AN ENERGY SAVING ROBOT MOBILITY DIVERSITY ALGORITHM FOR WIRELESS COMMUNICATIONS

Daniel Bonilla Licea[1*], *Des McLernon*[1], *Mounir Ghogho*[1,2] *and Syed Ali Raza Zaidi*[1,2]

[1]University of Leeds
[2]International University of Rabat, Morocco
eldbl@leeds.ac.uk, d.c.mclernon@leeds.ac.uk, m.ghogho@ieee.org and elsarz@leeds.ac.uk

ABSTRACT

There are emerging applications in which a robot must explore some physical area or do some surveillance task and then communicate with a base station (BS) to transmit its information. Often this working environment has rich scattering and so the wireless channel will experience small scale fading. In this paper we develop an algorithm whereby the robot visits a specific number of locations with a pre-determined geometry, and transmits its data from one of these locations in an optimum way that minimizes the overall energy consumption. We show analytically (and via simulation) that this approach can both reduce the total energy required and obtain a diversity gain for robotic wireless communications.

Index Terms— machine-to-machine communications; mobility diversity; robotic communications.

1. INTRODUCTION

Robotic networks are a particular case of machine-to-machine communications and there has been an increasing interest in communication between robots [1]-[5]. It has been observed that in fading scenarios we can control the position of the robot to combat small-scale fading [1]-[3] by moving it to a position where a better wireless channel exists. This is because there are applications in which a mobile robot must fulfil some exploration or surveillance task and then transmit the information gathered during that task to a BS. The problem to be solved is this: (i) the robot wants to search for an "optimum" position corresponding to a channel with a large gain; (ii) the energy used to transmit its data will be E_1 (inversely proportional to the square of the channel gain); (iii) the energy used in searching for this "optimum" position will be E_2; (iv) the objective is to devise a mobility diversity algorithm that minimizes the total energy used, i.e., $E_1 + E_2$.

We are assuming that the application running in the BS is delay tolerant, i.e., the robot can defer by some time the transmission of the information and so the application does not suffer any inconvenience.

*The author acknowledge the funding of CONACYT, México.

In [1] the authors proposed to move the transceiver in either a linear, random, circular or spiral outward motion to look for a channel gain exceeding a specified threshold. Following this approach, the robot would need to estimate the channel during all its motion (i.e., it would need to execute the channel estimation algorithm a large number of times) and so the robot would consume significant energy. In [2] the robot has to follow a predefined trajectory in a certain amount of time in order to complete a surveillance task and the author proposes schemes in which the robot has to stop at some points along its trajectory according to some optimization rules. In [3] the author suggests that the robot randomly selects a fixed number of points in a small circular vicinity of its current location, explores those points, locates the point that has the best channel and then transmits from this point. In this last approach we can observe that there is not necessarily a clear understanding about how to chose these points and what is the gain that can be obtained from this kind of strategy.

This paper is now laid out as follows. In section 2 we describe the system model and in section 3 we present a mobility diversity algorithm. In section 4 we introduce the "E_{tot} metric" which allows us to analyse the robot performance in terms of overall energy consumption. In section 5 we introduce the concept of adaptive diversity order. In section 6 we briefly refer to channel estimation. Section 7 gives simulation results and we finish with conclusions in section 8.

2. SYSTEM MODEL

The robot explores N different stopping points. Each stopping point is represented by a coordinate q_i in $\mathbb{R}^2$. The robot is equipped with a transceiver and communicates with a BS.

So, the signal received by the robot (at the location q_i) from the BS is:

$$y_i(k) = h_i x(k) + n_i(k), i = 1, 2 \cdots, N \qquad (1)$$

where h_i is a complex, circularly symmetric, zero mean Gaussian random variable with variance $\frac{2}{\pi}$ and independent real and imaginary parts; $|h_i|$ is a Rayleigh distributed random variable with unit mean; and $n_i(k)$ is complex zero mean circular AWGN with variance $\sigma_{n_i}^2 = \sigma_n^2$. We assume:

1. Channel reciprocity: the channels observed in the downlink and the uplink are the same.

2. Flat fading: the channel is modelled as a complex scalar, random variable.

3. Time invariance: we will assume that although different channels are experienced, at each of the N stopping points, these channels remain approximately constant over the robot exploration time.

