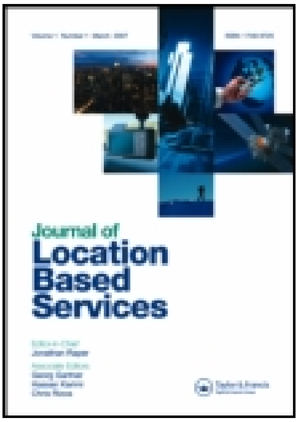

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Performance and limits of KNN-based positioning methods for GSM networks over leaky feeder in underground tunnels

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Localisation techniques have long been of major importance for safety systems and a lot of research has been conducted in the distributed computing field regarding its functionality and reliability. In the specific scenario of long yet narrow tunnels existing at CERN, localisation methods will enable a number of applications and processes to substantially reduce human intervention. In this article, we evaluate the use of fingerprinting techniques with GSM signal available throughout the LHC tunnel via a radiating cable and compare some methods to estimate the location. In the tests, 16 variants of the K-Nearest Neighbour algorithm, employing different distance weighting methods and fingerprint grouping functions, are taken into consideration and their performance is assessed with a specific rating algorithm. The existing GSM infrastructure and tunnel conditions seem to be favourable to the adoption of these fingerprinting methods. Nevertheless, significant variations in the signal have been observed which might be traced back to the presence of bulky equipment and different operational states of the accelerator. The performance limits of these fingerprinting methods are discussed for the current scenario and, based on that, an outlook for future research is given aiming at improving the system's accuracy under such challenging conditions.

Keywords: fingerprinting; KNN; GSM; leaky feeder; tunnels

1. Introduction

Location estimation has received considerable attention in the latest years after the success of the GPS system and the innumerable applications that emerged thereafter. Close to one billion GPS receivers are used worldwide, both for private, military and industrial uses, including process control and logistics management. GPS is nevertheless known to be very limited indoors and dense urban environments and its accuracy lies in the range of 10–100 m, depending on the receiver and the atmospheric conditions (Bajaj *et al.* 2002).

In the context of CERN (the European Organisation for Nuclear Research) activities, GPS is used at the surface being an integral component of general safety plans. Although GPS is not directly applicable underground, automatic localisation

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would also be highly advantageous for many applications of the various different technical departments at CERN. On the one hand, it would enable the tracking of people, which would not only allow optimised rescue plans for safety teams but also real-time monitoring of material transportation, guidance for underground work interventions, etc. On the other hand, achieving higher accuracy than common GPS implementations would be desirable as well. Of particular interest would be the application to the frequent radiation surveys carried throughout the entire accelerator complex by the radiation protection group. It involves radiation measurements in thousands of points around the accelerator facilities, for which an accurate position tag is required. In this context, the correct auto-determination of the position would allow for a much faster or even unmanned processing – a remarkable advantage in terms of efficiency, reliability and as a consequence also personnel safety.

Among indoor location techniques, those based in the Received Signal Strength (RSS) are of particular interest since they require neither the installation of extra infrastructure hardware nor allocation of extra spectrum (Bensky 2008, Weber *et al.* 2009). This is particularly important for the case of an accelerator tunnel where the risk of hardware damage due to radiation or interference with pre-existing components is high.

This article presents some preliminary results on the appropriateness of fingerprinting localisation methods for the specific tunnel environment. For that, several GSM fingerprints were collected in a limited sector of the tunnel and, subsequently, a first approach to estimate location was developed. The comparison of these methods' variants and their performance are explained and, in the end, an outlook of further research that will be carried out is provided.

2. Literature review

With the fast-paced development of wireless communications, the demand for accurate localisation of connected devices has increased. Depending on the application, different location parameters might be required and various wireless positioning technologies can be taken into consideration (Figure 1[1]). Indeed, accuracy is arguably the most critical factor when considering the different technologies; and as higher resolution levels are required the more sophisticated processing techniques are used on distinct signals and networks, from infra-red and radio-frequency (RF) to ultra-wideband, GSM to WLAN, Bluetooth or even GPS assisted by network information (A-GPS).

In particular, the indoor environment presents many challenges and, as such, positioning algorithms have been developed specifically to meet them, commonly taking advantage of several types of signal measurement.

2.1. *Distance finding principles*

Wireless positioning technologies build on three kinds of measurements to extract distance information. These are:

(1) Time-of-flight (ToF) or Time-of-Arrival (ToA)
(2) Angle-of-Arrival (AoA)
(3) RSS

