Radiation awareness in three-dimensional wireless sensor networks

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Introduction

Imagine a person moving in a smart environment with abundant heterogeneous wireless networking (such as WiFi, Blue-tooth, ZigBee and Cellular),

carrying wearable, on-body or even implanted wireless devices (such as smart phones, medical equipment and tiny smart sensors).

We call "radiation" at a target elementary surface (or area) the total amount of electromagnetic quantity (in terms of energy or power density) it is exposed to.

This additive/correlated impact of cumulative radiation may affect not only the human itself but also any carried sensitive nano-scale devices and vital equipment;

Even if this impact can be considered controversial we believe it is worth studying and control.

We study this issue for the first time from an ICT perspective.

Motivation

- Almost all wireless devices operate in frequencies of the non-ionizing spectrum (100 kHz-300 GHz)
- The impact of non-ionizing frequencies on humans: **thermal** and **non-thermal** effects.
- Safety levels for humans have been based on thermal effects $\Rightarrow$ thermal effects mechanisms long studied.
- Many scientists worry for:
  - non-thermal effects (far below established safety levels)
  - the radiation environment around human beings is continuously enriched (e.g. on-body or implanted wireless sensors, remotely controlled in-body medical devices).

EM Background

In a wireless communication environment people interact with a very complex time and space-dependent electromagnetic system.

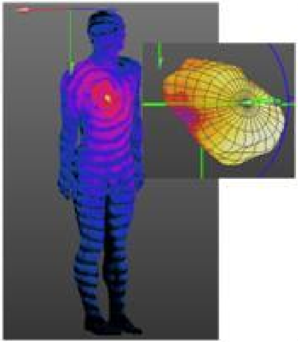
Field distributions are highly unpredictable and dynamically changeable.

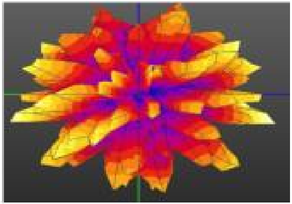
On-body and wearable electromagnetic devices, for example, will interact with each other depending on their inter-element distance, their relative position and their radiation characteristics.

More importantly, the radiation behavior will change due to biological media (human) presence.

EM Background (II)

The far-field radiation pattern of an antenna when placed on-body versus the case of distributing four antennas (same design) on two humans. As seen, the two humans, who are in close distance, greatly affect the radiation pattern of each antenna.





Overview

- Network model.
- Point radiation, path radiation.
- Radiation in random network topologies.
- The minimum radiation path problem.
- Four distributed heuristics and the off-line optimum.
- Experimental performance evaluation.
- Conclusions and future work.

Network Model

- n sensors deployed in a 3D area $\mathcal{A} \subset \mathbb{R}^3$.
- For two points $\vec{x}, \vec{y} \in \mathcal{A}$, we denote by $dist(\vec{x}, \vec{y})$ the Euclidean distance between them.
- r: wireless transmission range.
- λ: Poisson process modelling the data generation rate.
- T_e: an exponential random variable with parameter λ' representing the duration of a transmission, where λ' depends on the data packet size and the environment.
- $t(e)$ the time of occurrence of event e

Radiation Definitions: Point Radiation

Total point radiation during a time interval: the radiation at point $\vec{x}$ caused by sensor v due to data transmission related to an event e:

$$R_{\vec{x},e,\mathbf{v}} = B\frac{r^2}{(1 + dist(\vec{x}, \mathbf{v}))^{\mathbf{2}}}T_e, \tag{1}$$

where B a constant depending on the environment.
Total radiation caused at point $\vec{x}$ from data transmissions due to events e occurring in $[t_1, t_2]$:

$$R_{\vec{x}}([t_1, t_2]) = \sum_{\mathbf{v}} \sum_{e:t_1 \leq t(e) \leq t_2} R_{\vec{x},e,\mathbf{v}}. \tag{2}$$

Maximum point radiation in a time interval: Given a small time distance $\tau > 0$, the maximum radiation at $\vec{x}$ within $[t_1, t_2]$ is the random variable:

$$MaxR_{\vec{x}}([t_1, t_2], \tau) = \max_{t_1 \leq t \leq t_2 - \tau} R_{\vec{x}}([t, t + \tau]). \tag{3}$$