4. The covariance between the channel gains ($|h_i|$ and $|h_j|$) observed at points q_i and q_j is [6]:

$$C_{ij} = J_0^2\left(\frac{2\pi f_c ||q_i - q_j||_2}{c}\right), \quad i,j = 1,2,\cdots,N \tag{2}$$

   where $J_0(\cdot)$ is a zero-order Bessel function of the first kind, c is the velocity of light and f_c is the RF carrier frequency.

Let the channel gain vector be $\boldsymbol{h} = [|h_1|, |h_2| \cdots, |h_N|]^T$ and let $\boldsymbol{C}$ be the normalized covariance matrix of $\boldsymbol{h}$:

$$\boldsymbol{C} = \frac{N\mathbb{E}[(\boldsymbol{h} - \mathbb{E}[\boldsymbol{h}])(\boldsymbol{h} - \mathbb{E}[\boldsymbol{h}])^H]}{tr(\mathbb{E}[(\boldsymbol{h} - \mathbb{E}[\boldsymbol{h}])(\boldsymbol{h} - \mathbb{E}[\boldsymbol{h}])^H])}. \tag{3}$$

This definition (with C_{ij} defined in (2)) will be used later in section 3.2.

3. MOBILITY DIVERSITY

The motivation for the **M**obility **D**iversity with **M**ultiple **T**hreshold (MDMT) algorithm is to allow the robot to obtain a good channel for data transmission while using the smallest amount of total energy, i.e., the energy used for data transmission plus the energy used for channel estimation and energy used to move the robot (as described in section 1).

The principle of MDMT is as follows: given N possible positions the robot could visit them all and then return to the one with the largest channel gain in order to transmit its data. However, if during the search process the channel gain at one of the N stopping points is "large", then the probability of the robot finding a significantly higher channel gain at one of the remaining positions will be small (and the energy used in searching these remaining positions will be wasted). This motivates us to check if the channel gain at the visited stopping points exceeds a certain threshold, and then we can terminate the search process.

3.1. Mobility Diversity Algorithm

The MDMT algorithm works as follows:

First, we calculate the number of stopping points (N) that the robot is allowed to visit, according to some optimum criterion (see section 5). Once we have calculated N, we choose the optimum spatial configuration (see subsection 3.2) of the N stopping points $q_1, q_2, \ldots, q_N$. The next step consists of selecting a set of channel gain thresholds $\eta_1 = \eta_2 =, \ldots, = \eta_R = \eta$ (with $1 \leq R \leq N-1$). For $R = 0$, we assume that no thresholds are used.

Once all the parameters of the algorithm are obtained the robot proceeds to move. The stopping points are visited in ascending order starting at point q_1. When the robot is at q_i it estimates $|h_i|$ with $|\hat{h_i}|$. If $|\hat{h_i}| > \eta_i$ then the robot transmits from q_i and the algorithm terminates. If not, the robot moves in a straight line to the next stopping point (q_{i+1}). If the stopping point q_N is reached then the robot moves (if necessary) to position q_{max} and transmits, where:

$$q_{max} = q_{k^*},\ k^* = \arg\max_{k\in\{1,2,\cdots,N\}} \{|\hat{h_k}|\}. \tag{4}$$

The point at which the robot stops after executing the MDMT algorithm is called q_{opt} and $q_{opt} = q_{max}$ when there are no thresholds (i.e., $R = 0$) or when the channel gain of the first R stopping points is $< \eta$. Assuming independence between all the channels, the CDF of $|h_{opt}|$ can be derived from the MDMT algorithm description and is:

$$\begin{aligned}\mathbb{P}(|h_{opt}| < g) = \mathbb{P}(\textstyle\bigcap_{i=1}^{N}\{|h_i| < g\}, \bigcap_{i=1}^{R}\{|\hat{h_i}| < \eta\}) \\ + \textstyle\sum_{i=1}^{R}\{\mathbb{P}(|h_i| < g, |\hat{h_i}| \geq \eta)\prod_{j=1}^{i-1}\mathbb{P}(|\hat{h_j}| < \eta)\}.\end{aligned} \tag{5}$$

3.2. Geometry of the Stopping Points

It is well known [7] that in order to maximize the diversity gain we want $|h_i|$ and $|h_j|$ to be independent and so we choose the q_i's appropriately to give $\boldsymbol{C} = \boldsymbol{I}$.

To explain how this happens first consider (2), and let $D_{ij} = ||q_i - q_j||_2$. It is not difficult to show that the required $\boldsymbol{C} = \boldsymbol{I}$ can only be achieved exactly for $N \leq 3$ and with $D_{ij} = D$, where D is the smallest value (to minimize the energy) that also gives $J_0^2\left(\frac{2\pi f_c D}{c}\right) = 0$. The resulting geometries can be observed in Fig. 1 (a) and Fig. 1 (b).