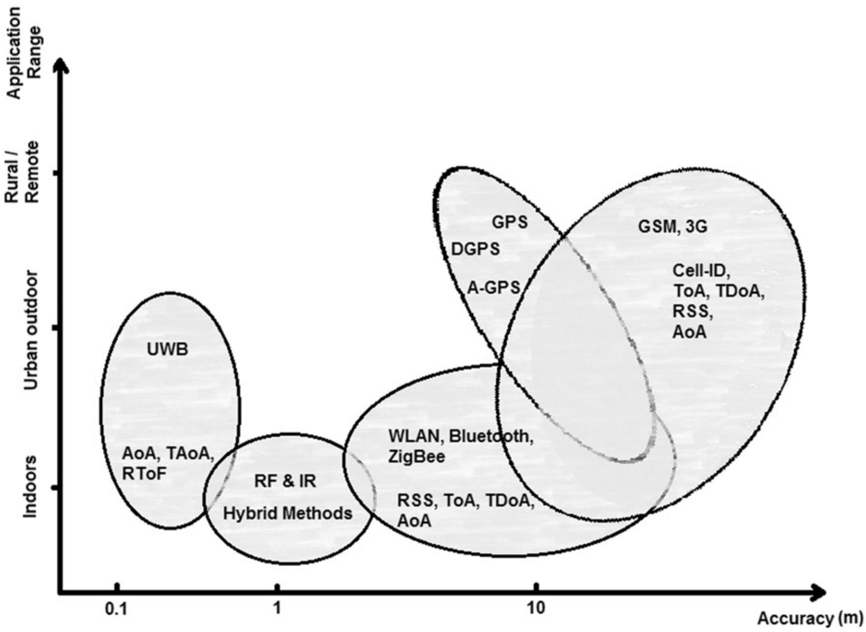

Figure 1. An overview of current wireless positioning technologies.

ToF/ToA techniques rely on the principle that the distance from the mobile target to the measuring unit is directly proportional to the propagation time. Radar is probably the best-known distance measurement system employing this principle, in which a device emits a RF pulse and measures the elapsed time until the reflected pulse is detected. In such configuration, the method is also known as Roundtrip ToF (RToF).

While techniques based on ToF measurement can be very precise, they must be implemented in dedicated hardware. Moreover, the precision of these systems is proportional to its clock frequency. Given that electromagnetic waves propagate nearly at the speed of the light, a very high time resolution is required to obtain an interesting spatial resolution: for instance, to achieve sub-meter accuracy in a Radar-like configuration, the hardware clock's frequency must be higher than 150 MHz. As a particular case of ToA, Time-Difference-of-Arrival takes advantage of the difference in time at which a signal arrives at multiple measuring units. This approach requires the measuring units to share a precise time reference but does not impose any requirement on the mobile target.

In AoA techniques, the angular position of the target is estimated by the measuring units by means of directional antennas. For that reason, localisation techniques based on this principle have been widely applied to cellular and other broadcast networks where such technology is already employed. Besides being simple, this approach requires no cooperation from the target object and works relatively well for very large distances, in the order of tens of kilometres.

Localisation techniques based on RSS measurements have lately received much attention since they work with virtually any existing wireless network. They rely on the fact that any signal suffers power attenuation as it propagates. The major drawback of this method is the unstable nature of the signal which is affected by different propagation conditions, interference, multipath and scattering effects. They are responsible for unpredictable fluctuations in the signal's power, which imply severe degradation of the positioning accuracy. To some extent, this issue can be mitigated using signal processing techniques.

2.2. *Positioning techniques*

All positioning techniques are based on the measurements described above, and very often on a combination of them. The use of several pieces of spatial information, usually from different measuring units, enables the determination of the position in a 2D or 3D referential. They can be subdivided into three categories: *Triangulation*, *Proximity* and *Fingerprinting*.

Triangulation builds on the principles of trigonometry to calculate a coordinate given the distance and/or angles formed by the mobile target and the measuring units. It is therefore very adequate to work with ToA and AoA measurements. In turn, the Proximity technique usually employs a dense grid of receivers whose position is well known. When a mobile node is detected in the vicinity of a receiver, its location is assumed to be the same as the receiver's. Detailed information on these two methods is out of the scope of this article. For more information, a good summary is given by Liu *et al*. (2007).

The Fingerprinting method calculates the best estimate of a position taking advantage of the measured RSS in two phases. During a first *off-line* or calibration phase, a *radio-map* containing the measured RSS is created. Such a map can then be used in the *online* or location estimation phase to calculate the best match with the RSS values of the location to be determined.

There are two kinds of algorithms to estimate the location during the online phase: (1) static algorithms, in which the collected fingerprints are individually considered in the calculus of a location and (2) filtering algorithms that take into account the previous measurements in addition to the current ones. Fingerprinting methods have, however, the severe drawback of requiring an updated *radio-map* so that the conditions of the off-line and on-line phases are identical.

Fingerprinting methods have been studied mostly over IEEE 802.11 networks (WLAN) where multiple Access Points (APs) enable a dense coverage in a limited area, like university campuses or building floor, e.g. RADAR (Bahl and Padmanabhan 2000). Nevertheless, they have lately been studied with quite different networks and configurations. In the first place, these techniques have also been explored for GSM networks (Otsason *et al*. 2005). Many improvements have been made in order to improve accuracy in these networks, including taking advantage of all 488 GSM carriers (Denby *et al*. 2009) or taking into consideration the signals from both the GSM and WLAN networks (Zhou *et al*. 2008). Furthermore, many different methods, like those based on neural networks, database correlation, tracking algorithms and RSS pre-processing, have been explored to address this issue and accuracies of 5 and 75 m for indoor and outdoor environments, respectively, have been achieved (Varshavsky *et al*. 2006). However, the reported accuracies vary among the previous studies, which are mostly due to the different network and test configurations, like the number of detected GSM channels, the presence of obstacles and the calibration granularity.

In the second place, Fingerprinting has also been tested for WLAN over Leaky-Feeder cable. Besides the coverage advantages in tunnels and long halls, Leaky-Feeders allow for wider available Line-of-Sight (LoS) conditions and therefore localisation accuracy is likely to be less sensitive to environmental changes (Weber *et al*. 2009).

