Smart Spatio-Temporal Fingerprinting for Cooperative ANN-based Wireless Localization in Underground Narrow-Vein Mines

(Invited Paper)

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***Abstract*—One of the main concerns in the mining industry is ensuring the safety and security of miners and their equipment. Being aware of the real-time position of personnel in such harsh environments within a special quasi-curvilinear topology is challenging and requires a sophisticated localization system. While traditional triangulation techniques fail to accurately localize in such indoor scenarios, new approaches that rely on fingerprints extracted from the Channel Impulse Response (CIR) succeed to localize with high accuracy using Artificial Neural Networks (ANNs) for fingerprint-location matching. Signatures collected from different locations in space, at different instances in time, are concatenated to form spatio-temporal fingerprints for improved localization accuracy. In this paper, we overview these novel and very promising localization techniques then investigate the impact of the spatial sampling grid's resolution in fingerprint collection on their accuracy in underground narrow-vein mines. We show by simulations that the significant accuracy gains reaped from the new exploitation of spatio-temporal diversity, if not needed in some applications, can be alternatively traded for remarkable and extremely useful cost reductions in the fingerprint collection step.**

***Index Terms*—Indoor localization, channel impulse response, artificial neural network, fingerprinting, cooperative localization, tracking, spatial diversity, temporal diversity.**

I. Introduction

Wireless localization systems are widespread in the modern world. While some location-based services are used for entertainment, other services such as the Global Positioning System (GPS) are becoming essential necessities for daily life applications. On the other hand, positioning services are demanded by industries for enhanced security measures such as localizing miners underground. The importance of an underground localization system reveals itself in incidents such as the one that happened in Chile in 2010 where miners were trapped more than 69 days underground [1]. A localization system built in the tunnel-shaped topology of the narrow-vein mine definitely simplifies the process of locating the miners and their equipment prior/after any accident. So what makes it hard to deploy?

First, narrow-vein mines are made up of humid rough surfaces that create adverse channel responses to wireless transmitted signals. Indeed, the geological nature of this tough environment causes severe reflections, refractions and non line of sight (NLOS) propagation, thereby making channel modeling and characterization more complex. Therefore, traditional localization techniques fail to accurately estimate the position of transmitters because many of these techniques would rely on conventional channel parameters such as the Received Signal Strength (RSS), Angle of Arrival (AOA), Time of Arrival (TOA) and/or Time Difference of Arrival (TDOA) [2] [3] [4]. Indeed, the tunnels in underground narrow-vein mines constitute a quasi-curvilinear topology which is nearly 1D. Even the y-dimension across the tunnels' width is less significant since it ranges mostly between 1 to 3 meters. In this quasi-curvilinear topology, using the AOA does not reveal the exact direction of arrival because of the numerous reflections that take place in the confinement of the tunnels and their curvatures. For similar reasons, the TOA does not reflect the shortest path to the transmitter [5] [6]. Besides, in cases where junctions exist, estimating the distance to the transmitter is not enough due to the NLOS propagation which makes cooperative localization techniques more desirable.

The challenges summarized above elevate the complexity level of a localization system expected to perform effectively in the confinement of mine galleries. Introducing ANN-based fingerprint-position matching for wireless localization that is fed by a set of useful parameters extracted from the CIR as an input signature is proven to perform accurately in narrow-vein mines [5] [6]. This novel concept was recently extended to exploit spatial diversity [7], temporal diversity [8], or both [9] for increased accuracy.

In this paper, we overview these novel and very promising localization techniques then investigate the impact of the

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spatial sampling grid's resolution for fingerprint collection on their accuracy in underground narrow-vein mines. Simulations suggest that the significant accuracy gains reaped from the new exploitation of spatio-temporal diversity, if not needed in some applications, can be alternatively traded for remarkable and extremely useful cost reductions in the fingerprint collection step. As one example, the cooperative version [7] that exploits a two-branch spatial diversity attains the same accuracy (of 1.5 m at 90% precision) of the original version [5] using for training only 50% of the collected fingerprints stemming from a sampling grid with half the resolution of the original one.