Note that for $N = 4$ we cannot satisfy $\boldsymbol{C} = \boldsymbol{I}$ exactly, but the geometry of Fig. 1 (c) is the best we could find[1] and it has the property that its covariance matrix minimizes $||vec(\boldsymbol{C} - \boldsymbol{I})||_0^0$, where $||\cdot||_0^0$ is the l_0 "norm".

Finally, although we only consider $N \leq 4$, this is the first paper to address the topic of finding the optimum position of stopping points to minimize the overall energy consumption. A future paper will address the case of $N \geq 5$.

[1] The geometry of Fig. 1 (c) was found by experimentation and was selected from all the geometries that we analyzed because: (i) it is the geometry which produces an $|h_{opt}|$ whose CDF is the closest to the case in which all the channels are independent; (ii) it is the geometry which demands that the robot travels the smallest distance while keeping $\boldsymbol{C}$ "close" to the identity matrix I.

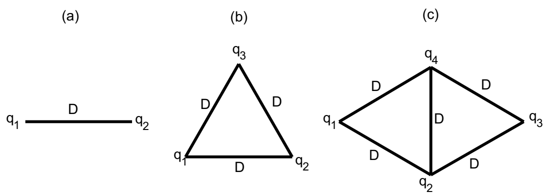

Fig. 1. Optimal configuration of stopping points $\{q_i\}_{i=1}^{N}$ for: (a) N=2, (b) N=3 and (c) N=4.

4. ENERGY CONSUMPTION

Consider a robot equipped with a transmitter using power control and with no restriction on its maximum transmitting power. Suppose the BS has to receive some minimum specified reference power (P_{ref}) to guarantee a certain BER. Suppose that the robot executes the MDMT algorithm with N stopping points.

The minimum power transmitted by the robot from q_{opt} is then:

$$P_{tx}(N) = \frac{P_{ref}}{|h_{opt}|^2} \tag{6}$$

and so the corresponding transmitted energy is:

$$E_{tx}(N) = P_{tx}(N)MT_b = \frac{P_{ref}MT_b}{|h_{opt}|^2} \tag{7}$$

where M is the number of bits to be transmitted and T_b is the bit duration.

For channel estimation, the robot receives S training symbols from the BS and uses energy:

$$E_{est}(N) = N_{tot}\Xi(S). \tag{8}$$

Here $\Xi(S)$ is the energy used to estimate the channel at a single stopping point. In addition N_{tot} is a random variable (dependent on η and R) indicating the total number of visited stopping points (i.e., with $R = 0$, $N_{tot} = N$).

Finally, the total energy used by the robot for mechanical motion (i.e., neither channel estimation nor data transmission) is given by:

$$E_{mech}(N) = f(s(q_{opt}, t), \mathbf{u}(q_{opt}, t)) \tag{9}$$

where $f(s(q_{opt}, t), \mathbf{u}(q_{opt}, t))$ is the work done by the robot (using the control law $\mathbf{u}(q_{opt}, t)$ [8]) to execute the MDMT algorithm and finishing at point q_{opt}. Here $s(q_{opt}, t)$ is the trajectory described by the robot when executing the MDMT algorithm and this trajectory starts at q_1 and finishes at q_{opt} (which is itself a random variable).

The work expended by the robot is the average force exerted by the robot in the trajectory times the distance travelled by the robot, i.e., $f(s(q_{opt}, t), \mathbf{u}(q_{opt}, t)) = \alpha(\mathbf{u}(q_{opt}, t)) \times L(s(q_{opt}, t))$, where $L(s(q_{opt}, t))$ is the length of the trajectory $s(q_{opt}, t)$ and $\alpha(\mathbf{u}(q_{opt}, t))$ is the average force exerted by the robot. Assuming that the control law governs directly the velocity of the robot then we have:

$$\alpha(\mathbf{u}(q_{opt}, t)) = \frac{m}{2T(q_{opt})D_0}\int_0^{T(q_{opt})} \|\mathbf{u}(q_{opt}, t)\|^2 dt \tag{10}$$

where m is the mass of the robot, $T(q_{opt})$ is the time that the robot takes to finish the trajectory $s(q_{opt}, t)$, and D_0 is a normalizing constant[2].

