Cooperative Geo-location in Underground Mines: A Novel Fingerprint Positioning Technique Exploiting Spatio-Temporal Diversity

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***Abstract*—Underground narrow-vein mines result in complex indoor scenarios which require sophisticated localization techniques to maintain basic security measures. While some traditional localization systems use the triangulation techniques for outdoor channels, fingerprint positioning techniques are mostly used in more complex indoor environments like mines. One of the techniques exploited in the quasi-curvilinear topology of underground mines is the Channel Impulse Response (CIR) based fingerprint positioning combined with Artificial Neural Networks (ANNs). This article innovates a CIR-based positioning technique within a cooperative memory-assisted approach that exploits both the temporal (from different time instances) and spatial (from different space positions) diversities of the collected fingerprints. Introducing memory-type signatures in a cooperative localization technique within the spatial confinements of the tunnel-shaped narrow-vein mines significantly increases the accuracy, precision and robustness of the localization system. The cooperative memory-assisted technique is capable of localizing a transmitter with an accuracy of less than 25 cm 90% of the time.**

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

I. Introduction

Chile August 2010, the mine collapsed and many miners were trapped. It took the rescue team 69 days to find the first miner, and 10 weeks to rescue the rest [1]. Localizing miners/equipments in underground and confined areas is not a feature added for luxury, but an essential basis for the well-known principle of the mining industry, "Safety First". However, the special nature of narrow-vein mines' topology which is made of interconnected tunnels challenges any localization system expected to precisely estimate the location of miners underground. Like most wireless localization systems, the distance to the transmitter is estimated based on the received signals' characteristics after being affected by the channel. In underground narrow-vein mines, wireless signals propagate within humid rough surfaces and non-line of sight (NLOS) branching tunnels forming complex multipath components. The received signals' components such as the Received Signal's Strength (RSS), Angle of Arrival (AOA), Time of Arrival (TOA) and Time Difference of Arrival (TDOA) are altered once multipath reception takes place. And since most traditional localization systems use one or more of the mentioned parameters (i.e., RSS, AOA, etc ...) to localize [8] [9] [10] [11] [12], they fail once deployed in underground narrow-vein mines. Another challenge present in narrow-vein mines is the spatial confinement of the interconnected quasi-curvilinear tunnels which prevents a 2D-meshed deployment of localizing units or access points (APs) to further increase the accuracy and precision of underground geo-location.

A search for an alternative led to the innovation of a localization technique that uses artificial neural networks (ANNs) and fingerprints collected from the channel's impulse responses (CIRs) [2]. The system accurately estimates the distance to a transmitter using one receiver only (i.e., solitary localization) with an estimation error of less than 2 meters for 90% of the collected measurements. Since wireless coverage requires more than one AP in the confinement of narrow-vein mines, the use of another localizing unit introduces geolocation as a cooperative technique that exploits the spatial diversity of the collected fingerprints. The cooperative memoryless localization technique using two receivers later proposed in [3] reduces the location error to less than 1m for 90% of the data making use of two spatially distinct fingerprints to better estimate the user's location. It also introduces two ANN structures that exploit these two fingerprints separately or jointly to better estimate cooperatively the position of the miner in underground narrow-vein mines.

The spatial confinement of the tunnel-shaped topology of narrow-vein mines facilitates the prediction of the patterns of motion. In other words, training ANNs on different motion patterns collected at short time instances enriches the set of fingerprints corresponding to the transmitter's positions. In some localization techniques [15] [16] [17], tracking is a process that follows estimating the position of the users (i.e., post-

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processing the results). Few are the techniques that implement a prioiri tracking within an ANN-based localization system. Enhancing the accuracy within this spatial confinement is possible once the system exploits the temporal diversity of the collected fingerprints over short periods of time, a concept proven more recently to be right and promising in [4]. Using one localizing unit, the technique in [4] takes advantage of the limited motion patterns (i.e., spatial confinement) to create a rich database used for fingerprint positioning. The memory-assisted system in [4] targets position accuracies of less than 40 cm for 90% of the collected fingerprints. Yet, the localization system in [4] which exploits the temporal diversity of the collected fingerprints uses one localization unit only, which means that it can be further enhanced once introduced in a cooperative memory-assisted technique that exploits both the spatial and temporal diversities of the signatures.