In Sec. II, we briefly describe the original measurement campaign conducted for fingerprint collection [5]. In Sec. III, we overview the novel ANN-based localization techniques and the ways spatial and temporal diversities are exploited in the spatio-temporal fingerprints. In Sec. IV, both the solitary [5] and cooperative memoryless [7] localization techniques are, as two representative examples, challenged by lower spatial sampling grid resolutions in the fingerprint collection step to illustrate how accuracy gains can be traded for lower fingerprinting costs. Conclusions are finally drawn out in Sec. V.

II. Measurement campaign for CIR-based fingerprinting

Measurement campaigns are unavoidable with any fingerprint-based localization technique. Fingerprint-based positioning systems mainly rely on the collected measurements to create the ground rules of the localization algorithms. In other words, localization using the fingerprinting technique is a way of mapping the received wireless signals (i.e., fingerprints) taken at specific locations to the transmitter's position (i.e., distance from the receiver). The grid resolution of the measurement campaign plays an important role in the accuracy of the localization technique. Increasing the grid resolution to improve localization accuracy is time consuming and is not recommended. Therefore, the spatial sampling grid resolution should be optimized to guarantee accuracy without increasing the cost incurred from collecting numerous measurements. We will show here how smart spatio-temporal fingerprinting that exploits both spatial and temporal diversities allows, among numerous benefits, conducting lower-cost measurement campaigns over lower-resolution grids while maintaining accuracy.

A measurement campaign was conducted in CANMET gold mine in Val d'Or Quebec from which a new approach to CIR-based localization was introduced in [5]. A total of 480 measurements were taken in a tunnel as shown in Fig. 1. The original grid resolution is set to 1 meter increment per x-position while respecting the boundary conditions of the tunnels. For each position, seven parameters are extracted to form a fingerprint. These parameters are the mean excess delay ($\bar{\tau}$), the root mean square (τ_{rms}), the maximum excess delay (τ_{max}), the total power of the received signal (P), the number of multipath components (N), the power of the first arrival (P_1) and the delay of the first path component (τ_1). Throughout this article, a fingerprint is denoted by $f = (\bar{\tau}, \tau_{rms}, \tau_{max}, P, N, P_1, \tau_1)$ and it corresponds to a transmitter at a distance d away from the localizing unit or receiver R. Given the quasi-curvilinear topology of narrow-vein mines, the variation along the y-position is considered insignificant (i.e., the x-position is taken as the total distance d). However, the fingerprints are taken for all y-positions to simulate the fact that signals fluctuate for the same x-position.

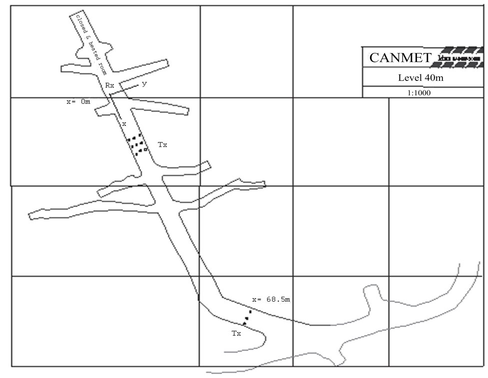

Fig. 1. Map of the underground tunnels.

III. Overview of ANN-Based Localization Techniques using Fingerprinting

A. Original Technique

Matching the set of fingerprints $S = \{f_1, f_2, f_3, ..., f_n\}$ to the corresponding set of distances $D = \{d_1, d_2, d_3, ..., d_n\}$ is performed using Artificial Neural Networks (ANNs). With their ability to perform complex calculations of nonlinear functions, ANNs are easy to train and operate and they estimate the transmitter's position instantaneously and accurately. In case where only one receiver is present as shown in Fig. 2, the input layer of the ANN is composed of 7 neurons that correspond to the length of each fingerprint in S. The output layer is made of one neuron representing the output distances in D matching the input fingerprints in S.

