# Radio-Localization in Underground Narrow-Vein Mines Using Neural Networks with In-built Tracking and Time Diversity

Shehadi Dayekh*, Sofiène Affes*†, Nahi Kandil†, and Chahé Nerguizian‡†

* INRS-EMT, Université du Québec, Montréal, QC, Canada, H5A 1K6
† Université du Québec en Abitibi-Témiscamingue, Rouyn-Noranda, QC, Canada, J8X 5E4
‡ École Polytechnique de Montréal, Montréal, QC, Canada, H3T 1J4

Emails: {affes, dayekh}@emt.inrs.ca; nahi.kandil@uqat.ca; chahe.nerguizian@polymtl.ca

***Abstract*—In the mining industry, knowing the position of miners and/or equipments is an important safety measure that reduces risks and improves the security of that facility. Being an indoor environment, wireless transmitted signals in underground narrow-vein mines suffer multiple kinds of distortions due to extreme multipath and non-line of sight (NLOS) conditions. One of the proposed solutions to accurate localization in such challenging environments is based on extracting the channel impulse response (CIR) of the received signal and using the fingerprinting technique combined with cooperative artificial neural networks (ANNs). Such localization systems use the spatial domain where the reference localizing units are implemented at different positions away from the transmitter. In this article, we introduce a localization technique that uses fingerprints successively recorded in time with in-built tracking as an alternative method to localize. Unlike the spatial-domain technique where cooperative localizing units collect memoryless fingerprints from different locations, this technique uses one localizing unit and is capable of estimating the position of a transmitter precisely using its current and previous registered fingerprints in time. Localization using time-domain fingerprinting (i.e., tracking) and ANNs is introduced as a new method that exploits time diversity and improves the accuracy, precision and scalability of the positioning system.**

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

## I. Introduction

One of the vast numbers of applications of wireless communication systems is position estimation or localization. Outdoor localization systems such as the Global Positioning System (GPS) are already in the market and are available to anyone providing an important service that can locate the user's position precisely. Different localization techniques base their estimations on one or more extracted parameters out of the received signal such as the received signal strength (RSS), angle of arrival (AOA), time of arrival (TOA) or the time-difference of arrival (TDOA). Other systems use scene-analysis or fingerprinting techniques which include using ANNs as matching algorithms. Once a transmitted signal is received at different locations in space, the variation in the signals' fingerprint, RSS, AOA, TOA, or TDOA is calculated and the position of the transmitter is estimated accordingly. Nevertheless, indoor localization is still a challenging topic due to the fact that the transmitted signals indoor undergo several distortions caused by reflections, refractions, NLOS regions and multipath effects. Unlike outdoor mediums where signals relatively travel almost freely in open spaces, indoor environments such as underground mines stem from more complicated scenarios that need to be modeled in order to estimate how the signal would be received after reacting with the channel. Surveys on wireless indoor positioning techniques [1],[2] provide multiple detailed discussions of different localization approaches.

A new approach to localization in tunnel-shaped underground narrow-vein mines is presented in [3] and is based on extracting the CIRs of the received signal as fingerprints of the transmitter's positions, then using these fingerprints to localize the source of transmission with one receiver or Access Point (AP). Several parameters extracted from the CIR give this approach uniqueness unlike other approaches [5],[6],[7],[8],[9] that mainly base their fingerprints on the RSS only. However, this technique was not able to cover the whole curve-shaped topology of underground mines until the cooperative localization concept was introduced in [4]. Cooperative localization using the CIR technique benefits from the presence of multiple receivers which collect multiple fingerprints in tunnels before estimating the position of the transmitter. Leading to increased accuracy and precision, the developed technique in [4] uses different cooperative neural network techniques and exploits the spatial diversity of the collected fingerprints. However, in the case where spatial diversity is limited by one localizing unit, the system in [4] fails.