This article introduces a cooperative memory-assisted localization technique that exploits both the spatial and temporal diversities of the assembled signatures. The power of a spatio-temporal fingerprint is in its ability to project the signal on two spatially separated receivers with an additional projection in time (i.e., by introducing memory). ANNs are trained to localize all different scenarios of motion in a cooperative localization technique that takes into account the signatures of two APs. The next section highlights different CIR-based fingerprint positioning techniques that use ANNs to localize. The cooperative memoryless (i.e., exploiting the spatial diversity only) [3] and the memory-assisted (i.e., using the temporal diversity only) [4] localization techniques are briefly summarized. In section 3, the cooperative memory-assisted localization technique that exploits both the spatial and temporal diversities is introduced. Simulation results are reported and discussed in section 4. Conclusions are drawn out in section 5.

II. Localization in mines using CIR-based fingerprinting and ANNs

The fingerprinting or scene analysis technique is used in scenarios where the channels cannot be easily modeled due to the severe distortion that signals encounter on their way to the receiver. Fingerprint positioning is based on extracting some of the parameters of the received signals (i.e., RSSs, AOAs, etc ...) at different distances and saving them in a database. Different matching algorithms such as probabilistic methods, k-nearest neighbour (kNN), support vector machine (SVM) or ANNs are then used in real-time scenarios to localize [6] [7]. These algorithms try to match the collected fingerprint to the saved measurements in order to estimate the distance to the transmitter. In underground narrow-vein mines, localization based on RSS, AOA, or TDOA is neither accurate nor precise [2] [5] [3]. Increasing the accuracy of position estimation in confined areas requires deploying more APs to overcome the multipath components and the signals' fluctuation effects. Another approach to accurate positioning innovated in [2] uses seven parameters extracted from the CIR of the received signal to form a fingerprint. The 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). A fingerprint is denoted by $f = (\bar{\tau}, \tau_{rms}, \tau_{max}, P, N, P_1, \tau_1)$ and it corresponds to a distance d. Due to the narrow quasi-curvilinear topology of underground tunnels and for simplicity, the distance to the transmitter d is taken along the x-axis only neglecting the small variation along the tunnels' confined width (i.e., y-axis). It is also a way to ensure that the localization system takes into account the fluctuations of wireless signals for the same position (i.e. more than one fingerprint f may represent the same separation distance d). A measurement campaign at a carrier frequency of 2.4 GHz was carried out in CANMET mine in Val d'Or Canada where the fingerprints were extracted along with their corresponding distances for 480 positions as illustrated in Fig. 1. It should be noted that the distance between the consecutive measurement points along the x-axis is one meter. Mapping the set of

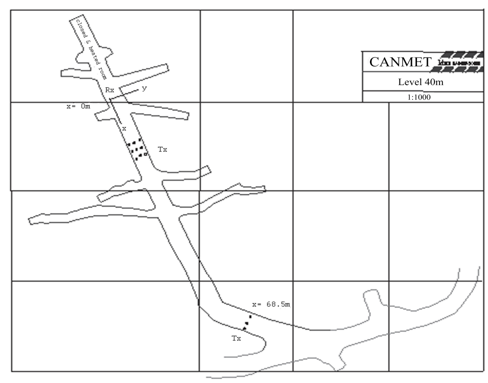

Fig. 1. Map of the underground tunnels.

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 successfully achieved using ANNs. The measurements conducted in [2] for the stationary positions along the tunnel as shown in Fig. 1 are used to simulate memory-type fingerprints. For more technical information about the experimental setup, please refer to [2].

ANNs are defined as computational models capable of approximating a function. They are capable of performing non linear regressions which make them suitable for localization in harsh environments [2] [13] [14]. The power of ANNs is that they are relatively simpler than traditional estimation techniques such as Kalman filters especially when modeling a non-linear function which is, in our case, of order 7 (i.e., seven parameters as inputs). An MLP feed-forward ANN with a back-propagation learning algorithm is proven effective for underground geo-positioning [2] [5] [3] [4]. During the learning phase, the neural network is given the training data that corresponds to 75% of the collected measurements. Then, in the testing phase, ANNs are tested using 25% of the fingerprints which are not seen in the training phase.