So, let the total energy used (i.e., for data transmission, channel estimation and robot motion) normalized by $P_{ref}MT_b$ be:

$$\begin{aligned} E_{tot}(N) = {} & \tfrac{1}{|h_{opt}|^2} + \tfrac{N_{tot}\Xi(S)}{P_{ref}MT_b} \\ & + \tfrac{\alpha(\mathbf{u}(q_{opt},t))L(s(q_{opt},t))}{P_{ref}MT_b}. \end{aligned} \tag{11}$$

We observe in (11) that if we have a lot of data to send or if the robot does not need too much force to move, then we can increase the number of stopping points (and probabilistically getting a larger $|h_{opt}|$) and the total energy spent by the robot will be reduced, due to the reduction in the term $\frac{1}{|h_{opt}|^2}$.

A measure of the average energy used will then be the expected value of $E_{tot}(N)$:

$$\begin{aligned} \mathbb{E}[E_{tot}(N)] = {} & \mathbb{E}\left[\tfrac{1}{|h_{opt}|^2}\right] + \tfrac{\Xi(S)}{P_{ref}MT_b}\mathbb{E}[N_{tot}] \\ & + \tfrac{\alpha(\mathbf{u}(q_{opt},t))}{P_{ref}MT_b}\mathbb{E}[L(s(q_{opt}, t))]. \end{aligned} \tag{12}$$

When the threshold η in section 3.1 reduces there are better channels that sometimes are not taken into account and as a consequence $\mathbb{E}\left[\frac{1}{|h_{opt}|^2}\right]$ is a decreasing function of η. Also when η reduces $\mathbb{E}[N_{tot}]$, as well as $\mathbb{E}[L(s(q_{opt}, t))]$, are both reduced (because the robot will move less) which implies that they are increasing functions of η. This implies that $\mathbb{E}[E_{tot}(N)]$ has a unique minimum with respect to η. A similar reasoning can be stated for N which implies that $\mathbb{E}[E_{tot}(N)]$ has a unique minimum with respect to N. In section 5 we will discuss this in more detail.

In general it is difficult to obtain a closed form expression for (12) that evaluates the $\mathbb{E}[\cdot]$ terms. But it can be obtained numerically via simulation, and this is what we do in section 7. However, it is interesting to note that for the special case when we use the stopping point configurations of Fig.1 with $R = 0$ (i.e., no channel gain thresholds) we obtain the following expressions:

$$\mathbb{E}[L(s(q_{opt}, t)] = \frac{N^2 - 1}{N}D \tag{13}$$

$$\mathbb{E}[N_{tot}] = N. \tag{14}$$

[2] $D_0 = 1$m and it has the purpose of making the units of $\alpha(\mathbf{u}(q_{opt}, t))$ Newtons as $f(s(q_{opt}, t), \mathbf{u}(q_{opt}, t))$ has units of Joules.

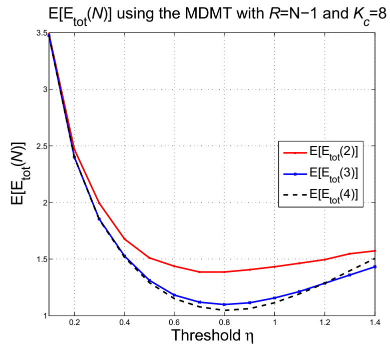

Fig. 2. $\mathbb{E}[E_{tot}(N)]$ versus η

And then using Maple software we can evaluate the remaining terms in (12):

$$\mathbb{E}[\frac{1}{|h_{opt}|^2}] = \frac{\pi}{2}\ln(2), \quad \text{for} \quad N=2$$
$$\mathbb{E}[\frac{1}{|h_{opt}|^2}] = \frac{\pi}{4}(6\ln(2) - 3\ln(3)), \quad \text{for} \quad N=3 \qquad (15)$$
$$\mathbb{E}[\frac{1}{|h_{opt}|^2}] = \frac{\pi}{4}(20\ln(2) - 12\ln(3)), \quad \text{for} \quad N=4.$$

5. ADAPTIVE DIVERSITY ORDER AND THRESHOLD OPTIMIZATION

Note that $K_c = \frac{\alpha(\mathbf{u}(q_{opt},t))}{P_{ref}MT_b}$ in (12) can change over time (e.g., different size of file to send, change of modulation, etc.). When K_c changes and the robot wants to transmit it can find the optimum diversity order (N^*) for each occasion by solving:

$$N^* = \arg \min_{N \in [1,2,\cdots,N_{max}]} \{\mathbb{E}[E_{tot}(N)]\} \qquad (16)$$

where in this case $N_{max} = 4$ (see Fig.1). This optimization of the diversity order according to the current value of K_c before the algorithm execution introduces the new concept of *Adaptive Diversity Order*.