In this article, we will study localization in tunnel-shaped underground narrow-vein mines using the time-domain finger-

This work was supported by Bell Aliant and NSERC under the Cooperative Research and Development (CRD) program.

print diversity (i.e., tracking) technique combined with ANNs. This technique innovates the idea of integrating tracking within the ANN-based fingerprint matching algorithm for localization. The time-domain fingerprint is made up from a chain of CIRs which are collected for the same transmitter along its path to the position which has to be estimated. ANNs are properly then designed based on different chain length or memory levels then trained on all possible path scenarios. Because of the tunnel-shaped topology of underground narrow-vein mines which is quasi-curvilinear, information about the path that the transmitter is following within the confines of its well-mapped galleries adds valuable input to the ANNs and creates an accurate in-built tracking system. The following section summarizes the concept of cooperative localization using fingerprinting and neural networks in the spatial domain. In section 3, localization using tracking is introduced along with the theoretical fingerprinting approach. The results of both the spatial (i.e., cooperation) and time (i.e., tracking) diversity-based localization techniques are compared in section 4. In section 5, the major complexities/challenges that face the design are highlighted along with their proposed solutions. Finally, conclusions are drawn out in section 6.

## II. Localization using Fingerprinting and Neural Networks

We will briefly describe below as a background reference a localization technique that uses the spatial domain in order to localize a transmitter in a mine tunnel. The system is capable of localizing a transmitter using two receivers that work separately or cooperatively using different neural network techniques. A more detailed discussion of these techniques can be found in [4]. But before doing so, we will study below the underlying fingerprinting technique from which extension using multiple APs was developed in [4].

### A. *Localization in the presence of one receiver*

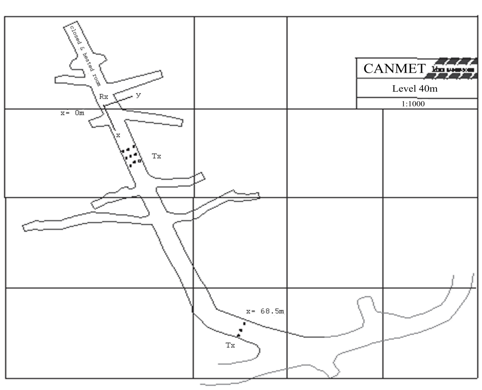


Fig. 1. Map of the tunnel.

Due to the special nature of underground narrow-vein mines which are made of quasi-curvilinear connected tunnels as shown in Fig. 1, traditional wireless localization systems fail to provide accurate positioning services. This is mainly caused by the distortions of the basic parameters used in localization systems due to the multipath components and NLOS scenarios present in such environments. In such cases, the fingerprinting technique becomes a very promising alternative in that it confers to each position a specific fingerprint that is then identified by the localizing units using different matching algorithms. In this work, the fingerprinting technique is used to identify a position based on the extracted CIRs at that position.

After conducting a real-time measurement campaign in the CANMET gold mine in Val d'Or city [3], CIRs were collected. For each position across the tunnel in Fig. 1, seven parameters were then extracted from the corresponding CIR forming overall a set of fingerprints at different distances ($d$) away from the receiver as shown in Fig. 2. These parameters are the mean

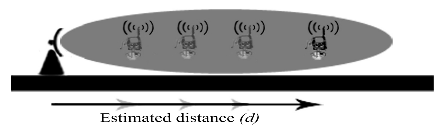


Fig. 2. Localization using one fixed receiver.

excess delay ($\bar{\tau}$), the root mean square ($\tau_{rms}$), the maximum excess delay ($\tau_{max}$), 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 ($\tau_1$). Estimating the position based on the fingerprints is performed using ANNs.

Being able to perform complex computational operations such as classification, control optimization, and function approximation, ANNs proved to be reliable computational models that are widely used for different localization approaches [3],[4],[10],[11],[12]. Every ANN needs to be trained using a set of training data which, in our case, is made up of 75% of the collected fingerprints, leaving 25% of the data for testing. The use of an MLP-type feed forward neural network with a back propagation learning algorithm has been proven to give accurate estimation results in underground localization studies [3],[4]. The simple form of the ANN used in localization in the presence of one receiver consists of 7 inputs, one hidden layer and one output that is the distance to the transmitter. The hidden layer for this system consists of 10 neurons and it uses a differential tan-sigmoid transfer function, whereas the output layer uses a linear-type transfer function. It was shown that position estimation using one receiver only is precise and that the error is less than 1.5 meters for 90% and 80% of training and non-training data, respectively [4]. Despite the promising accuracy of estimating the distance to the transmitter, this technique cannot by itself guarantee full coverage of the whole tunnel network of an underground mine.