The solitary memoryless localization system used in [2] estimates the distance to the transmitter instantaneously based on fingerprints extracted from the CIR of the received wireless signals. As shown in Fig. 2, this technique accurately

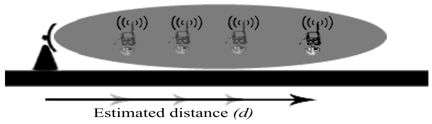

Fig. 2. Solitary localization using one receiver.

localizes based on the input of one localizing unit (i.e., one receiver or AP). A simple neural network with 7 input neurons, one hidden layer provides the transmitter's distance with an approximate accuracy of less than 2 m for 90% and 80% of the training and testing data, respectively.

A. Cooperative Memoryless Localization using Spatial Diversity

A global localization system requires the participation of multiple APs in estimating the transmitter's location within the quasi-curvilinear topology of underground narrow-vein mines. However, only the two nearest APs found at either end of any given section of a mine tunnel are needed to guarantee its wireless coverage. The cooperative memoryless localization system in [3] exploits spatial diversity taking advantage of the implemented APs to collect different fingerprints. As shown

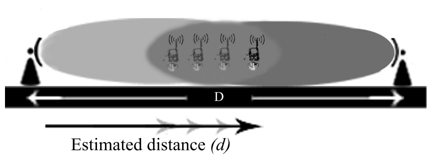

Fig. 3. Cooperative localization using two receivers.

in Fig. 3, the use of two APs within the spatial confinement of the tunnels not only enhances the accuracy of the estimated distance, but also provides correct positioning inside the quasi-curvilinear interconnected tunnels. In the cooperative approach, the sets of fingerprints $S^{R_1} = \{f_1, f_2, f_3, ..., f_m\}$ and $S^{R_2} = \{f'_1, f'_2, f'_3, ..., f'_m\}$ are collected from receivers R_1 and R_2, respectively. Two different ANN architectures are presented in [3] and both accurately estimate the position of the transmitter. One of the ANN designs is shown in Fig. 4 where the set of fingerprints $S = \{F_1, F_2, F_3, ..., F_m\} = \{(f_1, f'_1), (f_2, f'_2), (f_3, f'_3), ..., (f_m, f'_m)\}$ is the concatenation of both observations, S^{R_1} and S^{R_2}. The output of the ANN is the estimated distance to one of the transmitters $D = \{d_1, d_2, d_3, ..., d_m\}$. The exploitation of the spatial diversity of the collected fingerprints introduced a cooperative version of the CIR-based fingerprint positioning technique in [2] for underground geolocation and hence significantly increased its accuracy, precision and reliability.

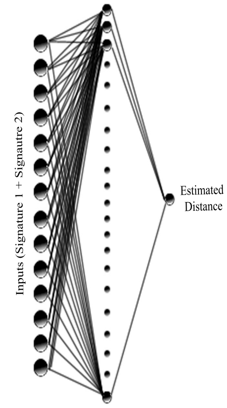

Fig. 4. Neural network based on multiple signatures.

B. Solitary Memory-Assisted Localization using Temporal Diversity

The accuracy of the cooperative memoryless technique discussed in Sec. II-A may only be enhanced by increasing the number of APs which is not practical given the spatial confinement of narrow-shaped tunnels. However, the narrow curvilinear topology is an advantage because it facilitates the prediction of the user's motion patterns. The memory-assisted localization technique in [4] utilizes the narrow-shaped topology to introduce an in-built tracking model that exploits the temporal diversity of the recorded fingerprints. The path fingerprint $f_i^j = \left(f_{i_{t_0}}, f_{i_{t_{-1}}}, f_{i_{t_{-2}}} ..., f_{i_{t_{-(l-1)}}}\right)$ represents a concatenation of the fingerprints recorded in time while moving towards a destination to be estimated (i.e., at a distance d_i). More than one path can lead to the same position to be estimated, i.e., more than one path fingerprint f_i^j correspond to the same distance d_i. While l represents the number of concatenated fingerprints or the so called memory level in [4], j is simply an index number that counts the number of possible tracks to a desired destination at a given memory level l. The terms memory level l and time depth are used interchangeably in the article and they represent the number of concatenated memory-type sub-fingerprints that constitute the temporal fingerprint for a given position at distance d_i away from R_1. The maximum number of path fingerprints j_{max} for a given position is limited by the upper bound N_{f_p}:

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

Since each fingerprint contains 7 parameters, the length of the temporal fingerprint defines the number of inputs of the ANN and it is given by:

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

The design of the ANN depends on l because the number of neurons in the input layer is equal to the length of the path fingerprint N_{inputs}. The number of neurons in the hidden layer is $N_n = 2N_{inputs} + 1$ for all architectures and the output is the distance to the transmitter. Figure 5 illustrates a simple fingerprint allocation for one position when $l = 2$.