Let P a specific trajectory (path) in A.
$\rightarrow \mathcal{P}[\tau_1, \tau_2]$ part of $\mathcal{P}$ that a moving particle traverses between time τ_1 and time τ_2

Radiation of a path:

$$R_{\mathcal{P}}([t_1, t_2]) = \sum_{\mathbf{v}} \sum_{e: t_1 \leq t(e) \leq t_2} \int_{\mathcal{P}[t(e), t(e)+T_e]} B \frac{r^2}{(1 + dist(\vec{x}, \mathbf{v}))^{\mathbf{2}}} d\vec{x}$$

Approximate the above by the sum:

$$R_{\mathcal{P}}([t_1, t_2]) \approx \sum_{\mathbf{v}} \sum_{e: t_1 \leq t(e) \leq t_2} \sum_{i: t_1 + i dt \in [t(e), t(e)+T_e]} B \frac{r^2}{(1 + dist(\vec{x}_i, \mathbf{v}))^{\mathbf{2}}} dt$$

Maximum radiation within $[t_1, t_2]$:

$$MaxR_{\mathcal{P}}([t_1, t_2], \tau) = \max_{t_1 \leq t \leq t_2 - \tau} R_{\mathcal{P}}([t, t+\tau]).$$

Point radiation in random geometric graphs (I)

Random Geometric Graph

The graph $G_{n,r} = (V, E)$ with vertex set the set of n points (sensors deployed uniformly at random in a target area $\mathcal{A}$) and edge set all pairs of vertices having euclidean distance at most r (i.e. $E = \{(u, v) \in V^2 : dist(u, v) \leq r\}$)

Assumption: The target area $\mathcal{A}$ of the random geometric graphs model $\mathcal{G}_{n,r}$ is $B(\vec{x}, r_{\mathcal{A}})$, i.e. the sphere of radius $r_{\mathcal{A}}$ centered at $\vec{x}$.

Point radiation in random geometric graphs (II)

Theorem

Let $G_{n,r}$ be a random instance of the random geometric graphs model on target area $\mathcal{A} = B(\vec{x}, r_{\mathcal{A}})$. Then, for the total radiation caused at point $\vec{x}$ from data transmissions due to events occurring in some fixed time interval $[t_1, t_2]$ we have:

$$(a) E[R_{\vec{x}}([t_1, t_2])] = \frac{3nB\Lambda r^2}{\lambda' r_{\mathcal{A}}^3} \left(\frac{2r_{\mathcal{A}} + r_{\mathcal{A}}^2}{1 + r_{\mathcal{A}}} - 2\log(1 + r_{\mathcal{A}}) \right)$$

$$(b) Var[R_{\vec{x}}([t_1, t_2])] = \frac{nB^2 r^4}{\lambda'^2} \cdot \left(\frac{\Lambda^2 + 2\Lambda}{(1 + r_{\mathcal{A}})^3} - \frac{9\Lambda^2}{r_{\mathcal{A}}^6} \left(\frac{2r_{\mathcal{A}} + r_{\mathcal{A}}^2}{1 + r_{\mathcal{A}}} - 2\log(1 + r_{\mathcal{A}}) \right)^2 \right)$$

where $\Lambda = \lambda(t_2 - t_1)$

Point radiation in nearest neighbor random graphs (I)

Suppose that we deploy n points uniformly at random in a target area $\mathcal{A} \subseteq \mathbb{R}^2$.

Given an integer $k > 0$, if we connect every point with its k closest points, then we get an instance of the k-nearest neighbor random graphs model $\mathcal{G}_{n,k}$.

Even though the deployment of the sensors in this model is similar to $\mathcal{G}_{n,r}$, the power (or radius) of each sensor is different (since it is as large as its distance to its k-th closest neighbor). This affects the radiation emanated from each sensor.

Effective Radius: $G_{n,k}$ an instance of the k-nearest neighbor random graphs model. For any node $\mathbf{v}$, effective radius is the distance of $\mathbf{v}$ to its k-closest neighbor.

Lemma

Let $G_{n,k}$ be a random instance of the k-nearest neighbor random graphs model on target area $\mathcal{A} = B(\vec{x}, r_{\mathcal{A}})$. For any $k < n$, the effective radius of every node $\mathbf{v}$ is at most $\xi \stackrel{def}{=} r_{\mathcal{A}} \sqrt[3]{2\frac{k \ln n + \ln^3 n}{n-k}}$ with probability at least $1 - O\left(\frac{1}{n^2}\right)$.

