GammaSense: Infrastructureless Positioning using Background Radioactivity

Doina Bucur and Mikkel Baun Kjærgaard

Department of Computer Science, University of Aarhus, Denmark
Email: [doina|mikkelbk]@daimi.au.dk

Abstract. We introduce the harvesting of natural background radioactivity for positioning. Using a standard Geiger-Müller counter as sensor, we fingerprint the natural levels of gamma radiation with the aim of then roughly pinpointing the position of a client in terms of interfloor, intrafloor, and indoor versus outdoor locations. We find that the performance of a machine-learning algorithm in detecting position varies with the building, and is highest for interfloor detection in the case of an old domestic house, while it is highest for intrafloor detection if the floor spans building segments made from different construction materials.

1 Introduction

Positioning is an important requirement for many novel applications. However, technologies for positioning often depend on extensive infrastructures, which limit the coverage of these technologies and create breakdowns in the user experience when a user crosses the—often invisible—infrastructure boundaries. One approach for solving this problem is the development of positioning technologies with pervasive coverage which minimizes the dependence on infrastructure.

Prior work on positioning has used the properties of physical phenomena such as hearable sound, ultrasound, and types of non-ionizing radiation (e.g. visible light and radio signals). In this work we consider the use of ionizing radiation (specifically, products of radioactivity: alpha, beta and gamma rays) for positioning. In our environment, the sources of such radiation include natural radioactivity in the soil and building materials, and cosmic rays.

In practice, gamma radiation is most relevant, since alpha and beta radiation have subcentimeter propagation range. The radiation appears naturally in the environment, and the geometry of its sources in a built environment gives more interesting variation patterns than the patterns of other radiation sources, such as visible light.

Harvesting gamma radiation to infer location has several advantages: (i) Gamma radiation is pervasive, therefore coverage is not confined to an area of infrastructure coverage; (ii) The geometry of radiation sources is strikingly different from that of other radiation, which makes gamma readings a desirable sensor input in e. g. sensor fusion; (iii) There exist many devices that sense gamma radiation, and the threat of terror might make them even more widespread. Doing positioning over gamma radiation also has disadvantages: (i) Radiation has no identifier embedded in the signal, so there exists only one signal source to use in location estimation. This is the same drawback as when using visible light. (ii) Compared to other signals, a longer sampling time is needed for detecting relevant statistical properties of received radiation patterns.

We make the following contributions: (i) We show that gamma radiation is a predictable signal for positioning (ii) We analyze which environment properties gamma radiation depends on (iii) We present the first positioning system based on background radioactivity named *GammaSense*, which positions a device using location fingerprinting over gamma readings.

The remainder of this paper is structured as follows: In Section 2, we present the relevant related work. Subsequently, we give a primer to gamma radiation and discuss it as a signal source for positioning in Section 3. Then the novel GammaSense positioning system is introduced in Section 4. Evaluation results for GammaSense are provided in Section 5. Finally, Section 6 concludes the paper and provides directions for future work.

2 Related Work

Our system examines the performance of doing localization on the basis of measuring the levels of background radioactivity (gamma rays) indoors, and employing the technique of location fingerprinting. While—to our knowledge—no other work does infrastructureless localization with background radioactivity, a wealth of existing research does explore the matter of doing localization indoors, based on a variety of technologies and types of infrastructure, such as infrared, ultrasonic and ultra-wideband, and their specific emitters and detectors.

The common drawback of these systems is their reliance on custom infrastructure, a fact which then diminishes their acceptance and easiness of deployment. GammaSense takes the very opposite approach and looks into making use of natural signals for indoor positioning, offering a degree of location detection completely independent of any infrastructure.

GammaSense uses the technique of *location fingerprinting*, which has already been applied in related work with radio waves, light and sound signals. It is based on the acquiring of a database of prerecorded signal measurements, denoted as location fingerprints. Clients' locations are then estimated by comparing them with the database of fingerprints [1].