### B. *Cooperative localization using two references in space*

Precisely, a search for an upgraded technique that can serve as a complete localizing system in underground mines led to the idea of cooperative artificial neural intelligence [4]. The concept of ANN-based cooperative localization using multiple receivers is based on collecting multiple signatures from different receivers forming one fingerprint that corresponds to a transmitter located between the reference endpoints as shown in Fig. 3. Because of the quasi-curvilinear topology of tunnels in underground narrow-vein mines, two APs should be enough to provide wireless coverage of the whole area in between in the corresponding tunnel section.

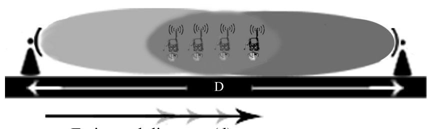


Fig. 3. Localization using two signatures of two receivers.

One of the two cooperative localization approaches, discussed in [4], is based on estimating the position of the transmitter by using a single neural network as shown in Fig. 4. Two extracted signatures of the transmitter from two different receivers are fed to this neural network. The latter, which has 14 inputs, is trained to localize a transmitter by estimating the distance to one of the receivers. The separation distance $D$ affects the number of fingerprints that are collected given that each AP (receiver) has a limited wireless coverage. For each separation distance $D$, a new neural network is created and trained. Unlike the first new cooperative approach in [4] that uses separate neural networks, this approach is based on one position estimation made by one neural network.

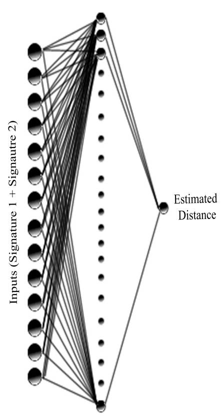


Fig. 4. Neural network based on multiple signatures.

## III. Localization using Tracking in the Time Domain

The major localization systems use the space domain in order to estimate the position of the transmitter. In other words, the reference points or APs that collect the RSS, TOA, AOA, or fingerprints from the transmitted signal at different positions are fixed in space. In the previous sections, we defined localization using one reference point and a cooperative localization technique using two references in space. Using these systems, the position of the transmitter is estimated regardless of the CIR at its previous positions. Tracking, as studied in the literature, is the algorithm of filtering the trajectory that the mobile unit (i.e., transmitter) follows in order to improve the localization accuracy. Most of these algorithms decrease the positioning error a posteriori by post-processing the estimated results [13],[14],[15]. To the authors' best knowledge, none of the proposed systems integrates a priori tracking within an ANN-based fingerprint matching algorithm for localization. In this section, we will introduce a localization system that properly exploits the time domain where the CIRs of the previous positions play an important role in estimating the new position within the ANN through in-built tracking.

### *A. Concept of time domain diversity with tracking*

Consider a walking miner who is transmitting wireless signals across the tunnel. One receiver is fixed and set on a time axis in a way that it starts localizing the miner after saving the CIRs from its transmitter up to a certain memory level $l$. Using one reference in time ($l$=1) is the same as using one reference in space; i.e., one CIR is recorded and the position is estimated for each location separately using the localization technique in sec. II-A [3] with one receiver only. However, the estimation of the same position would be more accurate if the neural network considers two signatures representing a motion pattern within the limits of the tunnel topology.

In order to estimate the miner's position based on two references in time, a fingerprint should be formed from two CIRs. The first CIR is extracted for the position to be estimated at $t_0$ while the other CIR is that for the previous position registered in memory at $t_{-1}$. The speed of motion plays an important role in defining all possible fingerprints a priori, but it does not vary too much between the two typical stationary and pedestrian speeds in the considered underground mining application. Due to the fact that a miner may come from different directions before reaching a current position, the neural network is trained on chains of all possible fingerprint combinations for each position in a tunnel. Localization using tracking with two memory levels ($l = 2$) exploits temporal diversity in the same way as cooperative localization in [4] does with spatial diversity using two references in space. The accuracy of the neural network (as shown in the following section) increases when increasing the memory level of the system. In this work, we study localization based on tracking using up to five references in time.