Mean value of total radiation at point $\vec{x}$ from data transmissions due to events occurring in some fixed time interval $[t_1, t_2]$:

Theorem

If $n \to \infty$ and $k = O(n^{1-\epsilon})$, for some fixed $\epsilon > 0$

$$E[R_{\vec{x}}([t_1, t_2])] \sim \frac{3nB\Lambda}{\lambda' r_{\mathcal{A}}^3} \left(\int_0^{\xi} z^2 f(z) dz \right) \cdot \left(\frac{2r_{\mathcal{A}} + r_{\mathcal{A}}^2}{1 + r_{\mathcal{A}}} - 2\log(1 + r_{\mathcal{A}}) \right)$$

The Minimum Radiation Path Problem

We are interested in finding exact or approximate algorithmic solutions to the following problem:

The Minimum Radiation Path Problem - MRP

Let G a sensor network deployed in a target area $\mathcal{A}$ and A, B two distinct points in $\mathcal{A}$. Find a trajectory $\mathcal{P}$ from A to B minimizing the expected radiation $R(\mathcal{P})$.

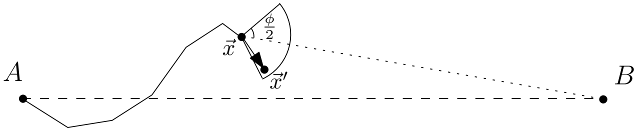
We provide:

- An *(offline)* optimum path given by a Dijkstra-like algorithm.
- Four *distributed, online* approaches:
  1. Minimizing total distance - Algorithm MinD,
  2. Minimizing the next step radiation - Algorithm MinR,
  3. Optimizing the radiation/progress to destination trade-off - Algorithm MinDR,
  4. A dichotomy algorithm - Algorithm MinDRD

$\rightarrow D(\vec{x}, r)$, the ball of radius r centered at $\vec{x}$

$\rightarrow S(\vec{x}, r, \phi) \rightarrow$ the area of all points $\vec{x}'$ that satisfy $\|\vec{x} - \vec{x}'\| \leq r$ and $\widehat{B\vec{x}\vec{x}'} \leq \frac{\phi}{2}$

At any point $\vec{x}$ during its movement, the entity chooses uniformly at random k points inside $S(\vec{x}, r, \phi)$ and moves in a straight line to the one that has the lowest expected radiation.



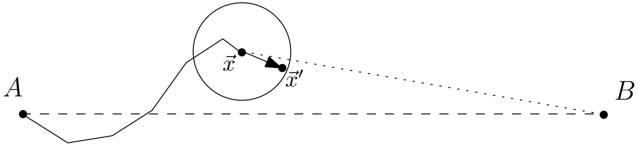
Weakness: the total distance traveled is not taken into account $\Rightarrow$ the resulting path can be quite long (but we can play with ϕ).

Optimizing the radiation/progress to destination trade-off - Algorithm MinDR

MinDRD is a composition of algorithms MinD and MinDR.

Algorithm MinDR: Optimizes the radiation/progress to destination trade-off.

At any point $\vec{x}$ during its movement, the entity chooses uniformly at random k points inside $D(\vec{x}, r)$ and moves in a straight line to the point $\vec{x}' = \arg\min_{\vec{y}} R(\vec{y}) \, \|\vec{y} - B\|$.



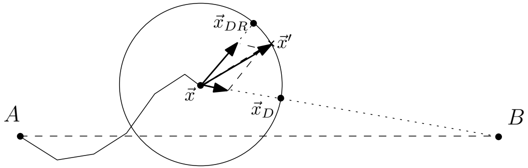
A dichotomy algorithm - Algorithm MinDRD (I)

MinDRD considers both moves that MinD and MinDR propose and finally makes a move that is a combination of those moves according to a parameter τ (initially $\tau = 1$) that describes its *trust* in them.

Let $\vec{x}_{DR}$ the point by MinDR, $d = \|\vec{x}_{DR} - \vec{x}\|$ and $\vec{x}_D$ the point by MinD. The algorithm computes:

$$\vec{x'} = \vec{x} + \frac{d(\tau(\vec{x}_{DR} - \vec{x}) + (1-\tau)(\vec{x}_D - \vec{x}))}{\|\tau(\vec{x}_{DR} - \vec{x}) + (1-\tau)(\vec{x}_D - \vec{x})\|}$$

as the next point (i.e., the weighted sum of the two suggestions).