3. Space characterisation and fingerprints collection

The LHC (CERN) tunnel at CERN is located 100 m below the surface; it is divided into eight sections and measures nearly 27 km in perimeter. The tunnel walls are made of concrete forming an arched layout with a radius of 2.2 m. Besides the LHC machine, a number of auxiliary support systems exist in the tunnel, including the cryogenics system and a large amount of cabling and electronics.

GSM network coverage is available all along the tunnel's length via a set of leaky-feeder cables installed at nearly two metres from the ground. For each tunnel section, two distinct radio signals are injected at each cable's ends (Figure 2), therefore creating two GSM cells. According to the vendor specifications (RFS), the cable is specifically designed for tunnels, providing low coupling loss variations. It propagates electromagnetic waves of up to 1950 MHz and it exhibits a longitudinal loss of 3.16 dB/km at 900 MHz. With this configuration, as one goes along the tunnel, one of the radio channels gets stronger while the other attenuates. Our objective is to exploit this radio environment for positioning inside the tunnel, thus avoiding the installation of further equipment.

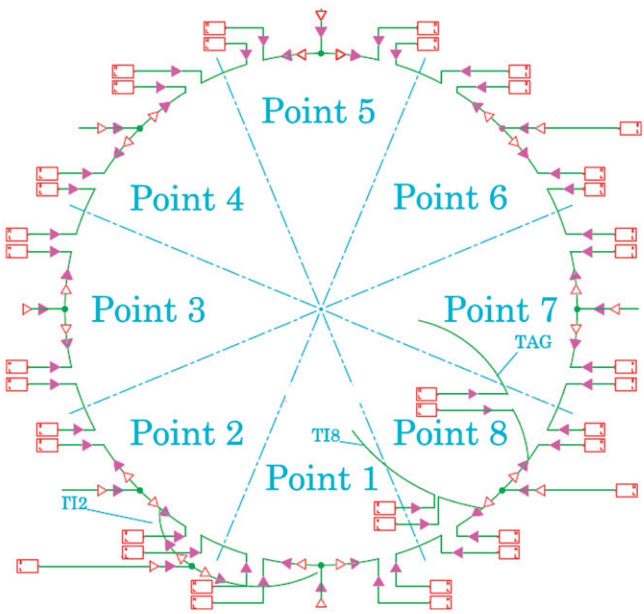

Figure 2. GSM frequencies along the tunnel. The pink arrows represent the injection points of GSM signal.

Figure 3. Equipment used for data collection.

3.1. *Fingerprints collection methodology*

In GSM networks, terminals can only be associated to a single cell. Nevertheless, they continuously monitor the conditions of adjacent cells so that the network can perform informed handovers and maintain the channel quality as high as possible. Several studies (Otsason *et al*. 2005, Denby *et al*. 2009) show that the use of the neighbour cells' information can definitely increase the performance of fingerprinting methods when compared to cases where only the data about the currently associated cell are used.

Except for specific vendor solutions, information about the neighbour cells is not directly accessible through the terminals' APIs. In our tests, we used the Nokia 6150 mobile phone in which we enabled the NetMonitor menus (Figure 3). These additional pages of information allowed us to individually acquire the signal strength of the six strongest cells at a rate of nearly every 2 s. All fingerprints were automatically recorded to a laptop running a capture and parsing software taking advantage of the Gammu utility (Čihař).

In a second phase, three of these terminals were used in parallel, controlled simultaneously by the fingerprint collection software. This configuration enabled the collection of triple the amount of fingerprints in the same time-frame and provided valuable hints on the signal changes on a short spatial scale.

3.2. *Measurements performed*

Measurements were taken in a tunnel sector comprising both straight and bending sections evaluating the performance applying four-fold cross-validation:

(1) *Comprehensive coarse-grained measurements* with fingerprints taken every 100 m throughout an entire LHC section of 3.5 km (35 fingerprints)

and 10 samples per fingerprint. It accounts for major network channel changes.

(2) *Detailed measurements* with fingerprints taken every 40 m in a section of 600 m (15 fingerprints) and 10 samples per fingerprint. Four of such sessions was carried out with 2–3 days interval between them.
(3) *Fixed location measurements I*, where 150 samples of the signal strength were collected at the same position to account for variations depending on the measurement conditions.
(4) *Fixed location measurements II*, where 200 samples of the signal strength were taken in identical measurement conditions, at the same position, to account for time-dependent network variations.

In a second phase, taking advantage of the three mobile terminals, several measurements were performed in a short-scale, not only along the cable direction but also at different distances to it. Two of those tests were:

(1) *Fine-grained measurements* with fingerprints taken every 50 cm over a section of 5 m and 1000 samples per fingerprint.
(2) *Radial measurements*, with fingerprints taken every 10 cm for a distance of 1.10 m between the wall and the LHC machine, at 50 cm from the ground, 1000 samples per fingerprint.

The collected data – one file per measurement session – were then parsed and analysed using Python scripts. For this purpose, a data query library for Python which mimics the SQL standard was implemented. Aided by these software utilities several time and statistical plots of the radio map were generated.

4. Location estimation

In a first attempt to estimate location a modified weighted K-Nearest Neighbour (KNN) approach, in 16 variants, was explored (Pereira *et al*. 2011). In this method, raw data are being pre-processed so that for each point of the *radio-map*, the average, the maximum and the standard deviation of the RSS values are calculated. These properties are then used as a weighting factor for the fingerprinting locations. The aim of this approach is therefore to take advantage of statistical information from the calibration set to select the nearest neighbour points in a KNN method, as opposed to strict probabilistic approaches (Roos *et al*. 2002).