One of the first location fingerprinting systems was the radio-based RADAR [2] system, which applied different deterministic mathematical models to calculate the coordinates of a client's position from WaveLan/IEEE 802.11 signal strengths. Similar methods were applied to GSM signals by Otsason et al. [3]. Unlike RADAR, later systems employed probabilistic models instead of deterministic ones. An example of a probabilistic system which calculates a client's coordinates was published by Youssef et al. [4]; a similar system determining the logical position or cell of a client was published by Haeberlen et al. [5].

A radio-based system named SkyFloor [6] focused on predicting the floor of a client.

The principle of location fingerprinting was also applied to sound signals by Patel et al. [7]; their system uses the electric wiring in a building to generate sound signals on several frequencies, which form distinctive sound patterns throughout the building. A tone detector then picks up these sound signals and uses them as location fingerprints. A positioning system based on location fingerprinting over visible light intensities was also proposed by Ravi et al. [8].

3 Gamma Radiation

3.1 A Primer on Radioactivity and Ionizing Radiation

Radioactivity is the natural phenomenon in which certain—possibly artificial—chemical elements emit radiation spontaneously, be it in the form of electromagnetic waves or of charged particles. The cause of this emission is radioactive decay, i.e. the spontaneous transmutation of an unstable parent element into a more stable daughter element; the decay rate is practically expressed with the term "half-life", meaning the span of time required for half the quantity of the radioactive element to transmute.

One form of radioactive decay is the beta decay. A neutron or a proton transform into the other within the parent nucleus, accompanied by the emission of an electron (or its positively charged version, a positron); this electron is called a *beta particle* or beta ray. If a neutron transmutes into a proton, a negatively charged electron e^- with high kinetic energy (a β^- particle) is expelled from the nucleus. The alternative transmutation with a positron emission (a β^+ particle) cannot occur without energy input, because the mass of a neutron is higher than that of a proton. Hence, β^+ rays are mostly produced artificially in particle accelerators ([9]).

Another produce of radioactive decay are *gamma rays*, an electromagnetic radiation having the highest frequency and the shortest wavelength within the electromagnetic spectrum. Neutrons and protons occupy well-defined energy levels in a nucleus, and when either particle is excited to a higher unoccupied level, the excited nucleus decays to a lower energy state, and the difference in energy is emitted as gamma radiation. This energy difference is much larger (in the range of MeV) than in the case of excited electrons, whose similar state mutations release visible, near-visible light or X-rays (with an energy of a few eV).

Beta particles typically have energies from a few KeV to a few MeV and the mass of an electron (atomic mass 1/1836). The range of beta particles is short: a 1.9mm sheet of aluminium stops a 1MeV beta particle ([10]). Because they are relatively light, beta particles do not travel in straight lines but follow a random path through material. Gamma rays are high-energy (0.1 to 3 MeV). Their range is long and penetration power high; their typical means of losing energy is by ejecting an electron from an atom and being scattered from the impact with reduced energy (the Compton effect). To reduce the intensity of a

0.5MeV gamma ray to 0.37 of its initial value, one needs to lay a shield of 4cm of aluminium, 0.59cm of lead or 28.6cm of tissue paper ([10]).

Beta and gamma radiation also accompany *alpha decay* (another omnipresent radioactive decay in which heavy nuclei disintegrate by emitting a positively charged nucleus of helium, ${}^4_2He^{2+}$, with an even shorter range than beta particles, due to their large atomic mass of 4). Many alpha sources are accompanied by beta-emitting radiodaughters, and alpha emission is followed by gamma emission from the remaining negatively charged nucleus.

All three forms of radiation produced by radioactive decay can ionize atoms or molecules in their path (either due to their electric charge, or to their kinetic energy), transforming them into ions by adding or removing changed particles. Hence, along with other rays, they are collectively called *ionizing radiation*.

3.2 Natural Sources of Radioactivity

Background radiation is omnipresent, and has always existed naturally. Its sources are *cosmic rays* (from outer space and the Sun) and *terrestrial radioactivity* naturally occurring in soil, building materials and in air, water, foods and the human body (as in Table 1, after [11]).