Since a miner's movements inside the tunnels of an underground narrow-vein mine are predictable within the confines of its well-mapped galleries due its quasi-curvilinear topology, we are able to add valuable information to our model by creating chains of predictable fingerprint combinations to be fed to the neural network. We assume that a miner may walk to a position from different directions in the tunnel-shaped mine gallery taking into consideration the boundary conditions of the narrow tunnel. Using a time domain motion model, the number of input levels ($l$) that needs to be considered defines the combinatorial number of possible CIRs from which each fingerprint may be extracted. In the simplest case where $l = 2$, each fingerprint is made up of 14 parameters extracted from two CIRs. The first CIR is that of the position to be estimated at $t_0$ while the other CIR may be one of the five possible previous positions, as illustrated in Fig. 5 and listed in Tab. I. Measurements at either side of a position are included in the generated fingerprint; however, the output of the ANN is selected along the longitude of the tunnel (i.e., the $x$ dimension in Fig. 1), the other dimension (i.e., the $y$ dimension in Fig. 1) along the narrow tunnel's width being much less significant as a coordinate for localization (but still extremely useful for its accuracy along the $x$-axis). The star represents

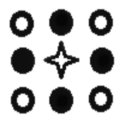

Fig. 5. Possibilities of previous positions for $l = 2$.

the transmitter at $t_0$ while the filled circles are four possible previous locations at $t_{-1}$ other than the current position (which is also among possible previous positions). For simplicity, motion across diagonals is excluded although our technique can easily take it into account.

TABLE I
FINGERPRINTS OF EACH LOCATION FOR $l$=2

| Fingerprint | Source of Parameters |
|---|---|
| 1 | $CIR_{t_0}$ & $CIR_{center}$ |
| 2 | $CIR_{t_0}$ & $CIR_{up}$ |
| 3 | $CIR_{t_0}$ & $CIR_{down}$ |
| 4 | $CIR_{t_0}$ & $CIR_{left}$ |
| 5 | $CIR_{t_0}$ & $CIR_{right}$ |

Once $l$ increases, more positions get involved in forming the paths (fingerprints) to the current position of the transmitter. Fig. 6 shows the positions that may be considered for creating a path to the current position for $l = 3$. Once again, if the path taken exceeds the boundary conditions of the mine gallery, this path is automatically excluded from being listed as a possible fingerprint. The positions involved in forming the

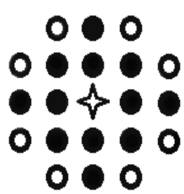

Fig. 6. Possibilities of previous positions for $l = 3$.

path are highlighted in Fig. 6, while the maximum number of fingerprints ($N_f$) extracted for the miner's position at level $l$ may be calculated using the following formula:

$$N_f = 5^{(l-1)}.$$

All possible fingerprints are gathered for all positions in the tunnel after specifying a certain level $l$; then the signatures and paths are saved in a database.

### *B. ANN structure with time-domain diversity using tracking*

The ANN used here is the same feed forward neural network with back propagation learning used in sec. II. The purpose of this choice is to properly compare the results of tracking with the original localization system in [3] and its first extension to spatial diversity (i.e., cooperation) in [4]. Here, the ANN is scalable up to the number of input levels to be used. Since we extract 7 parameters from each CIR signature, adding more signatures in time increases the number of inputs ($N_{inputs}$) of the neural network such that:

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

The memory level $l$ under study specifies the structure of the neural network used in the positioning system. For $l = 2$, the structure of the ANN is the same as in Fig. 4. On the other hand, the number of neurons ($N_n$) used in the hidden layer is based on the number of inputs of the neural network:

$$N_n = 2N_{inputs} + 1 = 14l + 1.$$

The output layer contains one neuron which represents the distance in meters to the receiver at time $t_0$. The combinatorial number of possible paths increases the combinatorial number of possible chains of CIRs from which the possible fingerprints or input parameters are extracted without necessarily requiring any increase in the number of CIR measurements. As a matter of fact, while keeping the size of measurement data unchanged, the combinatorial exponential increase in the size of the training data (from where stems temporal diversity) overwhelmingly surpasses the linear increase in the number of neurons required to match the corresponding increase in the so-called memory level $l$. Throughout the training process, 75% of the collected data are classified to train the neural network while 25% are left in order to test the performance of the neural network with data not seen in the training process. Localization using tracking is analyzed up to level 5 (i.e., using as a fingerprint 35 input parameters extracted from 5 CIRs).

## IV. EVALUATION RESULTS

The performance of the presented localization techniques is evaluated using the Cumulative Distribution Function (CDF) graph. In CDF graphs, the accuracy of the system is compared to its precision. The $x$-axis of the CDF is the estimation error which represents the difference between the estimated and the real position measured in meters. The second parameter is the precision or the percentage of occurrences for such an estimation error in the collected data.