A dichotomy algorithm - Algorithm MinDRD (II)

Parameter τ (trust of belief) is updated during the algorithm:

- a good move, which verifies that the assumption of MinDR is correct (i.e., radiation at the new point is similar to the expected radiation at that point), results in strengthening the trust to MinDR (measured by the parameter τ).
- A bad move (i.e. a move that increases the cumulative radiation more than MinDR expects) weakens this trust and re-inforces minD.

Finding the offline optimum (I)

- Without loss of generality, assume that the target area $\mathcal{A}$ is a cube.
- We tessellate $\mathcal{A}$ in n^3 equal cubes. Each cube is represented by its center.
- We construct $G_{n,\mathcal{A}} = (V_{n,\mathcal{A}}, E_{n,\mathcal{A}})$ as follows:
  - The vertex set $V_{n,\mathcal{A}}$ of $G_{n,\mathcal{A}}$ is the set of all cube center points $v_{i,j,k}$.
  - The edge set $E_{n,\mathcal{A}}$ of $G_{n,\mathcal{A}}$ contains all arcs from any point $v_{i,j,k}$ to the center points of its neighboring cubes.
- We create the node-arc adjacency matrix of $G_{n,\mathcal{A}}$, T:

$$T_{v,e} = \begin{cases} 1 & \text{, if } v = e_1 \\ -1 & \text{, if } v = e_2 \\ 0 & \text{, otherwise.} \end{cases}$$

  for any $v \in V_{n,\mathcal{A}}$ and $e = (e_1, e_2) \in E_{n,\mathcal{A}}$.
- Any path between A, B is composed by line segments between the points in the center of neighboring cubes of

Finding the offline optimum (II)

Find an optimal path between points A and B $\Rightarrow$

Find a minimum weight path between vertices A and B in $G_{n,\mathcal{A}}$.

- Let d the distance between nearby centers and t_d the time needed to travel at distance d
- Weight of each edge $e = (e_1, e_2)$ is: $\quad w(e) = R_{e_1}([0, t_d])$,
- implementation of Dijktra's algorithm $\rightarrow$ find a minimum path in $G_{n,\mathcal{A}}$ with edge weights $w(e), e \in E_{n,\mathcal{A}}$
- $|E_{n,\mathcal{A}}| = \Theta(|V_{n,\mathcal{A}}|)$ and $|V_{n,\mathcal{A}}| = n^3$
- Approximation to the optimal trajectory between A and B in $O(n^3 \log n)$ time.

Simulation Setup

- Simulation environment: Matlab R2008b
- Network region: 30x30x30m
- Network topologies: a grid and a random uniform placement
- Transmission range: $R = 5$m
- Number of sensor nodes: grid topology $\rightarrow$ 125 sensor nodes, random uniform placement $\rightarrow$ 250 sensor nodes
- We conducted 100 iterations.
- We measured the mean values of the **radiation** each heuristic resulted to and the **distance travelled** by the particle (i.e. the trajectory length).

Findings - the path formed by each algorithm

- On the background the radiation levels at each point of the network area.
- The brighter the color, the higher the radiation level, with the brightest spots being the radiation at the sensor nodes' locations.

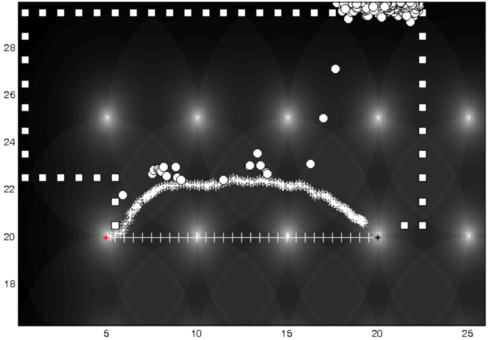
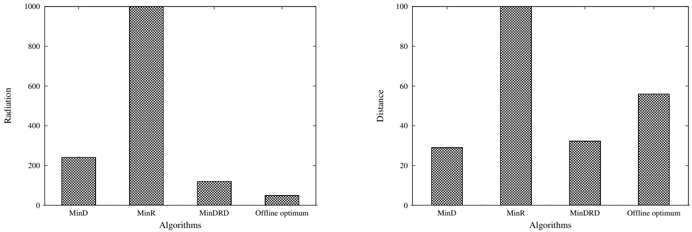