Table 1. Average worldwide exposure to natural air and soil radiation sources

Source of radiation	Percentage
Cosmic radiation total	18.48
of which ionizing (beta and gamma)	13.74
Terrestrial radiation total	82.46
soil and building materials: ${}^{238}U$, ${}^{232}Th$ (alpha), ${}^{40}K$ (beta)	22.74
air: radon ${}^{222}Rn$, thoron ${}^{220}Rn$ (alpha)	59.24

Out of the sources of radiation in Table 1, the ionizing component of the cosmic radiation, the radioactive elements in soil and construction materials (${}^{238}U$, ${}^{232}Th$ series and ${}^{40}K$, in approximately equal contributions), and the aerial radioactive gases radon (and, in small concentrations, thoron) are all measurable sources of beta and gamma rays (either directly or indirectly, as a side effect of alpha decay).

The specific concentrations of radioactive elements in soil are related to the types of rock from which the soils originate, which in turn correlate with the concentrations in air. The gas radon (a decay product of radium, with a half-life of 3.8 days) diffuses out of the soil. Radon and its decay products are the most important contributors to human exposure to radiation from natural sources.

Indoor concentration of gamma rays, mainly determined by the materials of construction, is inherently greater than outdoor exposure if earth materials have been used; the geometry of the radiation source changes indoors from a half-space to a surrounding configuration. The indoor to outdoor ratios range from 0.6 to 2.3, with a worldwide ratio of 1.4 ([11]).

3.3 Indoor Variations of Radiation Concentrations

Some of the radioactive sources are fairly constant and uniform geographically, while others vary widely with location. Naturally, cosmic rays are less intense at lower altitudes, and concentrations of uranium and thorium are elevated in certain soils. More interestingly, the building materials of houses and the design and ventilation systems strongly influence indoor levels of the most important contributors, radon and its decay products.

Advection from the soil is the main factor for high radon entry rates in buildings (as in Table 2, after [11, 12]). Radon is driven indoors by the pressure differential between the building and the ground around the foundation, produced by the higher indoor temperatures, ventilation, and to some degree by wind blowing on the building. The effectiveness of this pressure differential is dependent on the permeabilities of the building foundation and the adjacent earth. Also, wind can cause decreases in radon entry concentrations by its flushing effect on radon in soil surrounding the house. Because of differences in the pressure differentials and permeabilities, advection varies greatly from structure to structure, especially in temperate and cold climates. The non-masonry building in Table 2 has less accumulation of radon than the masonry one, due to a smaller radiation contribution from walls and ceilings.

Table 2. Representative radon entry rates in low-level residential houses: a masonry house and a wooden house in Finland [11]

Source of radon	Mechanism	Rate (Bq/m^3h) and percentage	
		Masonry house	Wooden house
Building elements			
Walls and ceiling	Diffusion	16 (18)	2 (3)
Subjacent earth			
Through gaps	Advection	66 (73)	60 (86)
Through slab	Diffusion	4 (4)	4 (6)
Outdoor air	Infiltration	3 (3)	3 (4)
Water supply	De-emanation	1 (1)	1 (1)
Total		90 (100)	70 (100)

Various surveys also find radon concentration variations between rooms in the same building. Ghany [13] and Sonkawade et al. [14] find that the mean values of radon concentration in bathrooms and kitchens were significantly higher than those in living rooms and bedrooms. The find is motivated by ceramic being a radon source, poor ventilation and the use of underground water and natural gas.

3.4 Experimental Results

Given the representative surveys in Subsections 3.2 and 3.3 upon the variations of radioactivity levels indoors, we expect to be able to harvest indoor radiation levels to use in localization. Two facts about the variability of the radiation levels are important when designing a localization algorithms based on fingerprinting: one is the geometric variability of the measurements within the building, and the other is the consistency of the signal levels at any given location. We give a brief account of our findings in the following.