As mentioned in section 4, $\mathbb{E}[E_{tot}(N)]$ posses a unique minimum with respect to the channel gain threshold η and therefore we can optimize its value by solving:

$$\eta^* = \arg \min_{\eta \in \mathbb{R}^+} \{\mathbb{E}[E_{tot}(N)]\}. \qquad (17)$$

In Fig. 2 we plotted $\mathbb{E}[E_{tot}(N)]$ as a function of η for the three configurations of Fig. 1 to show that indeed (for a given K_c) $\mathbb{E}[E_{tot}(N)]$ has a unique minimum with respect to η.

It is worth pointing out that when $R = 0$ (i.e., no thresholds) and if we do not use the adaptive diversity mechanism, then from a mathematical point of view, then the MDMT algorithm is equivalent to selection combining [9]. But the advantage here is that we only need one RF chain and one antenna. In addition, the MDMT algorithm allows for adaptive diversity order. The use of the thresholds in the MDMT algorithm reduces the risk of doing movements which would lead to loss of energy while promising only a small improvement of the channel gain. This reduction in the risk saves energy and improves the robot's autonomy.

6. CHANNEL ESTIMATION

During the algorithm execution the BS uses TDD: in the first slot it transmits a training signal which is used by the robot to perform the channel estimation, while in the second slot the BS is in receiver mode waiting for a transmission from the robot. When the robot reaches the ith stopping point it listens to the channel and waits for the training signal sent by the BS. When the training signal is detected the robot proceeds to perform a Data Aided Estimation of $|h_i|$. The robot can wait in the stopping point for another training signal to collect more samples if necessary before moving to the next stopping point.

7. MDMT ALGORITHM SIMULATION RESULTS

In order to perform the simulations, we generated Rayleigh distributed channel gains with unit mean and normalized covariance matrix $\boldsymbol{C}$ with elements given by (2). We considered a $SNR = 20$dB at the robot transceiver and used the following zero forcing channel estimator with $S = 16$ training symbols with unit modulus:

$$|\hat{h_i}| = \frac{1}{S}\left|\sum_{k=0}^{S-1} y_i(k)x^*(k)\right|. \qquad (18)$$

If $\Xi(S) \approx 0$ (because we estimate the channel only few times and therefore the energy used can be neglected) then we can rewrite (11) as:

$$E_{tot}(N) = \frac{1}{|h_{opt}|^2} + K_c L(s(q_{opt},t)). \qquad (19)$$

Simulation 1: Threshold effect in the MDMT algorithm

We have simulated the CDF of $|h_{opt}|$ and the CDF of E_{tot} (Fig. 3) for the MDMT algorithm with $N = 1$ (i.e., no diversity) and $N = 4$ (Fig.1(c)) with: (a) $R = 3$ and $\eta = 1.5$ and (b) $R = 0$.

First, we observe that the $|h_{opt}|$'s CDF is worse for $N = 1$ than for $N = 4$ (cases (a) and (b)). Also from the E_{tot}'s CDF we observe that the probability of expending high amounts of energy is bigger when we do not use the MDMT algorithm (i.e., when $N = 1$). Therefore, the utilization of the MDMT algorithm saves energy and selects "better" channels.

In addition, when we use channel gain thresholds we obtain a small degradation of the $|h_{opt}|$'s CDF but at the same time the E_{tot}'s CDF rises more quickly for smaller values, i.e., there is a bigger probability of having small values. For case (a) we have $\mathbb{E}[E_{tot}] = 0.9254$ and for case (b) $\mathbb{E}[E_{tot}] = 1.1102$. Therefore, case (a) is saving more energy than case (b). This shows that we save more energy if we

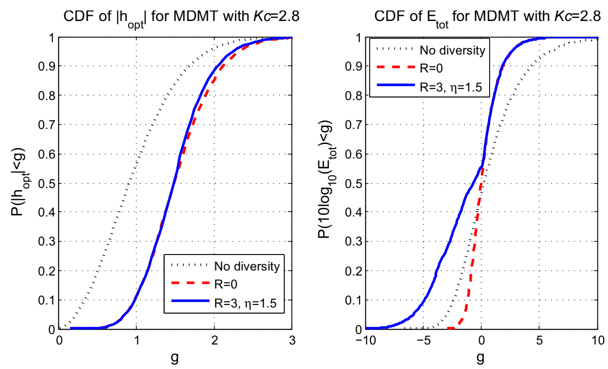

Fig. 3. CDF's of $|h_{opt}|$ and E_{tot} for the MDMT algorithm with N=4 and N=1 (no diversity).

use the MDMT algorithm employing channel gain thresholds (i.e., $R > 0$).