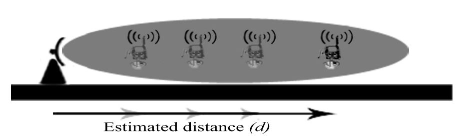

Fig. 2. Solitary localization using one receiver.

The ANN is trained to estimate 75% of the collected fingerprints then the remaining 25% of the fingerprints are tested to validate the generalization performance of the trained ANN. The use of MultiLayer Perceptron (MLP) ANN with back propagation learning algorithm gives more accurate and precise results for underground localization [5] [6].

B. Exploiting Spatial Diversity

Even though the original technique in [5] was a breakthrough in localization systems for underground and confined areas, recently it was further enhanced in [7] to exploit the spatial diversity of the collected fingerprints. By using the principle of cooperation between multiple Access Points (APs), the cooperative localization technique proved that concatenating more than one fingerprint collected from different locations enriches the information about the exact position of the transmitter. As shown in Fig. 3, the transmitter's position is estimated even in the presence of junctions, interconnected tunnels and NLOS scenarios. Cooperative memoryless localization in [7] only relies on the spatial diversity of the collected set of fingerprints $S^{R_1} = \{f_1, f_2, f_3, ..., f_m\}$ and $S^{R_2} = \{f'_1, f'_2, f'_3, ..., f'_m\}$ measured at receivers R_1 and R_2, respectively. These receivers may choose to exchange the fingerprints or position estimates collected at an instant t depending on the pre-defined ANN architectures. In case where both receivers feed together their fingerprint measurements, one super ANN shown in Fig. 4 concatenates the subset of observations S^{R_1} and S^{R_2} to form the total set $S = \{F_1, F_2, F_3, ..., F_m\} = \{(f_1, f'_1), (f_2, f'_2), (f_3, f'_3), ..., (f_m, f'_m)\}$. The input layer of the ANN is made of 14 neurons while the output layer is the transmitter's distance in the set $D = \{d_1, d_2, d_3, ..., d_m\}$ referenced to R_1.

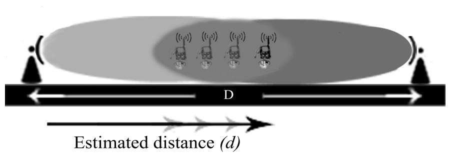

Fig. 3. Cooperative localization using two receivers.

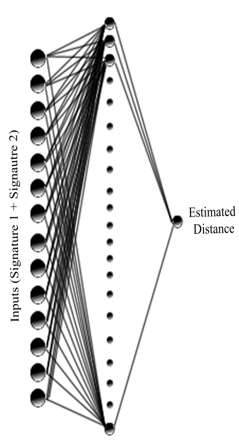

Fig. 4. Neural network based on multiple signatures.

C. Exploiting Temporal Diversity

In a tunnel-shaped topology, two APs are sufficient to provide wireless coverage for the whole section of the gallery in between. In other words, localization using spatial diversity could be limited to two fingerprints per position. This diminishes, however, its capability of attaining higher accuracies and precisions. A search for better performance led to the development of the memory-assisted localization technique in [8] where temporal diversity is exploited. Using one receiver, solitary memory-assisted fingerprinting is illustrated in Fig. 5 where the star represents the transmitter's position to be estimated at time instant t_0.

Fig. 5. Possibilities of previous positions for $l = 2$.