Our experiments did confirm the expected indoor geometry of the radioactivity source. In one of our testbed buildings (a two-level domestic house, as seen later in Subsection 5.1), both the mean and the variance of radioactivity readings differ visibly between the two rooms on different floors, as in Fig. 1. The mean over a 1-hour-long continuous length of 1-minute counts shows a 10.32% decrease from the ground-floor room (mean 30.79 counts per minute) to the first-floor room (mean 27.61 counts per minute), and a striking difference in standard deviations (a 26.43% decrease, from 5.75 on level zero to 4.23 on the first level). This fact verifies that the major radiation source indoors is the subjacent earth, with its influence being diminished and smoothed with rising levels.

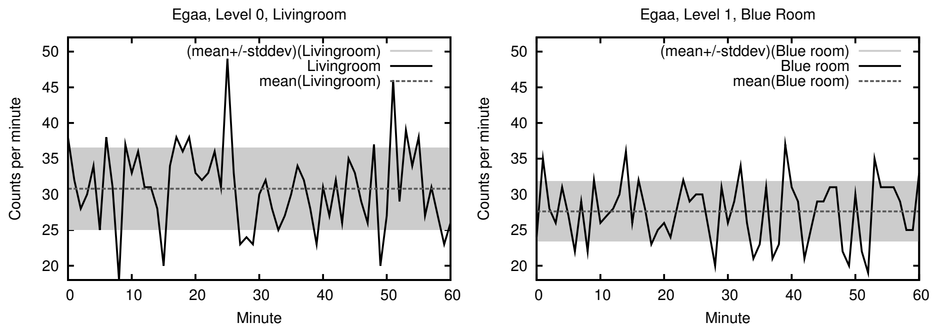

Fig. 1. The difference in radiation measurements over 1-hour periods between rooms on different floors in a domestic house in Egaa, Denmark

To confirm the stability of the signal, we then refer to Fig. 2, which depicts the typical variation in readings in a fixed position over a 1-day-long period of time. In another of our testbeds (a public institution, more on which in Subsection 5.1), subjected to a fair level of human activity during a working day, the signal doesn't exhibit significant variation.

4 GammaSense

The sensor we used for measuring radiation levels was a radioactivity meter composed of two devices: a commercially available Geiger-Müller tube and a pulse ratemeter (i. e. counter, either battery- or AC-powered) designed to feed the Geiger-Müller tube with voltage and to handle the pulses delivered by the tube. Both were manufactured by a small local company called *Impo electronic*,

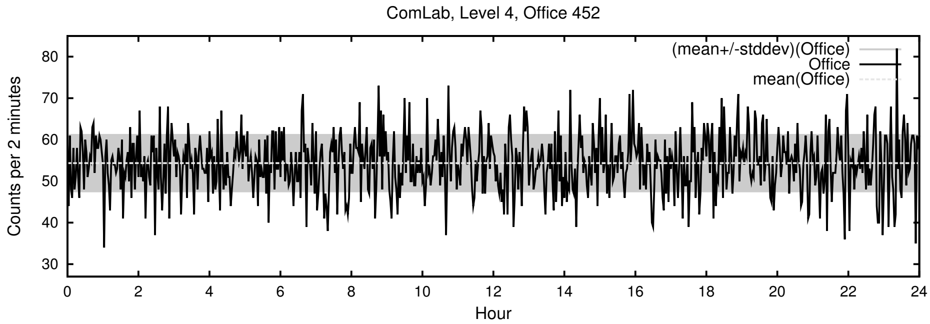

Fig. 2. Signal stability over a 24-hour period

for use in education. The setup and the tube's technical specification are depicted in Fig. 3.

A Geiger-Müller tube is one of the several radioactivity detectors whose functionality is based on the ionizing capability of the radiation produced through radioactive decay. The tube is filled with a mixture of inert gases, in which incoming ionizing radiation creates electrons and positively charged ions. The tube wall constitutes the negative electrode or cathode, while a thin central wire is highly charged with positive voltage and is an anode. The strong electric field created by the electrodes accelerates the ion towards the cathode and the electron towards the anode, giving them sufficient energy to ionize further gas molecules through collisions, thus creating an avalanche of charged particles.

The result is a short, intense pulse of current which passes from the negative electrode to the positive electrode and is counted as one ionizing particle. The counter also includes an audio amplifier that produces a beep upon pulse detection. The number of pulses per time unit measures the intensity of the radiation field. Cheap and robust, a Geiger-Müller tube can detect the intensity of radiation (particle frequency), but not particle energy.