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

The star represents the current position of a transmitter located at a distance d_i to be localized showing the previous possible positions [1]. While respecting the spatial boundary limits of the tunnels, any previous position is selected to create the potential path fingerprints. The length of the combinatorial set of fingerprints for the same position is dependent on l and the geometry of the narrow tunnels. In this example, the combinatorial subset of possible fingerprints collected from a transmitter located at d_i (i.e., star position) within the total set $S = \{S_1, \ldots, S_i, \ldots, S_m\}$ over all distances D is:

$$S_i = \left\{F_i^1, F_i^2, F_i^3, F_i^4, F_i^5\right\}.$$

where,

$$\begin{aligned} F_i^1 &= (f_i, f_i), \\ F_i^2 &= (f_i, f_{i_{north}}), \\ F_i^3 &= (f_i, f_{i_{south}}), \\ F_i^4 &= (f_i, f_{i_{west}}), \\ F_i^5 &= (f_i, f_{i_{east}}). \end{aligned}$$

are all the possible path fingerprints reaching the star position when $l = 2$. The exponential increase in the number of fingerprints N_{f_p} due to the linear increase of temporal memorization level l overwhelmingly enriches the information given to ANNs about each position inside the tunnels from the same original set of data measurements.

Speed plays a significant role in defining the sampling time interval that precedes the collection of the memory-type fingerprints. In order to allow the same trained ANN to accurately localize a transmitter regardless of its limited speed in the confinement of narrow-vein mines, the sampling time at which the sub-fingerprints are collected should be adjusted accordingly. In other words, sampling time is set to allow the extraction of sub-fingerprints measured at any two positions (separated by the distance covered by the transmitter in motion at a velocity below or equal to a given maximum speed) that is shorter than the grid resolution times the memory level or time depth.

Introducing temporal diversity and in-built tracking to the CIR-based fingerprinting technique in [4] outperforms the localization system in [3] in terms of accuracy, precision and scalability within the narrow quasi-curvilinear topology of mine tunnels. However, solitary localization using temporal diversity alone does not benefit from the possible cooperation between multiple localizing units (having each an overlapping radio footprint with their two nearest adjacent neighbors) required anyway for proper coverage of the whole mine galleries and, additionally, it cannot resolve the location ambiguity arising from the presence of tunnel junctions. On the other hand, as shown in the following, the collaboration of memory-assisted localizing units (i.e., spatio-temporal diversity) with lower memory levels allows significant reduction of the complexity encountered when using solitary memory-assisted localization performing at higher time depths while offering better accuracy.

[1]Motion across the diagonals is excluded because it exponentially increases the combinatorial set of path fingerprints without a significant gain.

III. Cooperative Memory-Assisted Localization Exploiting Spatio-Temporal Diversities

Based on a combination of the two previous solutions, an even more intelligent localizing system integrates the in-built tracking technique at a given memory level l in a cooperative spatial localizing system (i.e., spatio-temporal diversity). This leads to higher performances that could match those of memory-assisted localization alone at higher memory levels l (i.e., only time diversity). Mixing both spatial and temporal diversities is a technique that further enriches the information given to ANNs resulting in a better mapping of the limited motion patterns in narrow quasi-curvilinear tunnels.

This work innovates a localization system that uses the memory capability (i.e., in-built tracking) cooperatively between two spatially-separated localizing units before estimating the position of the transmitter. Within the spatial confinement of the tunnels and over short periods of time, the signatures recorded at consecutive time instances and collected from two spatially-separated receivers guarantee less-fluctuating spatio-temporal fingerprints. Unlike the system introduced in [4] which exploits the temporal diversity of a solitary receiver, this approach creates chains of path fingerprints from two nodes before training the ANNs. The scalability of the system allows the ANNs to be trained to localize at different separation distances D and memory levels l. The subset of path fingerprints $S_i^{R_1} = \left\{F_i^{R_1,1}, F_i^{R_1,2}, F_i^{R_1,3}, ..., F_i^{R_1,j_{max}}\right\}$ collected from R_1 at a distance d_i is properly combined path-wise with the other subset $S_i^{R_2} = \left\{F_i^{R_2,1}, F_i^{R_2,2}, F_i^{R_2,3}, ..., F_i^{R_2,j_{max}}\right\}$ gathered from R_2 at a distance $d_2 = D - d_1$ to form the spatio-temporal group of path fingerprints:

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

As discussed earlier in Sec. II-B, the length of the temporal fingerprint is dependent on the memory level l of the solitary receiver where localization is taking place. If we consider two spatially separated APs each collecting fingerprints at different time depths, we may create different scenarios denoted by (l_1, l_2) corresponding to receivers (R_1, R_2) respectively. For example, localizing a transmitter at a distance d_i and time instant t_0 with memory levels ($l_1 = 2, l_2 = 1$) is achieved by matching the measured spatio-temporal fingerprint $F_i =$

$(F_i^{R_1}, F_i^{R_2})$ where

$$F_i^{R_1} = (f_{i_{t_0}}^{R_1}, f_{i_{t_{-1}}}^{R_1}),$$

$$F_i^{R_2} = (f_{i_{t_0}}^{R_2}).$$

For $(l_1 = 2, l_2 = 1)$, R_2 provides a fingerprint $F_i^{R_2}$ of length 7 (i.e., memoryless fingerprint) while the fingerprint $F_i^{R_1}$ collected from receiver R_1 is the concatenation of two fingerprints recorded at the time instances t_0 and t_{-1} (i.e., memory-assisted fingerprint of length 14). Concatenating two fingerprints from two spatially separated receivers where at least one is introducing memory creates a spatio-temporal fingerprint for a given position. The length of the spatio-temporal fingerprint defines again the number of inputs N_{inputs} of the ANN and it is dependent on both l_1 and l_2 where:

$$N_{inputs} = 7(l_1 + l_2).$$

IV. Performance Results

The results of the localization techniques are presented using the Cumulative Density Function (CDF). CDF plots show the accuracy of the positioning technique (i.e., position error in meters) for a given percentage of the treated data. As mentioned earlier and shown in the following graphs, 75% of the collected fingerprints are trained by the ANN whereas 25% are left for testing the generalization of the ANN of any technique. These results are plotted in Figs. 6 and 7 and summarized in Tab. I.

The performance results of the spatio-temporal fingerprint positioning technique are compared to the localization technique that uses either spatial or temporal diversity alone. The memory levels of receivers R_1 and R_2 are denoted by l_1 and l_2, respectively. If one of the receivers is not participating in the localization process (i.e., solitary localization), its memory level is presented as $l = 0$. On the other hand, memoryless localizing units use one fingerprint to localize (i.e, $l = 1$) without the need of fingerprint concatenation. When the memory level is set to $l > 1$, the localizing unit would be concatenating fingerprints in short time instances before feeding them to the ANN. The notation (l_1, l_2) shows the different memory levels at which both receivers are performing their fingerprint allocation. Both observations from R_1 and R_2 are concatenated again and fed to a cooperative ANN that estimates the position of the transmitter.

Merging the temporal path fingerprints of two spatially different receivers and feeding them as one concatenated spatio-temporal fingerprint to one ANN is a breakthrough in the fingerprint positioning techniques (i.e., cooperative memory-assisted technique). The results of spatio-temporal localization are compared to the techniques discussed in II and presented in Figs. 6 and 7 for the training and testing data, respectively. These results clearly show the increased accuracy of spatial and temporal combination in the CIR-based localization approach.

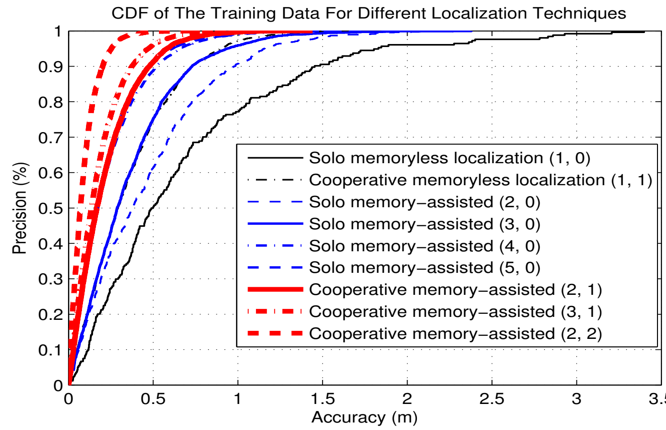

Fig. 6. CDF of the training data for different localization techniques at memory levels (l_1,l_2).