4.1. *Tested KNN variants*

Since each fingerprint contains RSS information from a number of GSM channels, and given that it is difficult to predict which norm will provide the best performance, we tested both Manhattan and Euclidian norms. The non-dominant channels' RSS are also taken into account since the detectability of a channel is considered dependent on the current position and as such contains valuable information about the location as well. In the case of a missing channel, either in the sample or in the *radio-map* fingerprint, the device's sensitivity threshold -115 dB is assumed. Each difference is additionally weighted by one out of four methods, trying to take advantage of the standard deviation of each fingerprint in the *radio-map*.

To summarise, the variants of the method result from the combination of the following parameters:

(1) RSS grouping function:
  (a) Average
  (b) Maximum
(2) Distance measurement norm:
  (a) Manhattan (1-norm)
  (b) Euclidean (2-norm)
(3) Weighting method:
  (a) No weighting
  (b) Weighted by Cumulative Distribution Function (CDF) of the normally-approximated RSS values in each fingerprint
  (c) Weighted by squared standard deviation
  (d) Weighted by standard deviation

For a given RSS sample *i*, a score is computed depending on the method's variant against each point *k* of the *radio-map*:

$$\mathrm{score}_{i,k} = \sqrt[q]{\sum_{c=1}^{C} \left[W \cdot \left| s_{i,c} - S_{k,c} \right|^{q} \right]} \quad (1)$$

In expression (1), C channels are taken into account while the weighting factor W and distance norm q depends on the method's variant. In the simplest case (3.d-Weighted by the standard deviation), $W = 1/\sigma$, while in (3.b-Weighted by the Cumulative Distribution Function) we attempt to assess the uncertainty in terms of the probability of the fingerprint to be compliant with the normally-approximated RSS distribution. For example, in the case of Figure 4, the RSS of the collected fingerprint (green mark) deviates 1.5σ from the mean RSS in the *radio-map* which yields $W = 0.13$

In the end, the probability of a point *k* in the *radio-map* being the correct one is calculated as the inverse proportion of its score against the sum of all the points'

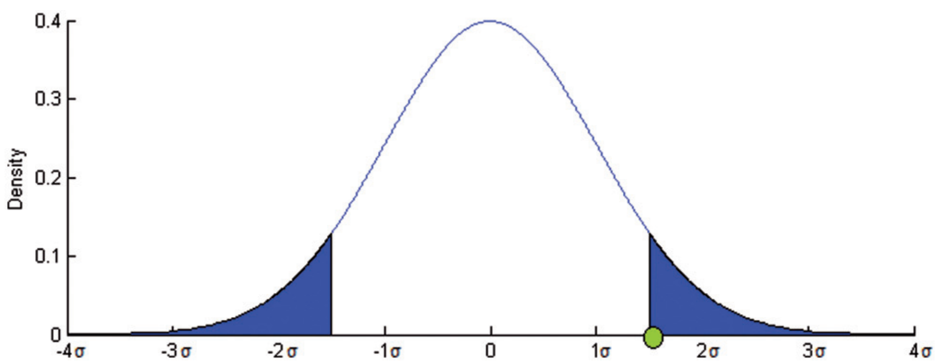

Figure 4. Weighting according to method 3.b.

scores, as:

$$P_{i,k} = \frac{1/\mathrm{score}_{i,k}}{\sum_{j=1}^{N} 1/\mathrm{score}_{i,j}} \tag{2}$$

Supposing, a scenario where point A was given score 4 and four other points were given score 8, this point will be given probability of 1/3 while the others will be given 1/6.

4.2. *Methods ranking*

In order to compare the method's variants and evaluate which one provides the best results, a scoring method was applied to data collected in the detailed measurements. It takes every signal sample out of 600 samples collected during the *Detailed measurements* (Section 3.2) and processes them against all *radio-maps* except the one they belong to, i.e. three out of the four maps. This technique is similar to that used by Otsason *et al*. (2005). The *a priori* knowledge of the actual position of the sample allows to automatically assessing the effectiveness of the method by calculating a score according to the guess order of the point k, the calculated probability P and the distance Δ to the actual position, in the following way:

$$\mathrm{Rank}_{\mathrm{Method}} = \sum_{i=0}^{n_{\mathrm{samples}}} \sum_{k_i=0}^{5} \frac{P_{i,k}}{2^{\Delta_i} * 2^{k_i}} \tag{3}$$

This method accepts contributions until the 5th most probable guess to allow the best score to be achieved when the correct point and the four closest neighbours are given the highest probability in the right order. By applying equation (3), the ideal method with ideal data would be given 1 for every sample and therefore the method's score is bounded effectively by the number of samples.

5. Results evaluation

5.1. *RSS according to position*

It was noticed that the RSS can change significantly as one goes along the tunnel. In Figure 5, we present the mean and standard deviation of the RSS values for the detailed measurements (Section 3.2) as a function of the distance. We can clearly see two dominant GSM channels (blue and green lines) and several traces of other different frequency channels from nearby tunnel sections. In the plot we can also identify two distinct areas, specifically before and after measurement at 240 m. In fact, the *leaky-feeder* splits at this location and the signal propagating in opposite direction, i.e. channel 123, is blocked. Therefore it experiences high attenuation in the first measurement points. From point 6 to point 14, the propagation occurs normally in the cable and, besides lower, the attenuation is similar for both frequencies. In this region, approximating the RSS evolution to a linear function, we obtained attenuation factors of 3.9 and 4.5 dB/km, slightly larger than the attenuation of the cable.