We performed all measurements maintaining the anode voltage strictly at the recommended, mid-plateau voltage of 575V (as described in Fig. 3(b)), for best independence of counts from voltage supplied, both when powering the device from battery and when plugged into the power supply infrastructure. The counter allows the configuration of a small number of counting parameters, such as different count times (between 1 and 120 seconds) after which the total number of particles is reported, and has the ability to count and report continuously for such subsequent fixed periods.

The results are either reported on the counter's small screen, or sent through the counter's RS-232 interface to a laptop, stored in a volatile memory (which only holds 50 counts), or stored in a non-volatile datalog (with a capacity of 250 counts). In our experiments, we used either the sending of each count in real time to the laptop, or the downloading of the contents of the datalog—when

(a) Geiger-Müller tube in holder (left) and pulse ratemeter with data log and serial interface (right)

Sensitive to:	*beta, gamma* rays.
Effective diameter:	$27.8mm$.
Window material:	*mica.*
Window thickness:	$[2\frac{mg}{cm^2}, 3\frac{mg}{cm^2}]$.
Gas filling:	*neon, argon, halogen.*
Plateau:	$[450V, 700V]$.
Recommended voltage:	$575V$.
Dead time at 575V:	$19\mu S$.

(b) The tube's technical specifications. The *plateau* is the voltage interval where counts/sec is least dependent of voltage.

Fig. 3. The experimental setup: Geiger-Müller tube and counter with technical specifications

full—to the laptop; in both cases, the readings were saved in the ratemeter's format in raw data files.

On the laptop side of the RS-232 interface, we used a Linux Debian with *minicom*, a text-based, GPL-licensed terminal emulator for Unix-based operating systems.

For implementing location fingerprinting using gamma readings we used the machine-learning tool Weka [15]. Weka implements a range of machine-learning algorithms and several GUIs for configuration, experimentation, and visualization. Before selecting a machine-learning algorithm to use, we experimented with different algorithms, and concluded that the *LogitBoost* algorithm was most fit. LogitBoost is based on additive logistic regression, which means that the algorithm—given a simpler algorithm—iteratively constructs a better detector by combining several instances of the simple algorithm. We used a decision stump (i.e. a simple boolean classifier) as the simple algorithm.

In order to feed our data to Weka, we implemented a small Java program that reads the raw data files and outputs ARFF data for the Weka tool. The program also calculates certain features from the raw gamma readings: aggregated 60-second counts, and the mean and variance of the latest five 60-second counts. These features are then written to the ARFF file together with ground truth about whether the data was collected indoor or outdoor, on which floor, and at which horizontal location.

5 Evaluation

5.1 Data Collection

We collected the location fingerprints we used in our indoor localization study over an 8-month period ending in June 2008. For the study, we chose four testbed buildings with diverse construction parameters (i. e. number of floors, building materials and age of construction) located in two countries. We give a superficial visual impression of the four testbed buildings in Fig. 4, where we also list the identifiers by which we refer to the testbeds in the rest of the paper.

(a) an old village house in Egaa, Denmark (Egaa)

(b) the Computing Laboratory at the University of Oxford, UK (ComLab)

(c) the Mathematics Department at the University of Aarhus, Denmark (Math)

(d) the Computer Science Department at the University of Aarhus, Denmark (CS)

Fig. 4. The testbed buildings, ordered by age of construction; the building identifier is listed in parentheses

Their construction parameters are then recorded in Table 3, in terms of the year the building was finished, the type of construction materials and the number of building levels. For building Egaa, 1829 is the building year, while 1960 is the year when three of the perimeter walls have been renewed. Testbed ComLab is an extensive building composed of a number of smaller constructions, linked together: four old Victorian houses built before 1901 formed the southern wing, to which a identically-styled northern wing was added by 1993, for then a fully-modern segment to be attached by 2006.