Simulation 2: Adaptive diversity mechanism

Consider a surveillance robot equipped with a transceiver which has a mass m of 3 Kg, moving at a constant speed v of 2 cm/s between the stopping points which gives $\alpha = 0.0006$J/m. Let the carrier frequency be $fc = 2.14$GHz which gives $D = 5.37$cm. Assume P_{ref} =1mW in (6) and $T_b = 10$ns. Consider that the robot can produce three different types of files depending on the information recorded by its sensors: measurements, images and video files; suppose that their size are: 256kB, 800kB and 6MB respectively. All this gives the following values of K_c for each type of file: 28.6102, 9.1553 and 1.1921 respectively. Also assume that the robot produces a file of any type with the same probability.

Let the robot use the MDMT algorithm with the parameters $\eta = 1.5$, $R = N - 1$ and keep in memory the configurations shown in Fig. 1. Then (because of the *adaptive diversity order* mechanism (see section 5) and according to the solution[3] of (16)) the robot will run the MDMT algorithm using the optimal diversity order for each case, i.e., $N = 2$ for the transmission of a measurement file, $N = 3$ for the transmission of an image file and $N = 4$ for the transmission of a video file.

So if the robot applies the MDMT algorithm using its *adaptive diversity order* mechanism then $\mathbb{E}[E_{tot}] = 1.7455$ while if the robot applies the MDMT algorithm with $N = 4$ for all the files then $\mathbb{E}[E_{tot}] = 2.2729$ and if it uses $N = 2$ for all the files then $\mathbb{E}[E_{tot}] = 1.9224$. This shows that in order to save the maximum amount of energy we should use the MDMT algorithm using its *adaptive diversity order* mechanism.

[3] The solution is: $N^* = 4$ for $K_c \in [0, 4.2]$, $N^* = 3$ for $K_c \in [4.3, 10.7]$ and $N^* = 2$ for $K_c \in [10.8, \infty)$.

8. CONCLUSIONS

Using the MDMT algorithm the robot improves the channel gain without any extra hardware and with reduced energy expenditure. The channel gain threshold (η) lets the robot avoid expending energy in movements which have only a promise of low reward as regards improving the channel gain. The stopping points have to be chosen in such a manner that (i) their channel gains are uncorrelated and (ii) they are close to each other so that the robot reduces energy expenditure in moving through them. The E_{tot} parameter gives us a metric to quantify how much energy the robot can save. This is the first time that the geometry of the stopping points has been derived analytically to minimize energy consumption and maximize diversity gain.

9. REFERENCES

[1] J. M. Smith, M. P. Olivieri, A. Lackpour and N. Hinnerschitz, *"RF-mobility gain: concept, measurement campaign , and explotation"*, IEEE Wireless Communications, vol. 16, no. 1, February 2009.

[2] M. Lindhe and K. H. Johansson, *"Using robot mobility to exploit multipath fading"*, IEEE Wireless Communications, vol. 16, no. 1, February 2009.

[3] A. Ghaffarkhah and Y. Mostofi, *"Path planning for networked robotic surveillance"*, IEEE Transactions on Signal Procesing, vol. 60, no. 7, July 2012.

[4] X. Li, R. Falcon, A. Nayak, I. Stojmenovic, *"Servicing wireless sensor networks by mobile robots"*, IEEE Wireless Communications Magazine, vol. 50, no. 7, February 2012.

[5] J. H. Jung, S. Park , S. Kim, *"Multi-robot path finding with wireless multihop communications"*, IEEE Wireless Communications Magazine, vol. 48, no. 7, February 2010.

[6] W.C. Jakes, *Microwave Mobile Communications*, Wiley. IEEE Press, New York, 1994.

[7] A. F. Molish, *Wireless Communications*, Wiley. IEEE Press, 2011.

[8] D. E. Kirk, *Optimal Control Theory : An Introduction*, Prentice-Hall, 1970.

[9] M. K. Simon; M. Alouini, *Digital Communication Over Fading Channels*, Wiley. IEEE Press, 2005.