Despite the fact that the cable's longitudinal attenuation introduces measurable signal changes, the variations in the RSS values tend to obfuscate them. In a shorter scale this effect is more noticeable. According to the *Fine-grained measurements*

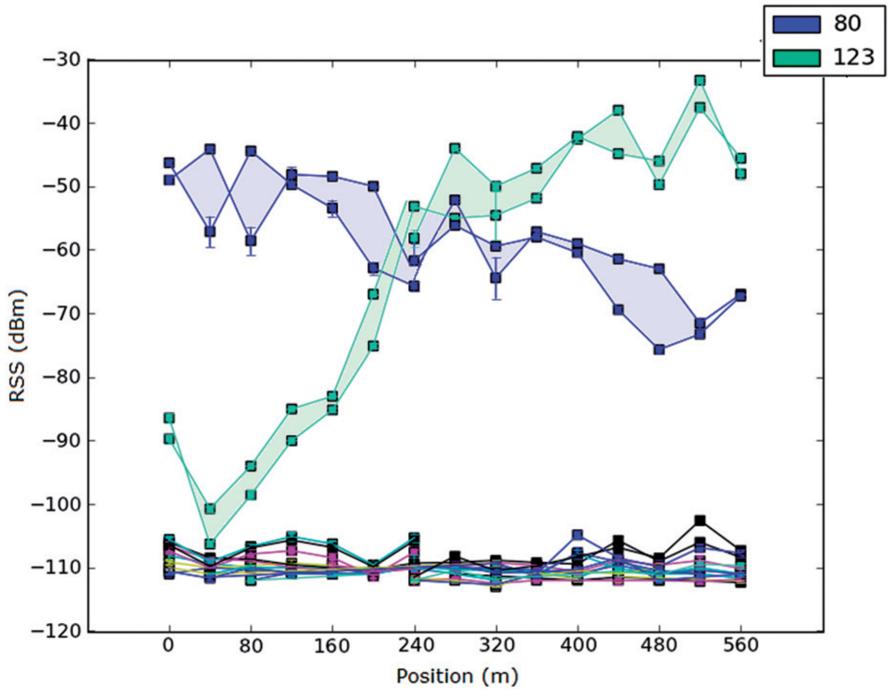

Figure 5. RSS for consecutive points of the detailed measurement. Each line colour represents a different frequency, error bars represent standard deviation and shaded areas are delimited by RSS values of the same frequency obtained in different measurements.

(Section 3.2) the averaged RSS fingerprints of both GSM channels as collected by each terminal (yielding six lines) are presented in Figure 6. Even though a large number of samples were collected, the changes in the signal level are mostly due to the different propagation conditions the signal experiences other that the *leaky-feeder* attenuation itself. In the case of the channel 123, it is even difficult to understand whether the power is increasing or decreasing.

These effects are generally caused by the volatility of the measurement conditions and also suffer the influence of *multipath* propagation in the tunnel and *multicoupling* in the *leaky-feeder* itself (Weber *et al.* 2010).

5.2. *Impact of the measurement conditions*

Although, the four detailed measurement sessions were performed in rather similar conditions, the observed RSS values at each point exhibit divergent behaviours. It was unexpected how one can have almost null variance in two consecutive measurements while their average differs by more than 10 dB (e.g. measurement at 200 m in Figure 5).

This fact motivated the stationary measurements (group 3 in section IV.A) in where we tested three slightly different conditions:

(1) *Optimal*: we ensured no one was close to the equipment during the measurement process, by at least 30 m

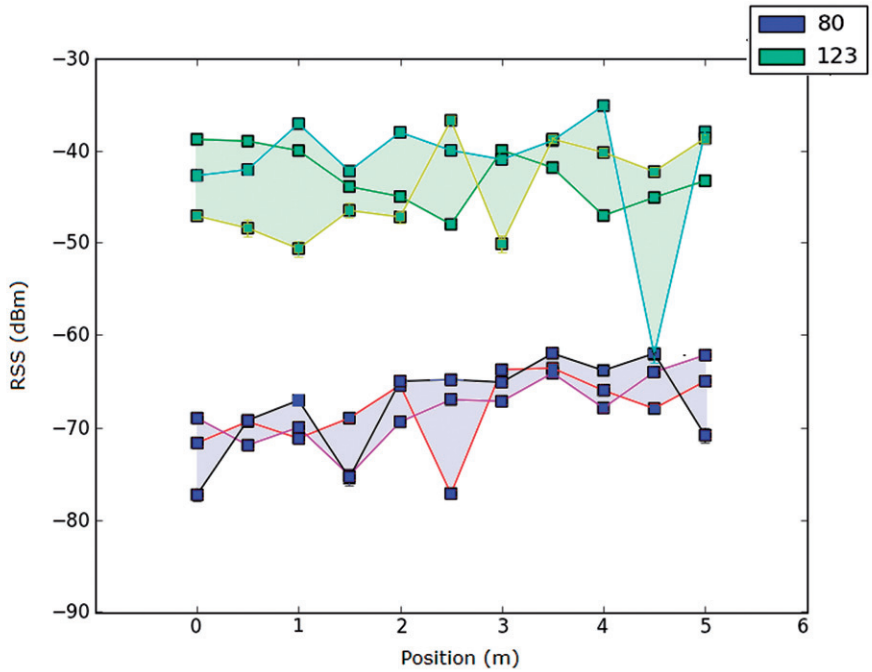

Figure 6. RSS for the fine-grained measurement set.