Using the setup in Fig. 3 detailed in Section 4, we collected fingerprints of the background radioactivity at fixed height for any particular building. For Egaa, we took sample counts in each of the four rooms for one hour, while for CS and Math we fixed one and three locations, respectively, on each floor, and took sample counts for 10 to 20 minutes. In ComLab, due to the complexity of the building, we divided the study cases in two: a vertical study aiming at distinguishing among

Table 3. The testbeds' characteristics

Building	Built by	Building materials	Floors	Use
Egaa	1829, 1960	Stone, brick, wood, straw	2	domestic
ComLab	1901, 1993, 2006	Brick, concrete	5	institution
Math	1967	Brick, concrete, stone, wood	5	institution
CS	2001	Concrete, steel, glass	4	institution

floors collected 20-minutes worth of samples from the same vertical location on each level, while for the horizontal study we took measurements on the fourth floor at six locations divided equally among the three wings of the building.

For an additional indoor-versus-outdoor study, in the case of ComLab we also collected samples from two outdoor locations in the very vicinity of the testbed building. Also, to verify the stability of the signal, we collected long-term counts: one over 5 days in a fixed location in a CS office, and one over 2 days in a ComLab office.

All sample measurements were collected as continuous counts, 10-second (in the majority of experiments), 1-minute or 2-minute-long; the continuous taking of short counts allowed us to aggregate these short counts into longer counts, as needed for the study.

5.2 Accuracy

The accuracy of GammaSense was evaluated by emulation on the collected data set. The technique of emulation tests the machine-learning algorithms in an environment emulated by the data set, for the ability to distinguish among indoor horizontal locations, indoor vertical locations and indoor versus outdoor. The emulations were run in the Weka tool (as described in Section 4) using fivefold cross-validation for splitting up the data sets into training and test data for the machine-learning algorithms. The features used in the emulations were 60-second gamma counts, and the mean and variance of the last five 60-second counts.

The performance of the localization algorithm is judged in the rest of this section based on quantitative measures, i.e. the *detection accuracy*, the *confusion matrix* and the *kappa statistic*. The detection accuracy is the percentage of correctly classified tests. A confusion matrix shows how many instances have been assigned to each class; the matrix elements show the percentage of test examples whose actual class (i.e. the actual location) is the row and whose predicted class (i.e. the predicted location) is the column.

The kappa statistic quantifies how much a detector is an improvement over a random detector. It can be thought of as the chance-corrected prediction agreement, and possible values range from +1 (perfect agreement between prediction and reality) via 0 (no agreement above that expected by chance) to -1 (complete disagreement).

Horizontal The aim for the indoor horizontal localization was to distinguish among different building segments based on their different gamma patterns.

The ComLab building consists of three wings built by 1901, 1993 and 2006, respectively, with the oldest two wings highly similar in style and material. We grouped our ComLab data into three classes, one for each building part. The emulation for this three-class recognition problem gave a detection accuracy of 67.7% and a kappa statistic of 0.51.

Further analysis of the prediction errors revealed that they were not distributed evenly between the three classes, as shown by the confusion matrix in Table 4(b). The highest confusion rates were between the 1901 and 1993 wings, a fact we explain by a high similarity in building materials and style, despite the different ages. Furthermore, if the data is regrouped into a two-class problem for distinguishing between the 1901/1993 and 2006 wings, the accuracy increases to 81.7% and the kappa statistic to 0.60, as summarized in Table 4(a). Hence, localization accuracy depends on similarity of construction. We conclude that GammaSense distinguishes between building segments of different construction parameters with moderate performance.

Table 4. ComLab horizontal results.

(a) Detection results for localization among the three wings (first row). The same if the oldest two wings are aggregated into a single wing (second row).

	Accuracy	Kappa
ComLab (3 wings)	67.7%	0.51
ComLab (2 wings)	81.7%	0.60

(b) Confusion matrix for the 3-wing study. Elements show the percentage of tests whose row is the actual wing and whose column is the predicted wing.