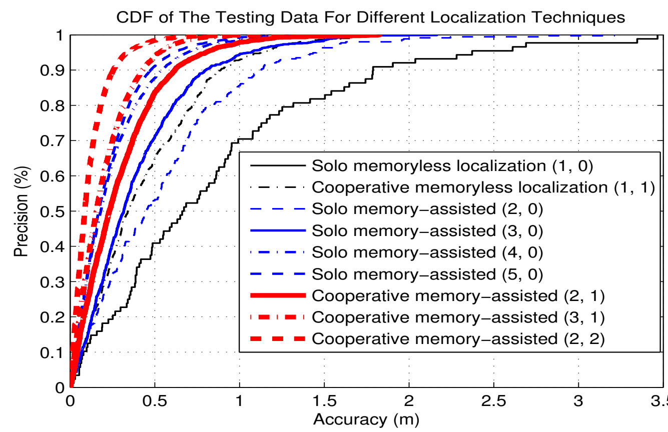

Fig. 7. CDF of the testing data for different localization techniques at memory levels (l_1,l_2).

Cooperative memory-assisted localization is a result of the collaboration of the receivers when at least one of them is introducing memory (i.e., producing path fingerprints). In the first cooperative memory-assisted approach, R_2 is kept at a memory level $l_2 = 1$ (i.e., without memory) while R_1's memory level varies (i.e., $l_2 = 2, 3$). In memory-assisted techniques, it is noticed that the cooperative approach that adds spatial diversity to the fingerprints performs better than the solitary technique even when the length of the fingerprints is the same. For example, solo memory-assisted localization at $(l_1 = 3,\ l_2 = 0)$ is less accurate than cooperative memory-assisted localization at $(l_1 = 2,\ l_2 = 1)$ even though both path fingerprints are of length 21. In addition to that, when $(l_1 = 3,\ l_2 = 1)$, merging spatial and temporal information further increases the location accuracy to values less than 40 cm surpassing the upper limit of solitary memory-assisted localization when $(l_1 = 5,\ l_2 = 0)$.

In the second cooperative memory-assisted approach, both receivers use in-built tracking or memory to form their fingerprints. Surprisingly, a one step increase in the memory level of R_2 creates uniform spatio-temporal fingerprints where two references in time are taken from two receivers in space. As shown in Figs. 6 and 7, location accuracy of the last curve drops to 20 cm and 25 cm for 90% of the training and testing data, respectively. It may be seen that the accuracy of a 2-by-2 spatio-temporal localization system [i.e., ($l_1 = 2$, $l_2 = 2$)] is double the accuracy of a 1-by-1 cooperative spatial system [i.e., ($l_1 = 1$, $l_2 = 1$)].

TABLE I
ESTIMATION ERRORS OF DIFFERENT LOCALIZATION TECHNIQUES

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

As shown by the results above, cooperative memory-assisted localization outperforms other memoryless/memory-assisted localization techniques even at lower memory levels or time depths. An optimum solution would uniformly exploit spatial-temporal (i.e., $l_1 = l_2 > 1$) to overcome the spatial confinement of the environment and significantly utilize the limited motion patterns inside the quasi-curvilinear tunnels. The spatio-temporal localization technique localizes with high accuracy, precision and scalability.

V. CONCLUSION

This article investigated the CIR-based localization techniques and innovated the spatio-temporal fingerprint positioning technique that uses ANNs. The concept of localization using the spatio-temporal diversity in underground narrow-vein mines is satisfied when fingerprints are recorded at short time periods and collected from two spatially separated receivers. This cooperative memory-assisted localization system (i.e., 2-by-2) is able to attain higher accuracies at lower memory levels using ANNs. The estimation error is reduced to 20 cm and 25 cm for 90% of the training and testing fingerprints, respectively. The proposed system is feasible given that its complexity is still affordable, and that it could be integrated into different wireless technologies.

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