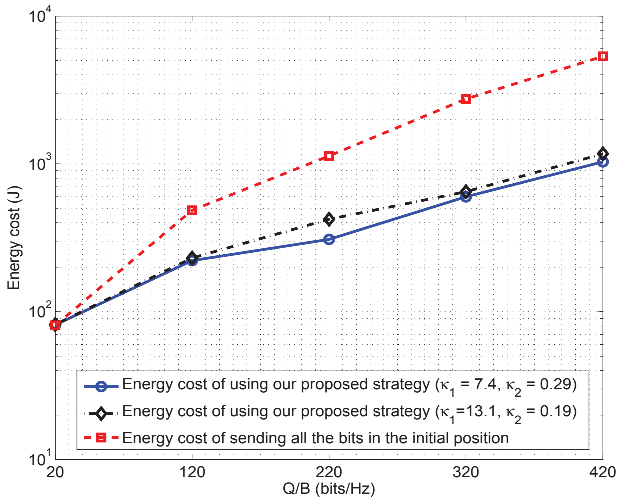

Fig. 2. Performance of our strategy as compared with the case where the robot sends all its data at its initial position. It can be seen that the robot can benefit more from motion as the number of bits increases.

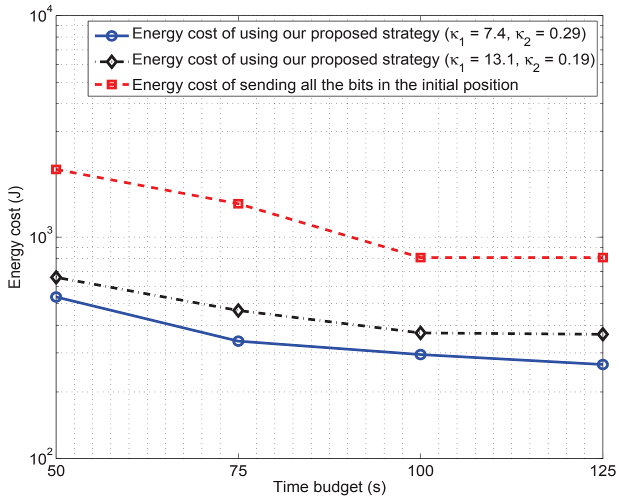

Fig. 3. Performance of our strategy as compared with the case where the robot sends all its data at its initial position. It can be seen that the robot can benefit from motion significantly.

5. CONCLUSIONS

In this paper, we considered a scenario where a robot needs to transmit a given number of bits to a remote station under time constraint and BER requirement, and while minimizing the total energy consumption. The robot is allowed to move along a predefined trajectory and design its transmission rate/power and motion policy (motion speed and possible stop times) accordingly. The goal of the robot is to minimize the total communication and motion energy costs. By co-optimizing the communication and motion strategies of the robot, we characterized the properties of the optimum policy, which shows that under several conditions it is more beneficial for the robot to spend energy on motion in order to move to a location that is better for communication. We also discussed a special case to see how the channel parameters and motion energy model impact the motion decision of the robot. Our simulation results showed that, by using our strategy, the robot can reduce its total energy cost significantly.

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