A temporal fingerprint is the concatenation of multiple signatures recorded along the path a transmitter takes reaching a desired position at t_0, separated by a distance d from the localizing unit. Concatenating only one previous fingerprint at a time instant t_{-1} creates a temporal fingerprint of length $l = 2$ (i.e., 2 fingerprints with a total of 14 parameters). The length of the temporal fingerprint depends on l and corresponds to the number of inputs N_{inputs} fed to the ANN where:

$$N_{inputs} = 7l.$$

In order to generalize the performance of the ANN, all the paths that lead to the star position should be considered as possible temporal fingerprints. This requires collecting all the combinatorial fingerprints surrounding each position while respecting the boundary limits and considering a consistent hop size. [1] It should be noted that a combinatorial set of generated temporal fingerprints exponentially increases from the original set containing 480 measurements. Training ANNs on all possible temporal fingerprints enriches the information given about one location based on fingerprints taken from possible motion patterns, a method that should not be confused with conventional tracking algorithms where the position estimates are enhanced after their estimation takes place [10] [11] [12]. A programmed MATLAB function is responsible for collecting all possible paths and then concatenating their corresponding fingerprints to form chains of temporal fingerprints for all positions in the tunnel based on the pre-defined memory level l. The performance of each ANN is tested for different memory levels up to $l = 5$ (i.e., chains of five concatenated fingerprints per position) after which no significant accuracy gain is reported. The temporal fingerprint is denoted by

$$f_i^j = \left(f_{i_{t_0}}, f_{i_{t_{-1}}}, f_{i_{t_{-2}}} ..., f_{i_{t_{-(l-1)}}}\right),$$

and it corresponds to one path that leads to a position at a distance d_i away from R_1 using memory capacity l. Since

[1] Motion across diagonals is excluded because it exponentially increases the length of temporal fingerprints without significant accuracy gain.

multiple paths may lead to the same position, the index j is introduced to count the number of temporal fingerprints that point to the same output distance d_i. The maximum number of temporal fingerprints per position j_{max} is affected by the boundary conditions that surround each position and it is proportional to l where:

$$j_{max} \leq= 5^{(l-1)}.$$

D. Exploiting Spatio-Temporal Diversity

Cooperative localization (cf. Sec. III-B) improves positioning accuracy by exploiting the spatial diversity resulting from the chained-topology of the deployed APs but this diversity is practically limited to two branches due to the curvilinear topology of underground narrow-vein mines. An advanced fingerprinting technique is developed in [9] to exploit both spatial and temporal diversities of the collected fingerprints. Cooperative memory-assisted localization is introduced as a technique that creates spatio-temporal fingerprints by concatenating the temporal fingerprints gathered from different localizing units before estimating the transmitter's position. The use of more than one fingerprint saved in time exploits the temporal diversity whereas gathering the fingerprints from multiple localizing units exploits the spatial diversity of wireless signals. The spatio-temporal fingerprint subset denoted by $S_i^{R_1} = \left\{F_i^{R_1,1}, F_i^{R_1,2}, F_i^{R_1,3}, ..., F_i^{R_1,j_{max}}\right\}$ is collected from R_1 which is at a distance d_i and it is concatenated path-wise with the other subset $S_i^{R_2} = \left\{F_i^{R_2,1}, F_i^{R_2,2}, F_i^{R_2,3}, ..., F_i^{R_2,j_{max}}\right\}$ measured at receiver R_2 which is at a distance $d_2 = D - d_i$ to form the group of spatio-temporal fingerprints:

$$S_i = \Big\{(F_i^{R_1,1}, F_i^{R_2,1}), (F_i^{R_1,2}, F_i^{R_2,2}), (F_i^{R_1,3}, F_i^{R_2,3}), ..., (F_i^{R_1,j_{max}}, F_i^{R_2,j_{max}})\Big\}.$$

The memory levels of receivers R_1 and R_2 are denoted by (l_1, l_2). The number of parameters that constitute each fingerprint is specified according to the total length of the spatio-temporal fingerprints (i.e., $l = l_1 + l_2$). A 2-by-2 spatio-temporal fingerprint design (i.e., $l_1 = 2, l_2 = 2$) may be achieved by matching the collected spatio-temporal fingerprints $F_i = (F_i^{R_1}, F_i^{R_2})$ where

$$F_i^{R_1} = (f_{i_{t_0}}^{R_1}, f_{i_{t\_1}}^{R_1}),$$

$$F_i^{R_2} = (f_{i_{t_0}}^{R_2}, f_{i_{t\_1}}^{R_2}).$$

In case where $(l_1 = 2, l_2 = 2)$, the temporal fingerprint collected at a distance d_i from R_1 is equal in length to that collected from R_2 for the same position, but the total concatenated spatio-temporal fingerprint F_i fed to the ANN at the time instance t_0 is of length 28 (i.e., $7l = 7(l_1 + l_2)$).