### *A. Results of cooperative localization in the spatial domain*

For the spatial localization approaches, each graph in Fig. 7 or 8 shows four CDF plots that correspond to the position estimation errors of the different techniques used in sec. II. The first two CDF plots represent the position errors caused by the separate estimations (i.e., cf. sec. II-A) of the first and second receivers, respectively. The third plot represents the result of cooperative localization based on separate estimations (i.e., averaging both estimation errors, cf. sec. II-B). The fourth CDF plot represents the position estimation error of the cooperative neural network technique using one neural network (cf. sec. II-B). At a separation distance ($D$) of 80 m, the CDF plots of the training and non-training data are shown in Figs. 7 and 8, respectively. Other plots for different

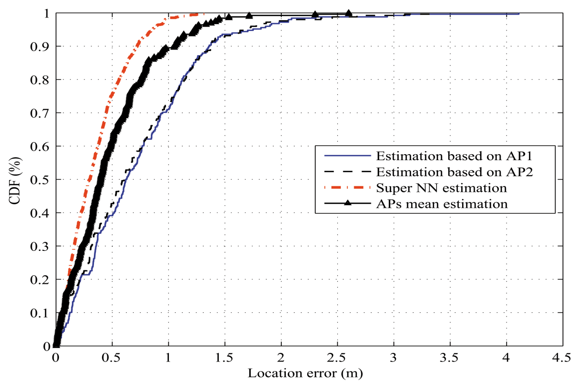


Fig. 7. CDF plots of the position estimation errors for the training data at a receivers' separation distance $D = 80$ m using several localization techniques.

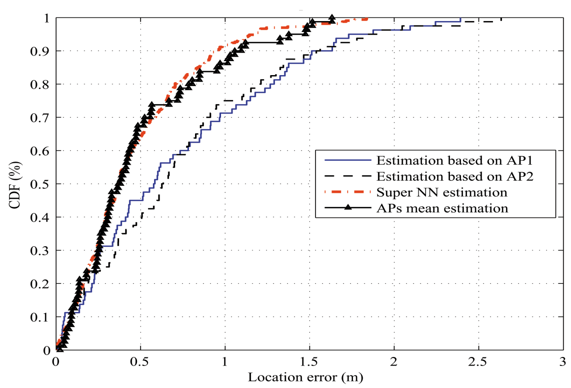


Fig. 8. CDF plots of the position estimation errors for the testing data at a receivers' separation distance $D = 80$ m using several localization techniques.

separation distances ($D$) are presented in [4]. The accuracy of position estimation using one of the receivers is found to be around 1.2 and 1.5 m for 90% of the training data at different separation distances ($D$). In the non-training set of data, the error varied between 1m and 2 m for 90% of the cases. The accuracy of the cooperative localization method based on averaging the two position errors was recorded to be around 1m and 1.5 m for 90% of the training and testing data, respectively. For the cooperative localization method using one neural network, the position estimation error was recorded to be less than 60 cm and 1m for the training and testing data, respectively.

### B. Results of localization using tracking in the time domain

The CDF plot is used again in order to show the results of localization using tracking at different memory levels. The input level $l$ is the number of signatures a neural network accepts including the fingerprint extracted from the CIR at time $t_0$. They are shown for the training and testing data in Figs. 9 and 10, respectively. For level two, localization

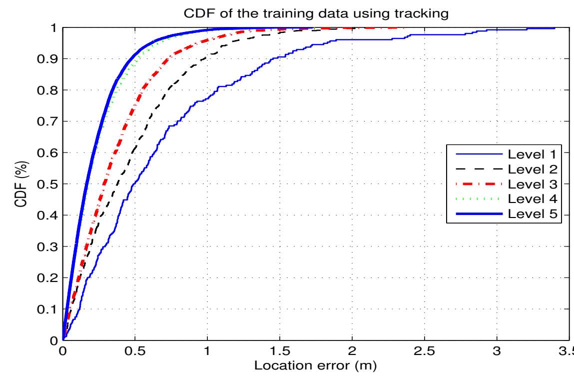


Fig. 9. CDF plots for the training data using tracking.