(2) *Sub-optimal*: at least one person was standing beside the equipment during the measurement
(3) *Realistic*: one person was holding the equipment and slightly moving it during the measurement

Figure 7 shows the RSS evolution for the measurements under the different conditions. For the two dominant channels, 80 and 123, the more adverse conditions the higher the variations and the averaged RSS values tend to drop. Such observations are clearly confirmed by their respective histograms (Figure 8), where one clearly notices a larger spread of the distribution as well as a small shift to the left.

The results of the stationary measurements provide us some insight of the existing background noise conditions and provide a strong argument supporting the hypothesis that the environment characteristics of this underground tunnel, under optimal conditions, are static enough to cause very little signal fluctuations, which is quite favourable for fingerprinting methods. However, for scenarios requiring some manual handling of the equipment, as it will be the case for radiation surveys, we must account for some signal variations.

Similar results were obtained in tests performed for WLAN networks (Weber *et al*. 2009). Even though the RSS is more stable using Leaky-Feeder cables than with regular APs, significant signal variations occur due to fast fading and eventual presence of obstacles.

To better account for these effects, a set of samples was taken in the same longitudinal position but slightly changing the distance to the cable, as specified

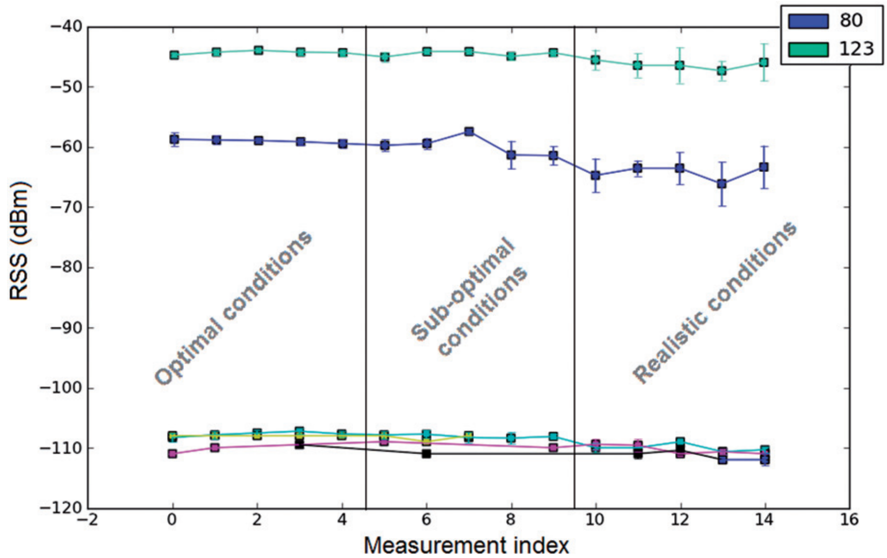

Figure 7. RSS dependence on measurement conditions. Each group was taken with slightly different conditions, being (a) optimal, (b) sub-optimal or (c) realistic.

in Section 3.2. Although the RSS values at each measured point were largely constant over time, they showed significant dependence on small-scale location changes and the overall distribution was found to be quite large (Figure 9).

To minimise these effects, it is important that calibration samples are all taken in the same exact locations and LoS propagation is available and dominant.

5.3. *Method variants comparison and performance*

The 16 variants of the method were tested according to the procedure described in Section 4.2. We tested all samples taken out of the calibration sets from the detailed measurement (group 2 in Section 4.1), which represents a realistic scenario where considerable signal variations exist. In these tests, all the variants using the average as the grouping function for the calibration map outperformed those using the maximum by a factor between 0.5% and 8%.

The impact of the different distance measurement norms and weighting methods, as captured by the ranking algorithm, is presented in Figure 10. We conclude that the Euclidean norm is better suited to this case in calculating the distance. Within this group the best results were obtained by weighting the difference by the CDF (method b.), followed by method a. then method d. and finally method c. It can be noted that the weighting method a. performed reasonably well although it did not make any use of the standard deviation. In turn, methods b. and c. clearly did not take the best advantage of it, which indicates that a smaller standard deviation does not necessarily represent a better fingerprint in the *radio-map*.