	1901	1993	2006
1901	15.6%	9.7%	1.1%
1993	8.1%	23.1%	7.5%
2006	1.1%	4.8%	29.0%

Vertical For the indoor vertical localization, the target was floor detection. The Egaa, ComLab, Math, and CS data sets were used in this evaluation, and the emulation for these buildings gave the results in Table 5(a). Overall, the Egaa domestic house allowed us a high degree of floor prediction agreement, while this decreased for the three public institutions.

From the confusion matrix for the vertical ComLab study (Table 5(b)) one identifies that one particular reason for the poor accuracy is the fact that the fourth and basement floors are comparable in gamma counts. While high counts were expected for the basement floor, one explanation for the high counts of the top floor is the fact that either the roof of the building is highly radioactive, or that the poor building ventilation has the radioactive gases accumulate under the roof. The Math building does not suffer from this issue and exhibits higher accuracy and kappa statistic. CS gave the poorest results for the kappa statistic, possibly because the CS building is new, the shielding between floors and from the subjacent earth is intact, and there exists an active ventilation system.

We then conclude that GammaSense distinguishes among floors in a building, yet there exists a set of parameters which decrease detection accuracy, such as roof accumulation of radon or good ventilation.

Table 5. Indoor vertical results.

(a) Results for each testbed quantified by detection accuracy and kappa statistic.

	Accuracy	Kappa
Egaa	72.2%	0.45
ComLab	43.4%	0.29
Math	48.6%	0.35
CS	49.2%	0.23

(b) Confusion matrix for ComLab vertical. Elements show the percentage of tests whose row is the actual floor and column the predicted floor.

	0	2	3	4
0	10.5%	1.3%	0.0%	9.2%
2	0.0%	5.3%	6.6%	9.2%
3	0.0%	5.3%	9.2%	6.6%
4	9.2%	0.0%	0.0%	11.8%

Indoor versus Outdoor An additional aim for GammaSense was to detect indoor versus outdoor locations. Indoor and outdoor data from ComLab was used in the evaluation; the outdoor data was collected at two locations: one in the atrium (a small open yard in the core of the building), and the other on the lawn in front. The emulation results were:

accuracy: 91.7% and kappa statistic: 0.55.

We hypothesize that the better "ventilation" outdoor, either in the absence of building materials (which is the case for the lawn location) or even in their presence (the case for the inner atrium, surrounded by walls and paved) resulted in lower counts outdoors.

Sensitivity Analysis As a further analysis, we looked into more detail over the localization accuracy of the GammaSense algorithm, in the ComLab horizontal study for detecting among the three building segments, which gave the results on the first row of Table 4(a).

Specifically, we tested the variation of the detection accuracy and the kappa statistic as a function of the window size (i.e. the number of the last 60-second measurements whose mean and variance are given, together with the current reading, to the localization algorithm; the value for all the results reported above was five). The variation is reported in Fig. 5. As expected, since radiation counts are fairly unstable in value from one count to the other (as clear in Fig. 1 and 2), localization accuracy improves by considering more measurements per location; up to a number of eight minute-counts, performance parameters increase.

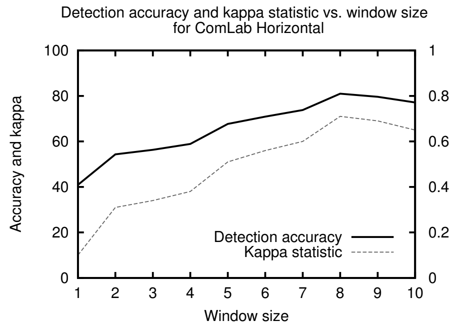

Fig. 5. The variation of detection accuracy and kappa statistic with window size (i.e. number of 1-minute measurements taken at each location)

6 Conclusions and Future Work

We investigated the performance of a machine-learning algorithm to pinpoint roughly the interfloor, intrafloor and indoor-versus-outdoor position of a client sensing background radioactivity levels indoors. We found that the accuracy results vary widely with the structure of the fingerprinted building, and report best performance for interfloor detection in a domestic house (a 72.2% detection accuracy) and intrafloor detection in a complex building made up of segments with different construction parameters (a 67.7% accuracy in wing detection). Also, we verify that the indoor-versus-outdoor detection for outdoor locations in the vicinity of the building has good performance (91.7%). Finally, we look into the variation of performance parameters with the window size (i.e. the number of minutes a client has to measure radiation levels at a location to have it detected) and report that performance increases with increasing window size, up to 8 minute-counts.