E. Overview of Performance Results

As a background overview, the results of all ANN-based localization techniques that use the fingerprinting approaches discussed above are summarized in Tab. I.

Based on the reported performance results, cooperative memoryless localization outperforms the solitary localization technique by exploiting the spatial diversity of the fingerprints providing and accuracy of less than 1 m for 90% of the collected fingerprints. Since cooperative memoryless localization is limited in diversity to two branches due to spatial confinement, memory-type fingerprints are then used to exploit the temporal diversity and achieve better performance results. By concatenating up to 5 temporal fingerprints, the solitary memory-assisted localization technique attains a high accuracy of 50 cm at the same precision. However, smart spatio-temporal fingerprinting achieves even higher accuracy gains by exploiting both the spatial and temporal diversities. Cooperative memory-assisted localization reduces positioning error to less than 25 cm 90% of the time.

TABLE I
ESTIMATION ERRORS OF DIFFERENT LOCALIZATION TECHNIQUES

Localization Technique with 90% Precision		*Errors (m)* *Training*	*Testing*
Spatial localization using one receiver [5]		1.5	1.65
Cooperative spatial localization based on separate ANNs [7]		1	1
Cooperative spatial localization based on one super ANN [7]		0.6	1
Solo memory-assisted localization [8]	$(l_1 = 2, l_2 = 0)$	1	1.25
	$(l_1 = 3, l_2 = 0)$	0.75	0.8
	$(l_1 = 4, l_2 = 0)$	0.5	0.5
	$(l_1 = 5, l_2 = 0)$	<0.5	<0.5
Cooperative memory-assisted localization [9]	$(l_1 = 2, l_2 = 1)$	0.48	0.62
	$(l_1 = 3, l_2 = 1)$	0.38	0.43
	$(l_1 = 2, l_2 = 2)$	0.20	0.25

IV. Impact of Spatial Sampling Grid Resolution

The performance of any localization system is governed by many factors which are not limited to the accuracy and precision of the positioning technique involved. Other factors such as complexity, cost and robustness are also of high importance. An optimized localization system should maintain accuracy, precision, robustness and simplicity at high standards. Because fingerprint positioning techniques require campaign measurements, they are considered of higher complexity or cost compared to conventional localization systems. However, fingerprint-based localization is proven to give much more accurate and precise estimation results in underground narrow-vein mines. A smart fingerprint positioning system would reduce the amount of fingerprints while maintaining the accuracy and robustness of performance results.

In this paper we investigate the effect that grid resolution imposes on the accuracy and precision of the fingerprint positioning system in [5] and [7]. As a rule of thumb, the denser the measurement grid provided to ANNs, the more robust position estimation is to new testing fingerprints. The ANN-based localization techniques discussed in Sec. III base their fingerprint positioning on a grid of 1 m/x-hop. In other words, the ANNs in [5] [7] [8] [9] are trained on sets of spatial and/or temporal fingerprints for positions 1 m apart along the longitude of the tunnel. Here, we investigate the performance of both the solitary [5] and cooperative [7] memoryless localization techniques once the spatial sampling grid's resolution is reduced to 2 m/x-hop or 3 m/x-hop in the fingerprint collection step (cf. Sec. II). This investigation amounts to splitting the original grid into 2 or 3 interleaved sub-grids, respectively. For each tested technique, [5] or [7], its ANN is then trained on 75% of a given sub-grid candidate then tested on the remaining 25% of the same sub-grid (i.e., x-positions seen during training) and on the 25% of each of the other sub-grids (i.e., x-positions never seen during training), thereby resulting into 2 or 3 ANN candidates, respectively. The cumulative distribution function of localization errors collected from the testing of all ANN candidates is plotted at each grid resolution for both the solitary and cooperative versions in Figs. 6 and 7, respectively. Both figures suggest, as expected,