The best method has the following characteristics: (1) it uses a *radio-map* whose calibration points were averaged; (2) the error distances are measured by the Euclidean norm and (3) the error distances are weighted by the CDF of the normally approximated power distribution. With these parameters over a *radio-map* with a

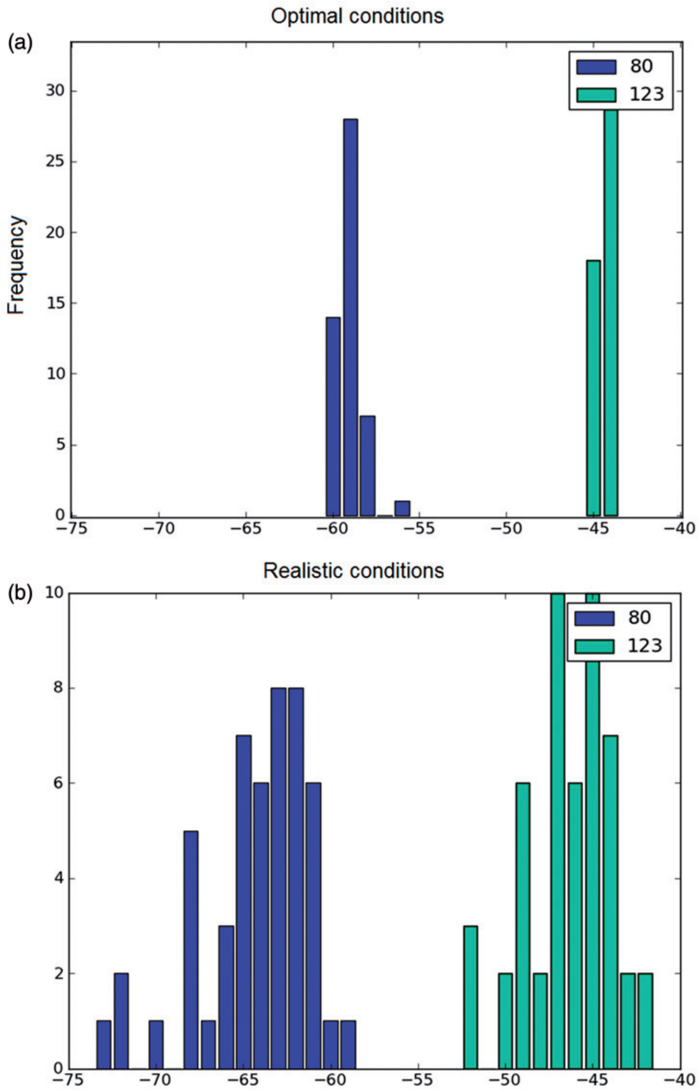

Figure 8. RSS histograms for two distinct measurement conditions.

resolution of 40 m, the method has yielded accuracy better than 80 m in 64% of the cases for the best guess (Figure 11).

Even though for the variants comparison the best five guesses are taken into account, only the first guess is being used to estimate the error. In these circumstances the error takes only discrete values which are multiples of the calibration resolution, i.e. 40 m.

6. Assessment on the method's performance and limits

In the previous chapters, we have assessed the performance of fingerprinting methods in 16 slightly different variants for localisation inside the LHC underground

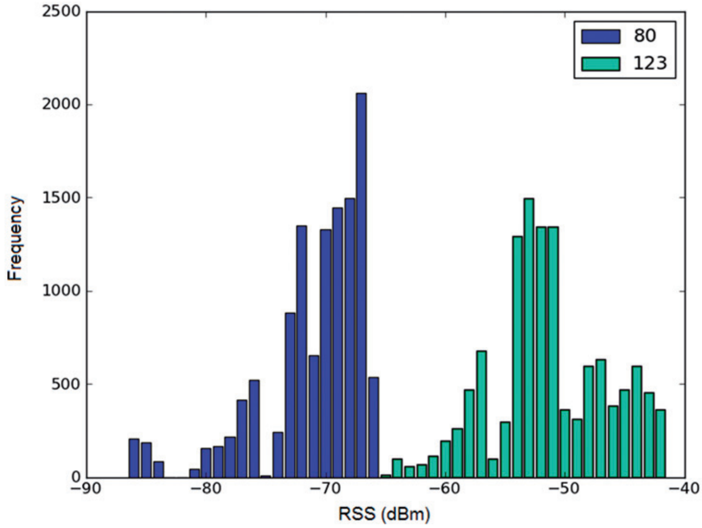

Figure 9. RSS histogram for measurements in slightly different distances to the leaky-feeder cable.

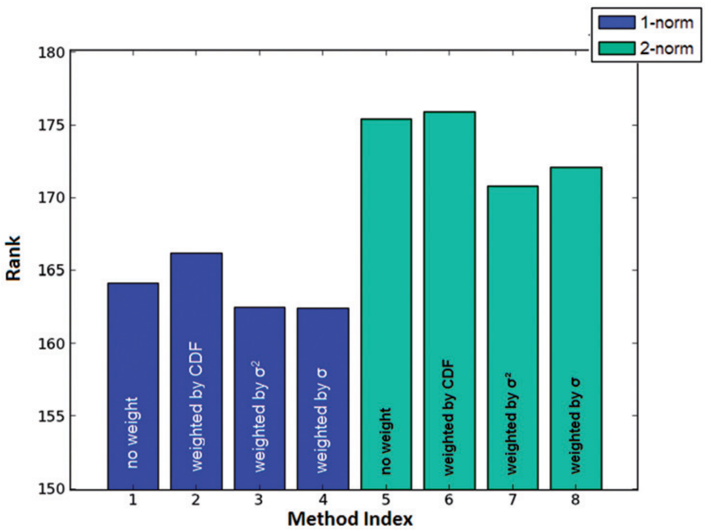

Figure 10. Rank of the different estimation methods.

tunnel. Nevertheless, the achieved performance in this specific environment might seem low as compared to that achieved in other fingerprinting test configurations which, as described in literature, can be below 10 m.