While we argue that harvesting natural parameters such as background radiation for location detection is worthy of research due to ease of deployment and a complete independence of infrastructure, we recognize that such techniques offer less performance and control than more standard, infrastructure-based techniques for localization. We state that—due to the geometry of its sources indoors—background radioactivity is a desirable signal for use in location estimation, especially one based exclusively on natural signals such as natural light, sound or the chemical components in the air (a potential future work).

The Geiger-Müller tube and counter that we used in our experiments are bulky for real-world deployments; however, miniaturized versions already exist–for instance, such sensors were integrated into mobile phones for early detection and localization of radioactive threats [16].

References

1. Kjærgaard, M.B.: A Taxonomy for Radio Location Fingerprinting. In: Proceedings of the Third International Symposium on Location- and Context-Awareness. (2007)
2. Bahl, P., Padmanabhan, V.N.: RADAR: An In-Building RF-based User Location and Tracking System. In: Proceedings of the 19th Annual Joint Conference of the IEEE Computer and Communications Societies, INFOCOM. (2000)
3. Otsason, V., Varshavsky, A., Marca, A.L., de Lara, E.: Accurate GSM Indoor Localization. In: Proceedings of the Seventh International Conference on Ubiquitous Computing. (2005)
4. Youssef, M., Agrawala, A.: The Horus WLAN Location Determination System. In: Proceedings of the Third International Conference on Mobile Systems, Applications, and Services. (2005)
5. Haeberlen, A., Flannery, E., Ladd, A.M., Rudys, A., Wallach, D.S., Kavraki, L.E.: Practical Robust Localization over Large-Scale 802.11 Wireless Networks. In: Proceedings of the Tenth ACM International Conference on Mobile Computing and Networking. (2004)
6. Varshavsky, A., Lamarca, A., Hightower, J., de Lara, E.: The SkyLoc Floor Localization System. In: Proceedings of the Fifth Annual IEEE International Conference on Pervasive Computing and Communications. (2007)
7. Patel, S., Truong, K., Abowd, G.: PowerLine Positioning: A Practical Sub-Room-Level Indoor Location System for Domestic Use. In: Proceedings of the Eighth International Conference on Ubiquitous Computing. (2006)
8. Ravi, N., Iftode, L.: FiatLux: Fingerprinting Rooms Using Light Intensity. In: Adjunct Proceedings of the Fifth International Conference on Pervasive Computing. (2007)
9. Ivan G. Draganić and Zorica D. Draganić and Jean-Pierre Adloff: Radiation and Radioactivity on Earth and Beyond, Second Edition. CRC Press (1993)
10. Royal Society of Chemistry: Essays on Radiochemistry: Alpha, Beta and Gamma Radioactivity. http://www.rsc.org/pdf/radioactivity/number3.pdf (unknown year)
11. United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR): ANNEX B: Exposures from natural radiation sources, subsubsection IIC2. www.unscear.org/docs/reports/annexb.pdf (2000)
12. European Commission: Commission recommendation of 21 february 1990 on the protection of the public against indoor exposure to radon. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=CELEX:31990H0143:EN:NOT (1990)
13. Ghany, H.A.A.: Variability of radon levels in different rooms of egyptian dwellings. Indoor and Built Environment **15**(2) (2006) 193–196
14. Sonkawade, R.G., Ram, R., Kanjilal, D.K., Ramola, R.C.: Radon in tube-well drinking water and indoor air. Indoor and Built Environment **13**(5) (2004) 383–385
15. Witten, I.H., Frank, E.: Data Mining: Practical machine learning tools and techniques. 2nd edn. Morgan Kaufmann, San Francisco (2005)
16. Venere, E., Gardner, E.K.: Cell phone sensors detect radiation to thwart nuclear terrorism. http://www.purdue.edu/UNS/x/2008a/080122FischbachNuclear.html (2008)