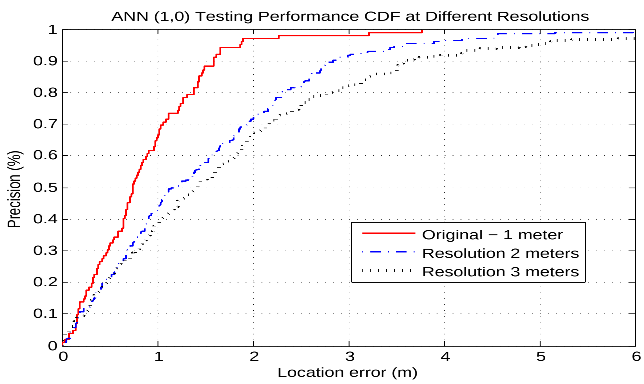

Fig. 6. Solitary localization performance at different resolutions.

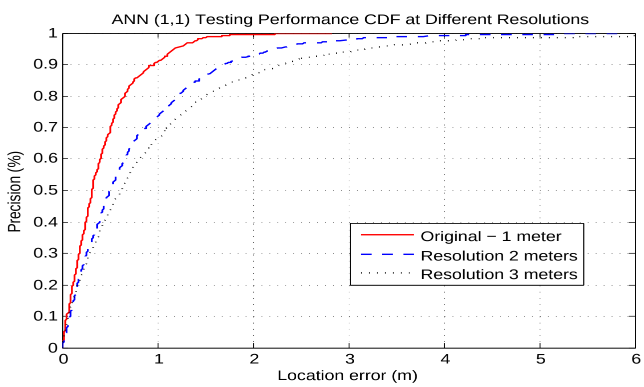

Fig. 7. Cooperative localization performance at different resolutions.

the localization accuracy of each technique degrading with the grid resolution decreasing. Yet at any given grid resolution, the cooperative version [7] always maintains an accuracy gain over the solitary one [5], thereby confirming again the net benefits of exploiting (spatial, but also temporal or spatio-temporal) diversity in fingerprinting for localization even at lower grid resolutions and even when testing positions are never seen during ANN training. Tab. II reports accuracies obtained at 90% precision in Figs. 6 and 7. They obviously suggest that the cooperative version [7] offers about the same accuracy (i.e., 1.5 to 1.6 m) of the original solitary version [5] using though for training only 50% of the collected fingerprints. The latter stem from a sampling grid with a resolution (i.e., 2 m) that is half of the original one (i.e., 1 m), thereby speeding up the fingerprinting campaign and reducing its cost by factor 2! Higher speed-up factors could be hence easily expected with the spatio-temporal fingerprinting version [9]. This is the subject of ongoing investigations.

TABLE II
PERFORMANCE RESULTS WITH MULTIPLE RESOLUTION

Localization Technique with 90% Precision	Grid Resolution Accuracy Results		
	1 meter	*2 meters*	*3 meters*
Solo memoryless technique	1.6 m	2.8 m	3.6 m
Cooperative memoryless technique	1 m	1.7 m	2.3 m

V. CONCLUSION

Using spatio-temporal fingerprinting in underground narrow-vein mine increases the performance of ANN-based localization systems in terms of accuracy and precision. Here, we show by simulations that the significant accuracy gains reaped from the new exploitation of spatio-temporal diversity, if not needed in some location applications, can be alternatively traded for remarkable and extremely useful cost reductions in the fingerprint collection step, thereby making the novel ANN-based wireless localization systems even more attractive due to their combined accuracy advantage and relatively reduced cost. These smart fingerprinting techniques could be implemented in different wireless localization services and integrated into any wireless technology.

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