6.1. *Accuracy upper limit imposed by the method*

According to the variants that were analysed the study focused on taking advantage of the known parameters of the power distribution to weight the difference between

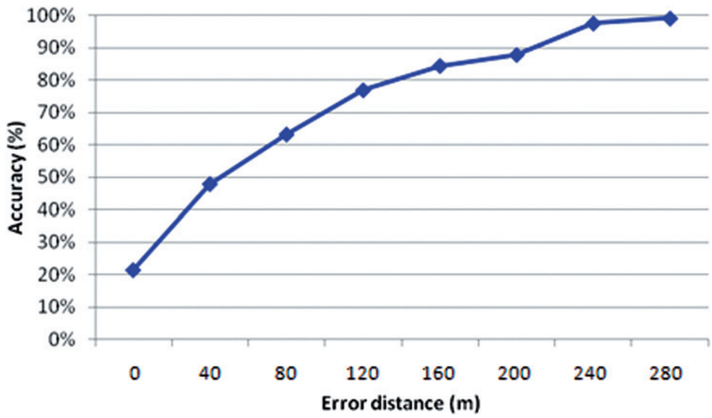

Figure 11. Accuracy of the method's first guess.

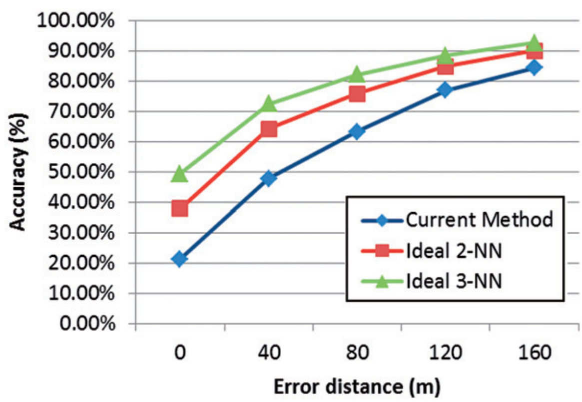

Figure 12. Performance of the ideal KNN, for $K=2$ and $K=3$.

the sample and the fingerprints. It was shown that this information could be useful even in situations where the *radio-map* contains fingerprints with a relatively large variance in the power distribution.

To assess possible improvements on the method's accuracy we modelled an ideal KNN working over our weighting method and computed its accuracy for $K=2$ and $K=3$. The ideal KNN works by yielding the actual measurement position if it corresponds to that of any of the K selected fingerprints. The result, as shown in Figure 12, expresses an overall improvement of the accuracy. It was found that the ideal KNN taking advantage of the three best-matched fingerprints (3-NN) could increase the accuracy by 27% in the best case. It should also be noted that the advantage of the 3-NN over the 2-NN approach is at best about 10%.

6.2. *Other factors limiting accuracy*

Although the results with the ideal KNN method are very interesting, they might still seem poor in the global scene, as to achieve an accuracy of 80% the error distance is up to 80 m. Nevertheless, we must take into consideration the conditions in which the tests and more specifically, the calibration were performed. In fact, given that the resolution of the current radio map is 40 m, 80 m correspond to the distance between three subsequent calibration points. If hypothetically our environment could offer the same signal characteristics for a *radio-map* taken with a resolution of 1 m, the achieved accuracy would then be in the order of 2 m for this ideal method and 3 m for our method, for a confidence of 80%.

Even though conditions for reliable signal stability can certainly be found in many static environments, the tests carried out in the underground suggest that under normal working conditions in an underground tunnel, where other pieces of bulky and massive equipment and personnel are present, such conditions are hardly possible to achieve. It should also be noted that in addition to the specific and unique nature of the accelerator equipment in the tunnel also their operation conditions might change at times, like the power conditions of magnets. Even though no specific studies on the influence of these parameters have been done yet, it cannot be fully excluded that there might be a notable impact.

Dedicated tests have been performed for a calibration with a resolution in the order of 1 m. It was found that the spatial and in-time variation of the network electromagnetic fields implies that the small attenuation caused by the propagation along a leaky feeder is not noticeable in a short scale.

7. Conclusions and future work

In this article, we presented the preliminary studies on using the pre-existing GSM infrastructure in the LHC tunnel for localisation using fingerprinting techniques. We realised that, although the RSS remained impressively constant under optimal measurement conditions, significant differences arise among different measurement sessions. This could be due to the fact that the equipment located in the accelerator tunnel changes their operation modes between different measurement sessions, or that the tunnel configuration promotes *fast-fading* phenomena. Despite this fact, it was shown that the RSS of different channels could be successfully used to determine the position within a reasonable range requiring neither additional hardware nor sophisticated algorithms.

Given the simplicity of the method and the absence of any kind of raw data filtering, one could expect that the results would still be conservative. However, it was shown that even an ideal KNN method could only yield an improvement by 20–30% in the accuracy, which is still insufficient for our application where localisation within a few metres is required. In this context it is envisaged to improve the calibration process by using an automated system travelling along a rail in the tunnel. This should allow for the collection of fingerprints at positions defined precisely within 1 cm. The improvement gained by this approach will have to be studied carefully as the influence of the changes in the environment condition (e.g. the powering of the magnets) is not yet fully understood. Furthermore, techniques taking advantage of dedicated hardware will be studied in detail.

Note

1. This figure is a modified version of Figure 6 in Liu *et al*. (2007).

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