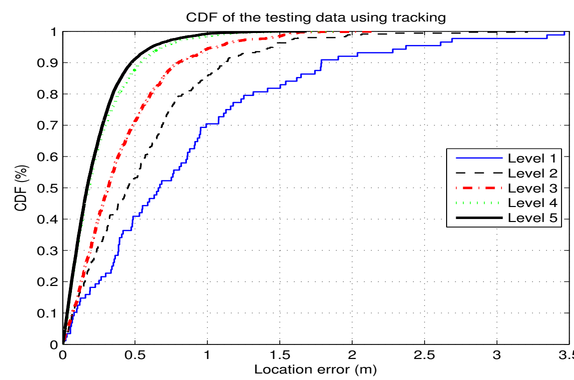


Fig. 10. CDF plots for the testing data using tracking.

using tracking with only one previous CIR shows an estimation error of 1 and 1.25 meters for 90% of training and testing data, respectively. As the input level increases, more paths get involved in the estimation of the current positions. As $l$ increases, the accuracy and precision of the neural network are enhanced forming a better estimation model of the motion principle and the variation of the CIR with respect to distance. At level three, estimation errors of 0.75 and 0.8 meters were recorded for 90% of training and testing samples, respectively. The performance was again improved when adding another previous position to the modeling process, and at level four, the estimation error decreased to 50 cm for 90% of training and testing data. An error of little less than 50 cm was reported at level five clearly suggesting saturation in performance at level 4 beyond which no significant gain is observed. At this level, the input of the neural network is five times larger in size than that of a neural network using one CIR and the number of neurons in the hidden layer is 71.

Both cooperative and tracking localization techniques provide high accuracy of position estimation with high precision. The limitation in space, however, prevents us from decreasing the position estimation errors with more than two APs in a narrow-vein mine tunnel given its quasi-curvilinear topology. On the other hand, due to the flexible scalability of localization using tracking, more inputs are introduced to the neural network resulting in better localization accuracy. At $D = 80$ m, it appears that using cooperative localization has almost the same estimation errors as that of localization using tracking when $l = 3$ and $l = 2$ for the training and testing data, respectively.

## V. System Design: Complexity vs. Accuracy

The accuracy of the proposed techniques is high compared to simple localization techniques because it uses the CIR as a fingerprint. The major challenge that faces this approach is to extract the CIR at the receivers' end. Being part of a wireless network, each receiver would be capable of transmitting the extracted CIRs to a main server that should handle the process of training the neural network using the separate or cooperative techniques discussed in sections II and III. The transmitting unit is supposed to be, in our case, a mini transmitter on the miner's cap. Since such system works using the fingerprinting technique, collecting multiple fingerprints in different parts of the tunnels is another essential step that builds up the database. Instead of taking measurements manually, collecting the fingerprints in real-time scenarios is easier once the infrastructure is ready i.e. the miners are automatically transmitting signals and the CIRs are collected at a computer server from the receivers.

Since the channel is dynamic, classifying the neural networks based on receivers' locations and the time of day would be an interesting feature that may lead to better estimation results. The variation of the channel due to human activity may also be adjusted by implementing some fixed transmitters along the galleries for calibration purposes.

Considering a system that uses tracking alone does not create a global localization system in underground mines because it uses one localizing unit as in [3]. The question arises as to whether we are capable of integrating the tracking system in a cooperative neural network technique where two references in space localize using the tracking algorithm and then a final estimation is drawn using one of the two cooperative neural network topologies discussed in sec. II. An ongoing study investigates whether integrating the tracking technique at a given memory level $l$ in a cooperative spatial localizing system (i.e., diversity both in space and time) would lead to higher performances that could match those of tracking alone with higher memory levels $l$ (i.e., only time diversity).

## VI. Conclusion

This article presented a new localization approach that exploits time diversity for radio-localization in tunnel-shaped underground narrow-vein mines. With an in-built tracking algorithm, this technique uses ANNs to localize a transmitter based on fingerprints extracted from chains of CIRs recorded in time. The proposed system is able to estimate the position of a wireless transmitter in narrow tunnels with high accuracy and precision of 50 cm for 90% of both training and testing data. Compared to cooperative localization in the spatial domain, geo-location using tracking is more accurate and precise with much more flexible scalability. The question of whether this system may be integrated in a cooperative localization technique that exploits spatial diversity is currently under investigation. Although this work was conducted for an underground environment such as mines, localization using tracking may be used in different indoor/outdoor environments. The proposed system may also use different wireless technologies such as UWB, WLAN, or mobile radio.

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