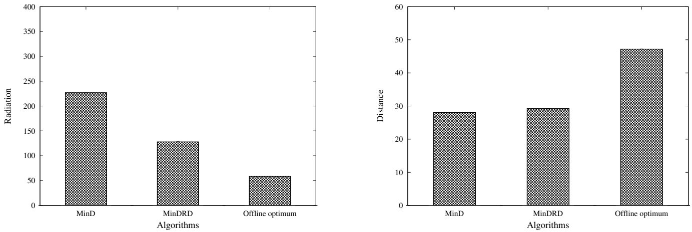
Figure : The path each algorithm follows: the offline solution's route is marked in squares, MinR's route with circles, MinDRD's route with "*" and MinD's route with "+".

Findings in the Grid topology - Total Radiation



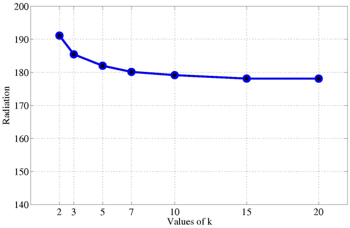
- MinR's performance is poor, because the algorithm tries to minimize the next step radiation and this can cause it to never reach the target.
- The shortest path algorithm gives the minimum solution in terms of radiation but the particle has to cover the largest distance.
- MinDRD achieves a nice trade-off between total path radiation and distance traveled.

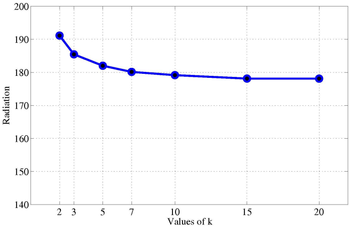
Findings in Random Uniform Placement - Total Radiation



- The performance of MinR is the same as in the grid topology.
- The shortest path algorithm gives the offline optimum for the total radiation of the path.
- MinDRD achieves a nice trade-off between total path radiation and distance traveled.

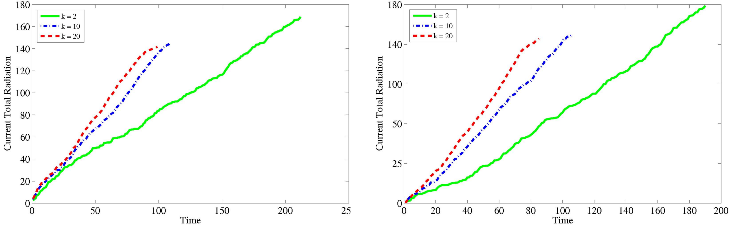
Multiple samples



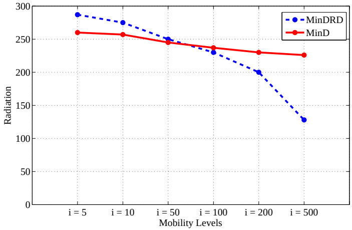


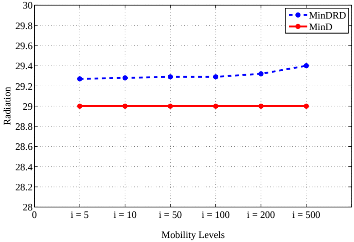
As k increases, the radiation tends to decrease. However, the improvement is negligible for $k > 10$

Radiation at path segments



The cumulative radiation as a function of time (namely of the number of steps) does not have any peaks
$\Rightarrow$ maximum radiation not high at any path segment.





- High mobility $\rightarrow$ MinD outperforms the MinDRD heuristic
- The difference between them becomes smaller as mobility decreases
- MinDRD uses neighborhood radiation levels to determine the next move — In high mobility any information on neighborhood radiation levels becomes quickly outdated.

Future Work

- Examine how the heuristics scale with a growing number of sensor nodes.
- Effectively incorporate the radiation aspect in fundamental networking problems, like in data propagation.
- Suggest on-line methods for network self-configuration, in a context-aware manner, to minimize radiation while still preserving good performance.
- Except the total point radiation, investigate the effect of the heuristics on the maximum point radiation quantity.
- Experiments with real devices and specialized equipment (like spectrum analyzers) $\longrightarrow$ more accurate radiation definition.
- Investigate the radiation aspects in broader, heterogeneous wireless network settings (not just sensors).